

Article

Efficiency and Productivity Performance of Selected ASEAN Manufacturing Industries

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Abstract

Manufacturing productivity in ASEAN has become increasingly important as the region joins global value chains and recovers from COVID-19 disruptions. However, it remains uncertain whether output growth results from true productivity improvements or from changes in factor utilization. This study analyses the efficiency and productivity trends in six ASEAN countries, namely Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam, from 2000 to 2022. It employs an input-oriented Data Envelopment Analysis (DEA) under both constant and variable returns to scale to assess technical, pure technical, and scale efficiency, while the Malmquist Productivity Index (MPI) decomposes total factor productivity into efficiency and technological change. Results show significant variation among countries and over time. Singapore and Malaysia consistently stay near the regional production frontier, whereas Indonesia, Thailand, and Vietnam lag in efficiency despite strong output and investment growth. Productivity shifts mainly stem from technological advances rather than efficiency gains, especially slowing during the pandemic. Scale inefficiency remains a key performance issue, particularly for Indonesia and Singapore, worsening after 2020. These insights indicate that ASEAN manufacturing competitiveness hinges not only on capital investment but also on converting inputs into productivity improvements. This study offers a comparative analysis of ASEAN manufacturing efficiency and productivity performance.

Keywords: data envelopment analysis; Malmquist Productivity Index; technical efficiency; total factor productivity; ASEAN manufacturing; productivity growth

1. Introduction

Manufacturing has long been central to ASEAN's development, supporting export growth, employment, and technological upgrading [1,2]. It remains the main channel for participation in global value chains and FDI, especially in electronics, machinery, and transport [3–5]. As networks restructure due to geopolitical tensions and COVID-19, manufacturing performance is vital for long-term growth and competitiveness [1,6–8]. Despite strong manufacturing growth since the early 2000s, it is unclear whether this reflects real productivity gains or just greater use of labour and capital. Differentiating these sources is crucial for policy. Growth from factor accumulation may be unsustainable, while productivity growth from efficiency and tech advances likely leads to lasting income gains [9–11]. This is especially relevant after COVID-19 disrupted networks and revealed weaknesses in emerging Asia's industrial systems [12,13].

A growing body of recent empirical research highlights that productivity growth in manufacturing sectors is often driven more by technological progress than by improve-



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ments in efficiency. For instance, Amodia et al. (2023) [14] found that in developing economies, technological change plays a dominant role in total factor productivity (TFP) growth, while efficiency improvements remain limited due to structural rigidities and institutional constraints. Similarly, Asian Productivity Organization (2024) [15] reports that productivity gains across Asia are uneven, with advanced economies benefiting from innovation and digitalization, while developing economies struggle with efficiency gaps despite increased capital accumulation.

More recent methodological advancements also contribute to the frontier analysis literature. Emrouznejad and Yang (2018) [16] provide a comprehensive review of DEA developments, emphasizing its flexibility in multi-country analyses where production technologies differ significantly. In addition, studies such as Fauzel (2025) [17] show that in late-developing economies, efficiency improvements tend to occur during specific phases of industrialization, particularly when institutional reforms and technological diffusion mechanisms are strengthened.

The current research on manufacturing productivity in ASEAN offers valuable insights but also has notable limitations. Studies employing Data Envelopment Analysis (DEA), stochastic frontier analysis, and growth accounting typically reveal modest productivity growth and significant differences across countries [15,18,19]. Evidence from specific countries shows that Singapore and Malaysia are generally closer to the technological frontier, whereas Indonesia, Thailand, and Vietnam often experience ongoing efficiency gaps [20–22]. Nonetheless, much of this research relies on short timeframes, examines only individual countries, or reports overall productivity without breaking it down into efficiency and technological changes. Consequently, it remains unclear whether ASEAN manufacturing productivity improvements are mainly due to catch-up effects or changes in the frontier itself [23,24].

Comparative long-term studies of ASEAN manufacturing productivity are still limited. Since the early 2000s, the region has undergone significant structural changes, such as deeper regional integration, greater involvement in global value chains, and rapid industrialization in latecomer economies like Vietnam [25]. These developments suggest that productivity trends may vary systematically across countries and over time [26,27]. Therefore, a multi-country framework that breaks down productivity changes into core components is essential to identify the main causes of performance gaps and to guide targeted policy measures [16,24].

This study examines the manufacturing sectors in terms of efficiency and productivity for Singapore, Malaysia, Vietnam, Indonesia, Thailand, and the Philippines, during 2000–2022. It employs an input-oriented DEA approach with both constant returns to scale (CRS) and variable returns to scale (VRS) to estimate technical efficiency, pure technical efficiency, and scale efficiency for each country-year. Productivity changes are assessed using the Malmquist Productivity Index (MPI), which breaks down total factor productivity growth into efficiency improvements (catch-up) and technological progress (frontier shift) [23,24,28].

This study has three main contributions. It provides a long-term comparative assessment of manufacturing efficiency and productivity in major ASEAN economies over more than two decades, including pre- and post-COVID-19 periods. By decomposing productivity into efficiency and technological change, it clarifies whether gains are due to better resource use or technological progress. Additionally, it emphasizes the importance of scale efficiency, revealing if countries operate at the optimal production scale compared to the regional frontier [4,29]. The rest of the paper is structured as follows. Section 2 provides the insight and literature in terms of theory and empirical evidence on production efficiency and productivity measurement. Following that, the subsequent section details the data

and explains the DEA and Malmquist index methods. This is followed by a discussion of the empirical results. Section 5 offers policy implications for efficiency and productivity growth in ASEAN manufacturing.

2. Materials and Methods

2.1. Literature Review

In production theory, outputs are created through transforming inputs like labour and capital with a specific technology. Productivity indicates the level of effectiveness of these inputs in turning into outputs, while technical efficiency measures a production unit's capacity to produce the maximum possible output from a given set of inputs [30,31]. Growth in total factor productivity (TFP) can stem from two main sources: efficiency improvements, which indicate progress toward the current production frontier, and technological advances, which cause the frontier itself to expand outward [10].

2.1.1. Production Function

A general production function specifies the maximum output attainable from given inputs under a particular technology. Let $x = (x_1, \dots, x_n)$ denote inputs (e.g., capital K , labour L , materials M), and let the output be Y . A technology is summarized by

$$Y = F(x_1, \dots, x_n),$$

with standard regularity: monotonicity $\partial F / \partial x_i \geq 0$ (more input does not reduce output) and diminishing marginal products $\partial^2 F / \partial x_i^2 \leq 0$. Quasi-concavity of F implies convex isoquants and well-behaved cost minimization [30,32]. The marginal product of input i is

$$MP_i(x) = \frac{\partial F(x)}{\partial x_i},$$

and the marginal rate of technical substitution (MRTS) between inputs i and j along an isoquant is

$$MRTS_{ij} = - \frac{dx_j}{dx_i} \Big|_Y = \frac{MP_i}{MP_j}.$$

Returns to scale are defined by homogeneity. If $F(\lambda x) = \lambda^r F(x)$ for all $\lambda > 0$, the technology has a degree r : constant ($r = 1$), increasing ($r > 1$), or decreasing ($r < 1$) returns to scale. For homogeneous F , Euler's theorem yields

$$\sum_{i=1}^n MP_i(x) x_i = r F(x).$$

Under constant returns to scale (CRS, $r = 1$) and competitive factor markets, input cost shares equal output elasticities, a workhorse result used in growth accounting [10,32].

A central question is how easily inputs can substitute for one another. For two inputs, the (Hicks) elasticity of substitution is

$$\sigma = \frac{d \ln(x_j/x_i)}{d \ln MRTS_{ij}} \Big|_Y,$$

which is constant and equal to one in the Cobb–Douglas case but flexible in CES technologies [33].

2.1.2. Empirical Studies

Empirical studies in ASEAN and emerging Asia show modest productivity growth and large differences. Using growth accounting and frontier methods, regional assessments

find TFP has contributed less to output growth than factor accumulation, especially outside high-income countries like Singapore and Malaysia [15,19,27]. Results indicate that regional structural changes depend more on labour and capital than on efficiency improvements.

Country-specific evidence further supports this pattern. In Malaysia, studies consistently show high average productivity along with significant variation across firms and industries, highlighting frictions in the spread of technology and managerial practices [18,34]. Thailand's manufacturing sector saw a slowdown in productivity growth after the Global Financial Crisis, with ongoing gaps between leading and lagging firms [21]. In Vietnam, research using DEA, SFA, and meta-frontier methods reveals technological progress alongside notable differences in technical efficiency among subsectors and ownership types, especially between export-focused and domestic firms [20,22]. For Indonesia and the Philippines, studies indicate modest productivity improvements and significant inefficiencies, driven by structural rigidities and uneven industrial upgrading [15,35].

DEA–Malmquist analyses at sectoral or national levels also show mixed productivity patterns. Many studies suggest that manufacturing productivity growth mainly results from technological change rather than efficiency gains, meaning countries adopt new technologies but find it challenging to optimize resource use [14,36]. Others highlight that efficiency improvements are more important in late-developing economies, especially during rapid industrial growth phases [17]. Overall, evidence indicates that ASEAN manufacturing productivity is influenced by both frontier shifts and uneven progress in catching up, with considerable differences across countries and over time.

Despite the growing research on ASEAN manufacturing productivity, three key gaps persist. First, most studies focus on individual countries or short periods, limiting understanding of long-term changes and cross-country differences; comparative, long-term studies are rare. Second, many analyses report aggregate productivity without breaking it down into efficiency and technological change, which is vital for policy, given ASEAN's varied industrial development. Third, little attention is given to scale efficiency, despite its potential impact during rapid industrial growth, with most research focusing only on technical efficiency, leaving the role of scale effects underexplored. Hence, this study assesses manufacturing efficiency and productivity in six ASEAN countries—Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam by combining DEA with the Malmquist index. It decomposes productivity change into efficiency, technological, and scale effects, offering nuanced insights beyond aggregate TFP measures. The paper contributes by providing a cross-country comparison over two decades, including industrialization and COVID-19 periods; clarifying the roles of efficiency and technological progress; and examining scale efficiency as a key performance factor.

2.2. Data

Empirical measurement of productivity has developed mainly through two methodological traditions. Parametric methods, especially stochastic frontier analysis (SFA), specify a functional form for production technology and account for random noise in the error term [23,37]. Non-parametric methods, mainly Data Envelopment Analysis (DEA), create a piecewise linear frontier based on observed data without assuming a particular functional form [4,38]. Although SFA provides statistical inference and models noise explicitly, DEA is particularly useful in multi-country and sectoral analyses where reliable price data are scarce and production technologies vary [16,39].

Caves et al. (1982) [28] proposed the Malmquist Productivity Index based on distance functions, later operationalized in a non-parametric DEA framework by Färe et al. (1994) [24]. The index's main benefit is its decomposition of productivity change into efficiency change

(catch-up) and technological change (frontier shift), which helps researchers identify whether productivity growth stems from better resource use or innovation.

2.2.1. DEA-CRS and DEA-VRS Specification

To measure the relative efficiency of the manufacturing sectors of the ASEAN-6 countries, this study employs input-oriented Data Envelopment Analysis (DEA) under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions. DEA is a non-parametric frontier technique that evaluates the performance of a set of decision-making units (DMUs) by comparing multiple inputs and outputs without requiring an explicit production function [38–40]. In the present context, each country's manufacturing sector in the year t is treated as a DMU, using inputs such as labour and capital to produce manufacturing output. An input orientation is adopted because policymakers typically have greater control over reducing or improving the use of inputs, while outputs (manufacturing Gross Domestic Product) are largely determined by market demand and broader macroeconomic conditions [23].

Assume there are n DMUs, each using m inputs and producing s outputs. For DMU o ($o = 1, \dots, n$), let x_{io} denote the quantity of input i ($i = 1, \dots, m$) and y_{ro} the quantity of output r ($r = 1, \dots, s$). The DEA-CRS (CCR) input-oriented envelopment model of Charnes et al. (1978) [38] is formulated as:

$$\begin{aligned} \min_{\theta, \lambda} \quad & \theta \\ \sum_{j=1}^n \lambda_j x_{ij} & \leq \theta x_{io} \quad i = 1, \dots, m, \\ \sum_{j=1}^n \lambda_j y_{rj} & \geq y_{ro} \quad r = 1, \dots, s, \\ \lambda_j & \geq 0 \end{aligned}$$

where λ_j are intensity variables that form linear combinations of observed DMUs and θ is the scalar efficiency score for DMU o . Under CRS, technology assumes proportionality between inputs and outputs, so that scaling all inputs by a factor leads to the same factor change in outputs [38]. The optimal value $\theta_o^* \in (0, 1]$ measures overall technical efficiency: a value of $\theta_o^* = 1$, combined with zero input and output slacks, indicates that DMU o is technically efficient and lies on the CRS efficiency frontier, while $\theta_o^* < 1$ implies that inputs could be proportionally reduced by $1 - \theta_o^*$ without lowering outputs [39,40].

However, in multi-country manufacturing data, it is unlikely that all DMUs operate at an optimal scale, due to factors such as imperfect competition, financial constraints, or regulatory distortions. To allow for non-constant returns to scale, this study also estimates the DEA-VRS (BCC) model of Banker et al. (1984) [4], which introduces a convexity constraint to capture variable returns to scale. The input-oriented VRS envelopment model is given by:

$$\begin{aligned} \min_{\theta, \lambda} \quad & \theta \\ \sum_{j=1}^n \lambda_j & \geq 1 \\ \lambda_j & \geq 0, \quad j = 1, \dots, n. \end{aligned}$$

The additional constraint $\sum_{j=1}^n \lambda_j = 1$ ensures that each reference point is a convex combination of observed DMUs and implies a variable return to scale (VRS) technol-

ogy, allowing for increasing, constant, or decreasing returns at different regions of the frontier [4,40]. The VRS efficiency score $\theta_{o,VRS}^*$ is interpreted as pure technical efficiency, net of scale effects. By estimating both CRS and VRS models, it is possible to decompose each DMU's efficiency into pure technical efficiency and scale efficiency, where scale efficiency (SE) for DMU o is defined as:

$$SE_0 = \frac{\theta_{o,CRS}^*}{\theta_{o,VRS}^*}, \quad 0 < SE_0 \leq 1$$

A value of $SE_0 = 1$ indicates that the DMU operates at the most productive scale size, whereas $SE_0 < 1$ suggests scale inefficiency [23]. In this study, the CRS scores are used to capture overall technical efficiency of manufacturing sectors in Malaysia, Vietnam, Indonesia, Singapore, Thailand, and the Philippines, the VRS scores to identify inefficiencies due purely to managerial or operational factors, and the SE measure to assess whether countries are operating at an optimal manufacturing scale over the period 2000–2022.

This study employs both CRS and VRS specifications to distinguish between overall technical efficiency and pure technical efficiency, thereby allowing the derivation of scale efficiency. While the CRS model assumes optimal production scale, the VRS model relaxes this assumption and captures scale heterogeneity across countries [4,23].

In the Malmquist Productivity Index (MPI) estimation, productivity change is computed under the CRS assumption, which ensures consistency with the theoretical decomposition of total factor productivity into efficiency change and technological change [24]. The CRS-based MPI captures overall technical efficiency change (catch-up), while the VRS estimates are used to interpret the sources of inefficiency by separating pure technical efficiency and scale efficiency effects.

Although scale efficiency is not explicitly decomposed within the standard MPI framework, it provides complementary insights into whether productivity changes are influenced by suboptimal production scale. Therefore, scale efficiency results are interpreted alongside MPI findings to better understand the structural sources of inefficiency in ASEAN manufacturing.

2.2.2. Malmquist Productivity Index (MPI)

The Malmquist Productivity Index (MPI) is a widely used measure of total factor productivity (TFP) change over time, grounded in the theory of distance functions and usually implemented with Data Envelopment Analysis (DEA). Building on Malmquist's (1953) [41] index-number work, Caves et al. (1982) [28] defined a productivity index using output (or input) distance functions, and Färe et al. (1994) [24] provided the now-standard non-parametric (DEA) interpretation and decomposition.

In an input-oriented setting, let $x^t \in \mathbb{R}_+^m$ and $y^t \in \mathbb{R}_+^s$ denote the input and output vectors of a decision-making unit (DMU) in period t , and let P^t be the production possibility set in that period. The Shephard output distance function with respect to the period- t technology is defined as:

$$D_0^t(x^t, y^t) = \sup \left\{ \theta : (y^t, \frac{x^t}{\theta}) \in P^t \right\}$$

which measures the maximum proportional expansion of inputs x^t that is feasible for given outputs y^t ; its reciprocal can be interpreted as an input-oriented technical efficiency score [23].

Using these distance functions, the input-oriented Malmquist TFP index between periods t and $t + 1$ for a DMU observed at (x^t, y^t) and (x^{t+1}, y^{t+1}) is defined as the geometric mean of two period-specific productivity ratios:

$$MPI = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)} \cdot \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^{t+1}(x^t, y^t)} \right]^{1/2}.$$

If $MPI > 1$, overall productivity has improved between the two periods; if it is equal to 1, productivity is unchanged; and if it is less than 1, productivity has declined [23,24]. The key contribution of Färe et al. (1994) [24] is to show that this index can be decomposed into an efficiency change component, reflecting “catching up” to the frontier, and a technical change component, reflecting shifts of the frontier itself. Specifically, the efficiency change (EC) between t and $t + 1$ is

$$EC = \frac{D^{t+1}(x^{t+1}, y^{t+1})}{D^t(x^t, y^t)},$$

which compares the DMU’s relative efficiency in the two periods: $EC > 1$ indicates that the DMU has moved closer to the best-practice frontier (improved technical efficiency), while $EC < 1$ signals a deterioration in efficiency.

The second component, technical change (TC), captures the shift of the production frontier between periods t and $t + 1$ and is given by the geometric mean of two “cross-period” evaluations of the same observations:

$$TC = \left[\frac{D^t(x^{t+1}, y^{t+1})}{D^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{D^t(x^t, y^t)}{D^{t+1}(x^t, y^t)} \right]^{1/2}.$$

Values of $TC > 1$ imply technological progress (an outward shift of the frontier), whereas $TC < 1$ reflects technological regress. The overall MPI can then be written as the product of these two components,

$$MPI = EC \times TC,$$

which provides a clear decomposition of total factor productivity change into changes in relative efficiency and technological progress. In empirical applications, the input distance functions are typically estimated using Data Envelopment Analysis (DEA), under either constant return to scale (CRS) or variable returns to scale (VRS), to evaluate productivity dynamics across firms, industries, or countries [23,24].

2.3. Methodology

This study examines the manufacturing sectors of six ASEAN economies over the period 2000–2022. These countries account for the majority of ASEAN’s manufacturing output and exports [42,43]; they represent different stages of industrial development, ranging from high-income and technology-intensive production (Singapore) to late-industrializing economies with rapidly expanding manufacturing bases (Vietnam and Indonesia) [1,26,27,44]. This heterogeneity provides a suitable basis for comparative efficiency and productivity analysis in a multi-country setting [23,39].

In this study, an input-oriented Data Envelopment Analysis (DEA) framework is employed to evaluate the efficiency of manufacturing sectors across selected ASEAN countries. The choice of input orientation is grounded in both theoretical considerations and policy relevance. In production theory, input-oriented measures assess the extent to which inputs can be proportionally reduced while maintaining a given level of output, thereby reflecting the efficiency of resource utilization [23,31]. This approach is particularly

suitable in macro-level and sectoral analyses where decision-makers have greater control over input allocation—such as labour and capital—than over output levels, which are often influenced by exogenous factors including global demand, trade conditions, and technological shocks.

In the context of ASEAN manufacturing, output (measured by manufacturing Gross Domestic Product) is largely shaped by participation in global value chains and external market conditions. Consequently, governments and policymakers are more directly able to influence productivity through improving input efficiency, such as enhancing labour skills, optimizing capital investment, and reducing resource misallocation, rather than directly increasing output levels. Therefore, an input-oriented DEA model is more appropriate for assessing how efficiently manufacturing sectors utilize available resources [23,39]. This approach has been widely adopted in cross-country productivity studies where the focus is on identifying potential input savings and improving operational performance [16].

In addition to orientation, the specification of returns to scale is a critical modelling decision in DEA. This study adopts both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions to provide a comprehensive assessment of efficiency. The CRS model, originally developed by Charnes et al. (1978) [38], assumes that outputs change proportionally with inputs and is appropriate when decision-making units (DMUs) are operating at an optimal scale. Under this assumption, the estimated efficiency scores reflect overall technical efficiency, incorporating both managerial performance and scale effects.

However, the assumption of optimal scale is often unrealistic in multi-country analyses, particularly in the ASEAN context, where economies differ significantly in size, industrial structure, and stage of development. Factors such as imperfect competition, financial constraints, regulatory environments, and infrastructure disparities may prevent countries from operating at their most productive scale [4,23]. To account for these real-world conditions, the VRS model is also employed. The VRS specification introduces a convexity constraint, allowing for increasing, constant, or decreasing returns to scale, and thus isolates pure technical efficiency, which reflects managerial and operational performance independent of scale effects.

By comparing CRS and VRS efficiency scores, this study is able to derive scale efficiency, which measures whether a country's manufacturing sector is operating at an optimal production scale. This decomposition is particularly important in the ASEAN region, where rapid industrialization and structural transformation may lead to scale inefficiencies, even in the presence of relatively high managerial efficiency. The combined use of CRS and VRS models, therefore, provides a more nuanced understanding of the sources of inefficiency and allows for clearer policy implications regarding both resource utilization and optimal scale of production.

Annual data are compiled from internationally comparable sources, primarily the United Nations Industrial Development Organization (UNIDO) and the World Development Indicators (World Bank). These databases provide harmonized series on manufacturing Gross Domestic Product, employment, and investment-related variables, ensuring consistency across countries and over time and reducing problems of cross-country measurement error [15,27]. All monetary values are expressed in constant U.S. dollars to remove the influence of inflation and allow productivity and efficiency changes to be interpreted in real terms [23,45]. In the empirical framework, each country-year observation is treated as a decision-making unit (DMU), yielding a balanced panel of observations for Data Envelopment Analysis (DEA) and Malmquist Productivity Index estimation [16,24,38].

Manufacturing output is measured by manufacturing gross domestic product (GDP), expressed in constant prices. The OECD (2024) [46] emphasizes that GDP is a primary indicator in productivity analysis due to its consistency, comparability across countries, and

ability to capture overall economic performance. In manufacturing-related research, GDP is frequently employed as a desirable output variable in efficiency models, particularly in cross-country studies where sectoral data may be limited but macroeconomic output remains available and reliable. Recent empirical studies further support this approach. For instance, Jin et al. (2024) [47] utilized GDP as an output variable in a network DEA–Malmquist framework to assess regional economic efficiency, demonstrating its applicability in productivity measurement. Similarly, Takayabu (2024) [48] incorporated GDP-based outputs in a multi-country manufacturing analysis, confirming that GDP remains a practical proxy for economic performance in comparative efficiency studies. Therefore, GDP is justified as a key variable in manufacturing efficiency and productivity analysis due to its standardized measurement framework, wide data availability, and strong empirical foundation in the recent literature.

Formally, the output variable is defined as:

$$Y_{it} = \text{Manufacturing Gross Domestic Product}_{it}$$

where i denotes country and t denotes year.

Two Conventional Production Inputs Are Employed: Labour and Capital

Labour input (L) is represented by the total employment in the manufacturing sector. This measure reflects the size of the workforce directly involved in manufacturing and is frequently used in cross-country productivity analyses when data on hours worked are not available [18,49].

$$L_{it} = \text{Manufacturing Employment}_{it}$$

Capital input (K) is estimated using real gross fixed capital formation (GFCF) within the manufacturing sector. GFCF indicates investments in machinery, equipment, and industrial infrastructure, acting as a flow proxy for changes in the capital stock when consistent capital stock data is unavailable across different countries [23,45].

$$K_{it} = \text{Manufacturing Gross Fixed Capital Formation}_{it}$$

All variables are expressed in constant prices to reflect real production, avoiding nominal price effects. The use of manufacturing gross domestic product as output and labour and capital as inputs follows standard theory and prior studies and is suitable for DEA–Malmquist analysis across countries where detailed inputs such as energy or materials are often unavailable. Labour and capital capture key inputs, while gross domestic product shows sector contribution. This setup is common in international efficiency and productivity studies of manufacturing [15,20,23]. The variables used in the study are described in Table 1.

Table 1. The description of used variables.

No	Variable Type	Variables	Definition	Source
1	Output variable	The Gross Domestic Product of manufacturing, GDP	The equation calculates manufacturing output in terms of GDP for the entire economy at current prices. The sources of data are official accounts in each country, which are adjusted by the Asian Productivity Organization.	[49–52]
2	Input variables	Labour employment in manufacturing, EMP	This is the number of employees in manufacturing industries in Malaysia, the Philippines, Thailand, Indonesia, Vietnam, and Singapore	[49,51–53]
		Gross capital formation, CAP	The terms of the wages and salaries paid to employees in the manufacturing sector for ASEAN member countries	[18,54]

All series are converted to constant U.S. dollars using deflators for comparability. Missing data are linearly interpolated for short gaps, with no extrapolation. Table 2 shows substantial cross-country variation in scale and growth, reflecting ASEAN's manufacturing diversity. This heterogeneity suits the DEA and Malmquist index methods that benchmark each DMU against the best-practice frontier [31,54].

Table 2. Descriptive statistics.

Input-Output Variables	Indonesia	Malaysia	Philippine	Singapore	Thailand	Vietnam
Output Variable						
Gross Domestic Product (Million USD)						
Mean	2,630,623.48	724,855.22	744,271.30	473,207.38	1,185,356.96	753,185.22
S.D.	846,091.35	246,499.35	257,079.45	159,279.61	250,165.39	325,912.50
Min	1,463,520.00	391,560.00	406,850.00	248,010.00	745,580.00	304,390.00
Max	4,027,240.00	1,176,750.00	1,197,670.00	724,850.00	1,512,340.00	1,377,450.00
Input Variables						
Gross Capital Formation (Million USD)						
Mean	173,372.80	40,893.34	32,537.99	26,401.92	84,534.97	57,645.23
S.D.	67,193.84	11,175.45	12,100.84	6530.93	18,332.26	30,559.80
Min	68,781.63	24,660.15	16,339.34	12,019.21	48,032.20	15,623.24
Max	263,368.38	65,373.17	56,121.67	35,606.02	114,296.54	121,557.48
Employees						
Mean	14,377,212.63	2,270,816.81	3,088,649.84	481,818.15	5,824,086.05	7,333,490.53
S.D.	2,498,539.59	210,403.61	149,436.11	36,003.95	421,685.15	2,780,707.82
Min	11,143,664.70	1,856,799.17	2,791,868.40	430,555.66	5,046,606.50	3,403,455.64
Max	18,861,567.62	2,612,688.95	3,354,258.01	546,413.58	6,491,982.75	12,646,704.98

3. Results

Table 2 presents the descriptive statistics, including the mean, standard deviation, minimum, median, and maximum values of the input and output variables used to calculate the efficiency and productivity indices for the manufacturing sector in selected ASEAN member countries during the period 2000–2022.

Indonesia, Thailand, and Vietnam have higher mean GDP and greater variation than Malaysia, the Philippines, and Singapore, indicating strong, non-stationary growth and scale effects during a period of rapid structural change in emerging ASEAN economies [26]. On the input side, gross capital formation varies significantly across countries, with Indonesia, Thailand, and Vietnam showing larger investments and volatility, reflecting cyclical and policy-driven growth patterns [55]. Employment levels differ markedly: Indonesia and Vietnam have larger workforces, while Singapore has fewer employees but higher output, implying a more capital- and knowledge-intensive production structure [45]. These differences in GDP, investment, and labour across these countries exemplify the heterogeneity the Malmquist Productivity Index captures by benchmarking output relative to inputs and analyzing efficiency and technical change [16,23].

3.1. Technical Efficiency

Table 3 shows that the average technical efficiency of manufacturing industries in Malaysia, Singapore, and the Philippines consistently increased throughout the study period. Conversely, Vietnam's average technical efficiency gradually declined from 2000 to 2022. Indonesia's efficiency fell from 0.5541 in 2000–2009 to 0.4696 in 2010–2019, then

rebounded to 0.5331 in 2020–2022. Meanwhile, Thailand’s manufacturing sector improved from 0.4451 in 2000–2009 to 0.5089 in 2010–2019, before slightly dipping to 0.5029 in 2020–2022.

Table 3. Technical efficiency of selected ASEAN manufacturing industry (2000–2022). Reprinted with permission from Ref. [56]. Copyright 2025 AESS Publications.

Years	Technical Efficiency					
	Indonesia	Malaysia	Philippine	Singapore	Thailand	Vietnam
2000	0.6538	0.4279	0.7651	0.4580	0.4770	0.5987
2001	0.6056	0.4742	0.6423	0.6202	0.4719	0.5278
2002	0.6422	0.4886	0.5962	0.6525	0.4644	0.4732
2003	0.5395	0.5125	0.6344	0.8949	0.4375	0.4400
2004	0.5667	0.5231	0.6183	0.6607	0.4244	0.4392
2005	0.5473	0.5606	0.6807	0.7074	0.3800	0.4390
2006	0.5281	0.5563	0.8059	0.6940	0.4160	0.4131
2007	0.5370	0.5860	0.8244	0.7379	0.4389	0.3586
2008	0.4697	0.6608	0.6950	0.6679	0.4122	0.4109
2009	0.4510	0.7759	0.8123	0.7482	0.5289	0.4138
2010	0.4449	0.6483	0.6872	0.7322	0.4534	0.4305
2011	0.4529	0.6508	0.6841	0.8020	0.4548	0.4553
2012	0.4413	0.6130	0.7350	0.7557	0.4595	0.4515
2013	0.4705	0.6178	0.7301	0.7989	0.4532	0.4492
2014	0.4678	0.6382	0.7435	0.8061	0.5051	0.4536
2015	0.4745	0.6684	0.7644	0.9187	0.5438	0.4153
2016	0.4884	0.6704	0.6991	0.9188	0.5775	0.4095
2017	0.4877	0.6789	0.7006	0.8530	0.5550	0.3822
2018	0.4794	0.7305	0.6868	0.8797	0.5184	0.3741
2019	0.4885	0.8063	0.7289	0.9128	0.5684	0.3676
2020	0.5091	0.8203	1.0000	0.9678	0.5668	0.3670
2021	0.5252	0.7345	0.8979	1.0000	0.4683	0.3462
2022	0.5651	0.7105	0.8156	1.0000	0.4737	0.3482
Average (2000–2009)	0.5541	0.5566	0.7075	0.6842	0.4451	0.4514
Average (2010–2019)	0.4696	0.6723	0.7160	0.8378	0.5089	0.4189
Average (2020–2022)	0.5331	0.7551	0.9045	0.9893	0.5029	0.3538

3.2. Pure Technical Efficiency

Table 4 indicates that Singapore’s manufacturing sector had the highest average pure technical efficiency among Indonesia, Malaysia, Thailand, the Philippines, and Vietnam during 2000–2009 and 2010–2019. However, in 2020–2022, the Philippines overtook Singapore, attaining the highest mean pure technical efficiency in manufacturing.

Table 4. Pure technical efficiency of selected ASEAN manufacturing industry (2000–2022).

Year	Pure Technical Efficiency					
	Indonesia	Malaysia	Philippine	Singapore	Thailand	Vietnam
2000	0.8769	0.4946	0.9557	0.9955	0.5065	0.8308
2001	0.8287	0.5747	0.7983	0.9650	0.4981	0.7133
2002	0.8994	0.5499	0.7299	0.9860	0.4847	0.6200
2003	0.7734	0.5704	0.7641	1.0000	0.4438	0.5588
2004	0.8312	0.5470	0.7291	0.9469	0.4256	0.5406

Table 4. *Cont.*

Year	Pure Technical Efficiency					
	Indonesia	Malaysia	Philippine	Singapore	Thailand	Vietnam
2005	0.8222	0.5834	0.7915	0.9319	0.3953	0.5269
2006	0.8106	0.5764	0.9248	0.8340	0.4515	0.4843
2007	0.8435	0.6030	0.9287	0.7994	0.4945	0.4101
2008	0.7317	0.6786	0.7759	0.8001	0.4948	0.4618
2009	0.7160	0.8102	0.9033	0.8632	0.5827	0.4589
2010	0.7188	0.6613	0.7503	0.8471	0.5693	0.4654
2011	0.7449	0.6621	0.7371	0.8552	0.5801	0.4828
2012	0.7563	0.6207	0.7824	0.8307	0.6283	0.4770
2013	0.8366	0.6238	0.7680	0.8494	0.5952	0.4705
2014	0.8821	0.6422	0.7504	0.8625	0.6508	0.4706
2015	0.9109	0.7077	0.7687	0.9354	0.7059	0.4262
2016	0.9607	0.7471	0.6993	0.9318	0.7529	0.4158
2017	0.9248	0.7909	0.7636	0.9291	0.7593	0.3833
2018	0.9395	0.8780	0.8031	0.9267	0.7402	0.4019
2019	0.9447	0.9533	0.8850	0.9521	0.8162	0.4195
2020	0.9773	0.9254	1.0000	0.9991	0.7821	0.4319
2021	0.9671	0.9207	1.0000	1.0000	0.6880	0.4254
2022	1.0000	1.0000	1.0000	1.0000	0.7047	0.4495
Average (2000–2009)	0.8134	0.5988	0.8301	0.9122	0.4778	0.5606
Average (2010–2019)	0.8619	0.7287	0.7708	0.8920	0.6798	0.4413
Average (2020–2022)	0.9815	0.9487	1.0000	0.9997	0.7249	0.4356

3.3. Scale Efficiency

Table 5 shows Thailand leading in mean scale efficiency in manufacturing from 2000 to 2009, with Vietnam overtaking in 2010–2019. After COVID-19 in 2020, Singapore became the leader from 2020 to 2022. Indonesia consistently lagged behind Singapore, Malaysia, Thailand, the Philippines, and Vietnam in all periods. The DEA results highlight significant heterogeneity in manufacturing efficiency across ASEAN. Singapore and Malaysia maintained closer proximity to the regional best-practice frontier, while Indonesia, Thailand, and Vietnam persistently had lower efficiency despite strong growth. While DEA applied to aggregated national data may have limited discriminatory power, the results should be interpreted as indicative of relative performance rather than definitive measures of managerial efficiency [16,57]. The findings, therefore, reflect broad structural and systemic efficiency patterns at the country level, rather than firm-level managerial practices. These interpretations are presented as plausible explanations and are supported by existing empirical studies, although they are not directly identified within the DEA–MPI framework. Consequently, conclusions are framed in terms of comparative efficiency and resource utilization rather than direct assessments of managerial quality. Singapore’s performance may reflect an advanced production structure and technological upgrading, which is consistent with empirical findings that link higher manufacturing efficiency to technology adoption and innovation capacity [15,21]. Decomposition shows Singapore’s high pure technical efficiency suggests effective management, but lower scale efficiency may be associated with high labour costs and land constraints, which have been identified as structural challenges in advanced manufacturing economies [58,59]. Indonesia, Thailand, and Vietnam show moderate pure technical but weaker overall efficiency, indicating managerial issues and

difficulties operating at optimal scale, which may reflect transitional structural constraints during industrialization, as suggested by studies highlighting resource reallocation and uneven technology diffusion in developing economies [20,26,60]. Additionally, the observed scale inefficiencies in several countries are consistent with returns to scale theory, which suggests that deviations from optimal production scale can reduce overall efficiency [4]. In rapidly developing economies, firms may operate either below or above the optimal scale due to market imperfections, infrastructure limitations, or policy distortions. The findings imply that policies solely expanding capacity need complementary measures for scale and resource optimization. In contrast, the relatively lower efficiency levels observed in countries such as Indonesia, Thailand, and Vietnam can be explained through the lens of structural transformation theory. During the process of industrialization, economies often experience transitional inefficiencies due to resource reallocation, institutional constraints, and uneven technological adoption [60]. In such contexts, rapid expansion of manufacturing output may not immediately translate into efficiency gains.

Table 5. Scale efficiency of selected ASEAN manufacturing industry (2000–2022).

Years	Scale Efficiency					
	Indonesia	Malaysia	Philippine	Singapore	Thailand	Vietnam
2000	0.7456	0.8651	0.8006	0.4601	0.9418	0.7206
2001	0.7308	0.8253	0.8047	0.6427	0.9474	0.7399
2002	0.7140	0.8885	0.8168	0.6618	0.9581	0.7632
2003	0.6976	0.8984	0.8303	0.8949	0.9858	0.7873
2004	0.6818	0.9562	0.8480	0.6977	0.9972	0.8124
2005	0.6656	0.9608	0.8600	0.7592	0.9612	0.8332
2006	0.6515	0.9651	0.8715	0.8321	0.9613	0.8530
2007	0.6367	0.9718	0.8877	0.9230	0.8875	0.8744
2008	0.6420	0.9738	0.8958	0.8348	0.8332	0.8898
2009	0.6299	0.9578	0.8993	0.8668	0.9075	0.9018
2010	0.6189	0.9804	0.9159	0.8643	0.7963	0.9250
2011	0.6080	0.9830	0.9281	0.9378	0.7839	0.9430
2012	0.5835	0.9877	0.9395	0.9097	0.7314	0.9465
2013	0.5624	0.9905	0.9507	0.9406	0.7614	0.9548
2014	0.5303	0.9937	0.9908	0.9345	0.7761	0.9638
2015	0.5209	0.9446	0.9944	0.9822	0.7703	0.9744
2016	0.5084	0.8973	0.9997	0.9861	0.7670	0.9848
2017	0.5274	0.8583	0.9176	0.9180	0.7310	0.9972
2018	0.5102	0.8320	0.8552	0.9493	0.7004	0.9309
2019	0.5172	0.8458	0.8236	0.9587	0.6963	0.8763
2020	0.5209	0.8865	1.0000	0.9686	0.7247	0.8497
2021	0.5430	0.7979	0.8979	1.0000	0.6806	0.8137
2022	0.5651	0.7105	0.8156	1.0000	0.6722	0.7747
Average (2000–2009)	0.6796	0.9263	0.8515	0.7573	0.9381	0.8176
Average (2010–2019)	0.5487	0.9313	0.9316	0.9381	0.7514	0.9497
Average (2020–2022)	0.5430	0.7983	0.9045	0.9895	0.6925	0.8127

The relatively small variation in the mean values of Technical Efficiency (TE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) across the sub-periods can be explained by both methodological and structural factors. First, the use of aggregated country-level data in DEA tends to produce stable efficiency scores over time, as national data smooth

out firm-level fluctuations [16,23]. Second, DEA measures relative efficiency against a contemporaneous frontier; thus, when countries exhibit similar structural characteristics, their relative positions change only marginally [38].

Second, DEA is a relative efficiency measurement technique, where each decision-making unit is evaluated against a contemporaneous best-practice frontier constructed from the sample itself [38]. In a relatively homogeneous group of countries, such as the selected ASEAN economies, the relative positioning of countries may remain broadly stable over time, leading to only marginal changes in average efficiency scores across sub-periods. This is particularly evident when structural characteristics such as industrial composition, labour intensity, and capital utilization evolve gradually rather than abruptly.

Third, the findings suggest that productivity dynamics in ASEAN manufacturing are driven more by technological change than efficiency change, as reflected in the Malmquist Productivity Index (MPI) results. While efficiency scores (TE, PTE, SE) remain relatively stable, technological progress shifts the production frontier outward, resulting in productivity growth without substantial changes in relative efficiency rankings [23,24]. This explains why efficiency indicators show limited variation across periods, while productivity measures exhibit more noticeable fluctuations.

In addition, structural persistence within ASEAN manufacturing sectors may contribute to the observed stability. Institutional frameworks, industrial policies, and factor endowments in these economies tend to evolve incrementally over time, resulting in gradual rather than dramatic shifts in efficiency performance [15]. This structural continuity reinforces the stability of DEA efficiency estimates across different time periods.

Regarding the selection of countries, this study focuses on six ASEAN economies—Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam—because they collectively represent the core manufacturing base of the ASEAN region and account for a substantial share of its industrial output and exports [26,27]. More importantly, these countries capture a wide spectrum of development stages, ranging from advanced, innovation-driven economies (e.g., Singapore) to middle-income and late-industrializing economies (e.g., Vietnam and Indonesia). This heterogeneity is essential for DEA, as it allows for meaningful comparison across different production technologies, efficiency levels, and industrial structures [15,39].

By incorporating countries at different stages of industrial development, the analysis is able to reflect both frontier economies and catching-up economies within a unified framework. This enhances the explanatory power of the study and allows for more robust insights into the sources of efficiency differences and productivity dynamics across ASEAN manufacturing sectors.

3.4. Super-Efficiency

Super-efficiency analysis was performed to differentiate and rank the DMUs that are already efficient (DEA = 1.000) under the CRS (CCR), input-oriented model. In standard DEA, all frontier units score 1.000, making it difficult to compare the best practice units meaningfully. The Andersen–Petersen super-efficiency method overcomes this by excluding the evaluated DMU from the reference set and re-estimating the frontier with only the remaining DMUs. This yields a super-efficiency score that can exceed one (for an input-oriented model), indicating how far an efficient DMU extends beyond the peer frontier and allowing ranking among efficient units. The results in Table 6 show that only three country-year observations are technically efficient in the CRS model, with super-efficiency providing a clear ranking: the Philippines in 2020 has the highest super-efficiency (1.2113), followed by Singapore in 2022 (1.0214) and 2021 (1.0104). In an input-oriented context, a super-efficiency score above one means an efficient DMU could proportionally

increase all inputs by that percentage and still remain feasible within the frontier set by other DMUs. Thus, the Philippine manufacturing in 2020 indicates a 21.1% buffer above the peer frontier after exclusion, while Singapore's manufacturing industry in 2022 and 2021 shows smaller buffers of about 2.1% and 1.0%, respectively. This suggests that the Philippine manufacturing industry in 2020 is not only efficient but also significantly more dominant compared to the remaining best-practice set.

Table 6. Super efficiency of selected ASEAN manufacturing industry (2000–2022).

Years	Super Efficiency					
	Indonesia	Malaysia	Philippine	Singapore	Thailand	Vietnam
2000	0.6538	0.4278	0.7651	0.4579	0.9196	0.5986
2001	0.6056	0.4742	0.6423	0.6201	0.4718	0.5278
2002	0.6422	0.4885	0.5962	0.6525	0.4644	0.4731
2003	0.5395	0.5124	0.6343	0.8949	0.4374	0.4399
2004	0.5667	0.5230	0.6182	0.6606	0.4244	0.4391
2005	0.5473	0.5605	0.6807	0.7074	0.3799	0.4389
2006	0.5281	0.5563	0.8059	0.6939	0.4159	0.4131
2007	0.5370	0.5859	0.8244	0.7378	0.4388	0.3585
2008	0.4697	0.6608	0.6950	0.6637	0.4122	0.4108
2009	0.4510	0.7759	0.8123	0.7482	0.5288	0.4138
2010	0.4449	0.6483	0.6871	0.7321	0.4534	0.4304
2011	0.4529	0.6508	0.6840	0.8019	0.4547	0.4553
2012	0.4413	0.6130	0.7350	0.7556	0.4594	0.4515
2013	0.4704	0.6178	0.7301	0.7989	0.4531	0.4492
2014	0.4677	0.6381	0.7435	0.8060	0.5051	0.4535
2015	0.4745	0.6684	0.7644	0.9187	0.5437	0.4153
2016	0.4884	0.6704	0.6990	0.9188	0.5774	0.4095
2017	0.4876	0.6789	0.7006	0.8523	0.5550	0.3822
2018	0.4793	0.7304	0.6867	0.8733	0.5184	0.3740
2019	0.4885	0.8063	0.7289	0.9128	0.5683	0.3676
2020	0.5091	0.8203	1.2112	0.9678	0.5668	0.3669
2021	0.5251	0.7345	0.8978	1.0104	0.4682	0.3461
2022	0.5650	0.7105	0.8155	1.0214	0.4435	0.3482

In 2020, Philippine manufacturing shows high super-efficiency, indicating a strong or possibly outlier performance that shifts the frontier inward when removed. This underscores its status as a benchmark under CRS and signals the need for robustness checks like VRS or slack-based models to confirm this dominance is not due to scale effects or data anomalies. The super-efficiency results differentiate country-year observations on the efficiency frontier; the Philippines leads in 2020, followed by Singapore in 2021 and 2022. Although scores above one suggest dominance, high values may also indicate outliers or scale sensitivity, as noted by [57,61]. The Philippines' high score likely stems from sectoral and pandemic-related factors rather than permanent shifts, supported by productivity declines after 2020. Conversely, Singapore's consistent scores post-pandemic reflect stable, technology-driven performance and manufacturing resilience [21].

3.5. Productivity of the Manufacturing Industry in Indonesia, Thailand, Malaysia, the Philippines, Singapore, and Vietnam

Table 7 shows Indonesia's Malmquist Productivity Index (MPI) from 2001 to 2022, driven by technological change as efficiency remained fixed at 1.0000 (no net efficiency changes). From 2001 to 2009, fluctuating technology effects caused alternating gains and declines. The period 2010–2019 saw generally positive technological change with steady growth and jumps in 2011, 2013, 2015, and 2016. Despite COVID-19, 2020–2022 stayed

positive, with 2022 showing a further rise, indicating ongoing technology adoption. Indonesia maintained frontier efficiency, but long-term growth relied on continued innovation, technology diffusion, and investment.

Table 7. Malmquist Productivity Index for the manufacturing industry in Indonesia (2000–2022).

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2000	-	-	-
2001	1.0000	0.9803	0.9803
2002	1.0000	1.0508	1.0508
2003	1.0000	0.9639	0.9639
2004	1.0000	1.0668	1.0668
2005	1.0000	1.0128	1.0128
2006	1.0000	1.0156	1.0156
2007	1.0000	1.0420	1.0420
2008	1.0000	0.9622	0.9622
2009	1.0000	0.9938	0.9938
2010	1.0000	1.0273	1.0273
2011	1.0000	1.0410	1.0410
2012	1.0000	1.0127	1.0127
2013	1.0000	1.0673	1.0673
2014	1.0000	1.0167	1.0167
2015	1.0000	1.0327	1.0327
2016	1.0000	1.0386	1.0386
2017	1.0000	1.0066	1.0066
2018	1.0000	1.0150	1.0150
2019	1.0000	1.0254	1.0254
2020	1.0000	1.0056	1.0056
2021	1.0000	1.0214	1.0214
2022	1.0000	1.0620	1.0620

Nevertheless, the impact of COVID-19 on manufacturing efficiency and productivity operates through several key channels. First, supply chain disruptions and trade restrictions reduced input availability and delayed production processes, lowering capacity utilization across manufacturing sectors [7]. Second, labour shortages and mobility restrictions constrained workforce availability, particularly in labour-intensive economies such as Vietnam and Indonesia. Third, firm-level adjustments to uncertainty, including reduced investment and production scaling, contributed to temporary inefficiencies.

The effects varied across countries. Singapore and Malaysia demonstrated greater resilience due to higher levels of automation and digitalisation, which mitigated labour disruptions. In contrast, Indonesia, Thailand, and Vietnam experienced more pronounced efficiency declines due to stronger dependence on labour-intensive production and global supply chains [5,62]. These differences highlight how structural characteristics and policy responses shaped post-pandemic productivity recovery.

As shown in Table 8, Malaysia's manufacturing productivity (MPI) mostly improved from 2001 to 2022, driven by technological change and early efficiency gains. From 2001 to 2009, MPI stayed above 1.0000, peaking in 2009 due to tech progress, with small slowdowns due to weaker efficiency offset by technology. The period 2010–2019 was volatile, with a decline in 2010 from tech regression, then recovery and moderate growth, with efficiency stable. From 2020 to 2022, MPI stayed above 1.0000 despite pandemic disruptions, again fueled by technology, with efficiency constant. Overall, Malaysia's productivity growth is mainly technology-driven, highlighting the importance of innovation and modern processes.

Table 8. Malmquist Productivity Index for the manufacturing industry in Malaysia (2000–2022).

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2000	-	-	-
2001	1.0047	1.0317	1.0366
2002	1.0529	1.0499	1.1054
2003	0.9903	1.0564	1.0461
2004	1.0162	1.0628	1.0800
2005	1.0322	1.0310	1.0642
2006	0.9676	1.0508	1.0168
2007	1.0250	1.0605	1.0870
2008	1.0303	1.0342	1.0655
2009	1.0000	1.2381	1.2381
2010	1.0000	0.8763	0.8763
2011	0.9992	1.0193	1.0185
2012	0.9778	1.0167	0.9942
2013	0.9729	1.0517	1.0232
2014	1.0061	1.0348	1.0411
2015	1.0456	1.0578	1.1060
2016	1.0000	1.0257	1.0257
2017	1.0000	1.0249	1.0249
2018	1.0000	1.0539	1.0539
2019	1.0000	1.0815	1.0815
2020	1.0000	1.0076	1.0076
2021	1.0000	1.0326	1.0326
2022	1.0000	1.0676	1.0676

Table 9 shows that the Philippines' MPI from 2001 to 2022 was very volatile, mainly driven by technological change, as efficiency remained near 1.0000 with minor deviations, like in 2019. From 2001 to 2009, productivity fluctuated sharply, with early declines in 2001–2002 and setbacks in 2004 and 2008, contrasted by tech-led gains in 2003, 2005–2007, and especially 2009. The 2010–2019 period was uneven, with more contraction years (2010–2011, 2013–2014, 2016–2018) than expansion, though modest gains occurred in 2012, 2015, and 2019. From 2020 to 2022, performance was mixed: a surge in 2020 driven by efficiency and tech progress, followed by declines in 2021–2022 due to tech regression. Overall, the pattern indicates challenges in maintaining consistent innovation and diffusion, emphasizing the need for stronger tech adoption and investment for long-term productivity growth.

Table 9. Malmquist Productivity Index for the manufacturing industry in the Philippines (2000–2022).

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2000	-	-	-
2001	1.0000	0.7470	0.7470
2002	1.0000	0.9085	0.9085
2003	1.0000	1.0641	1.0641
2004	1.0000	0.9407	0.9407
2005	1.0000	1.1124	1.1124
2006	1.0000	1.2430	1.2430
2007	1.0000	1.0218	1.0218
2008	1.0000	0.7819	0.7819
2009	1.0000	1.3322	1.3322
2010	1.0000	0.8206	0.8206
2011	1.0000	0.9731	0.9731
2012	1.0000	1.0758	1.0758
2013	1.0000	0.9312	0.9312
2014	1.0000	0.9477	0.9477
2015	1.0000	1.0210	1.0210

Table 9. *Cont.*

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2016	1.0000	0.9312	0.9312
2017	1.0000	0.9909	0.9909
2018	1.0000	0.9864	0.9864
2019	0.9859	1.0762	1.0610
2020	1.0143	1.2591	1.2771
2021	1.0000	0.8103	0.8103
2022	1.0000	0.9299	0.9299

Table 10 shows Singapore's MPI from 2001 to 2022 was consistently technology-driven, with efficiency fixed at 1.0000, indicating stable frontier operations. From 2001 to 2009, productivity was generally positive, with gains in 2003, 2005–2007, and 2009, and slight contractions in 2004 and 2008, suggesting brief stagnation. During 2010–2019, MPI stayed modestly above 1.0000 with small fluctuations and peaks around 2010, 2011, 2013, and 2015, reflecting steady progress. In 2020, MPI fell below 1.0000 due to COVID-19, but recovered in 2021–2022 as technological improvements resumed. Overall, Singapore maintained stable efficiency, relying on innovation, R&D, and advanced processes for long-term productivity growth.

Table 10. Malmquist Productivity Index for the manufacturing industry in Singapore (2000–2022).

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2000	-	-	-
2001	1.0000	1.0134	1.0134
2002	1.0000	1.0287	1.0287
2003	1.0000	1.0574	1.0574
2004	1.0000	0.9997	0.9997
2005	1.0000	1.0359	1.0359
2006	1.0000	1.0366	1.0366
2007	1.0000	1.0469	1.0469
2008	1.0000	0.9872	0.9872
2009	1.0000	1.0449	1.0449
2010	1.0000	1.0617	1.0617
2011	1.0000	1.0401	1.0401
2012	1.0000	1.0141	1.0141
2013	1.0000	1.0434	1.0434
2014	1.0000	1.0196	1.0196
2015	1.0000	1.0506	1.0506
2016	1.0000	1.0236	1.0236
2017	1.0000	1.0226	1.0226
2018	1.0000	1.0189	1.0189
2019	1.0000	1.0135	1.0135
2020	1.0000	0.9907	0.9907
2021	1.0000	1.0279	1.0279
2022	1.0000	1.0275	1.0275

Table 11 shows Thailand's MPI from 2001 to 2022 had mostly positive but fluctuating productivity, driven by technology change and efficiency. From 2001 to 2009, MPI was mostly above 1.0000, indicating moderate growth mainly from technological progress, with some efficiency contributions; only 2001 declined slightly. From 2010 to 2019, productivity varied: some years (e.g., 2012, 2014–2016, 2019) saw tech-led growth, but contractions in 2013 and 2017–2018 reflected efficiency losses and weaker tech momentum, indicating operational issues. During 2020–2022, pandemic pressures caused declines in 2020–2021 mainly due to lower efficiency, with a mild recovery in 2022 as technology improved despite below-frontier efficiency. Overall, Thailand's results show long-term productivity

depends on continued technology adoption and stronger, consistent efficiency and process management to prevent setbacks.

Table 11. Malmquist Productivity Index for the manufacturing industry in Thailand (2000–2022).

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2000	-	-	-
2001	0.9965	0.9959	0.9924
2002	1.0008	1.0449	1.0457
2003	0.9705	1.0790	1.0472
2004	0.9589	1.0856	1.0410
2005	1.0300	1.0021	1.0322
2006	1.0151	1.0605	1.0766
2007	0.9998	1.0427	1.0425
2008	1.0128	1.0346	1.0478
2009	1.0222	1.0176	1.0402
2010	1.0007	1.0077	1.0084
2011	0.9784	1.0386	1.0161
2012	1.0221	1.0354	1.0583
2013	0.8745	1.0623	0.9290
2014	1.0539	1.0207	1.0757
2015	1.0524	1.0253	1.0791
2016	1.0310	1.0213	1.0530
2017	0.9596	0.9972	0.9569
2018	0.9465	1.0015	0.9479
2019	1.0225	1.0478	1.0713
2020	0.9643	1.0177	0.9814
2021	0.9510	1.0145	0.9648
2022	0.9513	1.0578	1.0063

As shown in Table 12, Vietnam's MPI from 2001 to 2022 was volatile early on, stabilizing later, influenced by efficiency and technological change, often driven by technology. Initial declines in 2001–2002 reflected weak efficiency and regression, followed by gradual improvements and mixed results until 2009, with notable gains in 2008 from efficiency and positive 2009 outcomes from balanced contributions. During 2010–2019, MPI was mostly above 1.0000, with modest technology-led gains, but dips in 2015 and 2017 were mainly due to efficiency slippage, showing operational vulnerabilities. From 2020 to 2022, overall gains were modest, supported by technology in 2020 and 2022, but setbacks in 2021 resulted from reduced efficiency and moderate tech growth. Vietnam's long-term productivity depends on continued technology adoption and operational efficiency to minimize fluctuations.

Table 12. Malmquist Productivity Index for the manufacturing industry in Vietnam (2000–2022).

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2000	-	-	-
2001	0.8944	0.7583	0.6783
2002	0.8844	0.9115	0.8061
2003	0.9092	1.0293	0.9358
2004	1.0084	1.0023	1.0107
2005	0.9574	1.0566	1.0116
2006	0.9098	1.0705	0.9739
2007	0.8948	1.0330	0.9243
2008	1.2523	0.8973	1.1237
2009	0.9947	1.0291	1.0236
2010	1.0964	0.9729	1.0667
2011	1.0448	1.0236	1.0695
2012	0.9713	1.0310	1.0014

Table 12. *Cont.*

Year	Efficiency Change	Technological Change	Malmquist Productivity Index
2013	0.9778	1.0363	1.0133
2014	1.0156	1.0086	1.0242
2015	0.9398	1.0291	0.9672
2016	1.0003	1.0082	1.0084
2017	0.9828	0.9860	0.9691
2018	1.0146	0.9909	1.0054
2019	0.9502	1.0564	1.0038
2020	0.9227	1.0942	1.0096
2021	0.9595	1.0166	0.9754
2022	0.9693	1.0519	1.0196

The results of the Malmquist Productivity Index (MPI) show that, from 2000 to 2022, technological change primarily drives productivity shifts in ASEAN manufacturing, rather than efficiency change. For Indonesia and Singapore, efficiency has stayed near unity throughout the period, indicating that fluctuations in productivity are mainly due to movements in the production frontier. Similar trends are seen in Malaysia and the Philippines in later years, where efficiency remains relatively stable, and technological progress or regression determines overall productivity changes. This predominance of technological change aligns with earlier DEA–Malmquist research in emerging Asia, which emphasizes innovation, technology adoption, and diffusion over efficiency catch-up in influencing long-term productivity trends [14,24,36]. However, the long-term persistence of frontier-level efficiency may also reflect the limited discriminatory power of the DEA frontier in highly aggregated data, a known limitation in efficiency studies [16,57]. Thailand and Vietnam display a more varied pattern. In these countries, productivity declines are often linked to reductions in efficiency rather than technological setbacks, suggesting that operational disruptions and resource misallocation can offset technological gains. This is especially evident during COVID-19, when supply chain issues, labour shortages, and capacity underutilization negatively impacted efficiency in ASEAN manufacturing sectors [8,63].

4. Discussion

The empirical findings of this study can be more clearly understood when interpreted through established theoretical frameworks in productivity and efficiency analysis. From the perspective of production theory, technical efficiency reflects the ability of a decision-making unit to operate on the production frontier, producing maximum output from a given set of inputs [31]. The results showing that countries such as Singapore and Malaysia consistently perform closer to the frontier suggest that their manufacturing sectors are more effective in transforming inputs into outputs, reflecting superior resource utilization and production organization.

The estimation of productivity and efficiency performance in the manufacturing industry across the member countries in ASEAN revealed that, although Indonesia's manufacturing sector contributed the highest output among the selected ASEAN nations, Singapore's manufacturing industry consistently outperformed Indonesia, Malaysia, Thailand, the Philippines, and Vietnam in terms of efficiency and productivity. The outstanding performance of Singapore manufacturing in the manufacturing industry could be explained by the adoption of digital technologies such as automation, IoT, and artificial intelligence (AI) in the industry [58,59]. From the standpoint of endogenous growth theory, long-term economic growth is sustained by investments in human capital, innovation, and knowledge accumulation [64]. The strong and consistent performance of Singapore's manufacturing sector can therefore be interpreted as a result of sustained technological capability, research

and development (R&D) investment, and integration into global innovation networks. In fact, Singapore's manufacturing sector is characterized by a focus on high-value-added and high-tech industries, including semiconductors, biomedical sciences, precision engineering, and aerospace [58]. Unlike many ASEAN nations that depend heavily on labour-intensive production, Singapore has shifted toward Industry 4.0 practices such as automation, AI, and smart factories. Therefore, Singapore's manufacturing industry still leads in ASEAN.

By contrast, Vietnam's manufacturing sector experienced persistently subdued performance throughout the study period. The observed decline in Vietnam's average technical efficiency over the period 2000–2022 (as reported in Table 3) can be attributed to several structural and transitional factors associated with its rapid industrialization process. From a theoretical perspective, countries undergoing late-stage industrialization often experience efficiency losses during periods of rapid expansion, as resources are reallocated across sectors and firms with varying levels of productivity [60]. In Vietnam's case, the rapid growth of the manufacturing sector and it driven largely by foreign direct investment (FDI) and export-oriented production has led to significant heterogeneity in firm capabilities, resulting in uneven efficiency performance across the sector.

Empirical evidence supports this explanation. Vo and Nguyen (2021) [22] find that although technological progress has occurred, many domestic firms remain below the production frontier due to limited managerial capacity, weak technology absorption, and shortages of skilled labour. This indicates that technology inflows have not been evenly diffused across firms, thereby constraining overall efficiency improvements. In addition, the coexistence of export-oriented and domestically oriented firms contributes to efficiency disparities. Export-oriented firms integrated into global value chains tend to exhibit higher productivity and better access to advanced technologies, whereas domestically oriented firms often rely on more traditional production methods [27]. This dual structure can widen efficiency gaps within the manufacturing sector and reduce aggregate technical efficiency over time.

Furthermore, the decline in efficiency may also reflect scale and resource allocation issues. As manufacturing output expands rapidly, firms may operate at suboptimal scale due to infrastructure constraints, supply chain bottlenecks, and regional imbalances in industrial development [26]. These conditions prevent firms from achieving optimal input–output combinations, thereby lowering technical efficiency despite continued growth in output and investment. The COVID-19 pandemic further exacerbated these inefficiencies in the later years of the study period. Disruptions to global supply chains, labour shortages, and reduced capacity utilization negatively affected operational efficiency across ASEAN manufacturing sectors, including Vietnam [7]. Overall, the declining trend in Vietnam's technical efficiency reflects the challenges associated with structural transformation, uneven technological diffusion, and transitional dynamics in a rapidly industrializing economy.

While most of the studied ASEAN countries were able to improve efficiency and productivity in manufacturing between 2000 and 2022, technical efficiency in Indonesia, Thailand, and Vietnam remained low following the COVID-19 outbreak in 2020. Notably, Thailand's manufacturing sector experienced a decline in productivity growth in the aftermath of the pandemic. This is due to severe disruptions, including supply chain (materials) breakdown and labour shortages caused by COVID-19 in ASEAN manufacturing [7]. These disruptions will affect the productivity and efficiency performance of the manufacturing industry among the member countries of ASEAN. In fact, the result is also in line with the empirical findings presented by Suwantragul and Sriboonchitta (2022) [63], whereby average annual TFP declined by 3.8% and technical efficiency regressed by 4.1% during the pandemic period for Thailand's manufacturing industry. The result is also consistent with the argument presented by Tambunan (2021) [35], whereby the Indonesian manufacturing

industry experienced a significant contraction in 2020, with negative growth rates for several quarters, and subsectors such as textiles, automotives, and electronics were the hardest hit due to failing demand and disrupted supply chains.

Furthermore, the decomposition analysis of manufacturing efficiency in ASEAN countries indicated that poor utilization of resources and inputs was the primary cause of inefficiency in Malaysia, the Philippines, Thailand, and Vietnam for most of the time. In contrast, inefficiencies in Singapore's and Indonesia's manufacturing sectors were mainly due to challenges in operating at an optimal production scale. It is because in developed countries such as Singapore, the wages and operational costs are significantly higher than in developing countries, and it tends to reduce economies of scale, especially for labour-intensive manufacturing industries, making it difficult for firms to operate at the most cost-efficient scale [65]. Interestingly, the results suggest that the inability to maintain optimal scale operations significantly contributed to the decline in manufacturing efficiency for most of the ASEAN countries after the COVID-19 outbreak in 2020. It is because during the pandemic, firms were forced to operate below capacity due to lockdowns, labour shortages, or material supply delays, and this will break down economies of scale, where firms typically lower per-unit cost by producing more [63].

Across six countries, technological change is the primary driver of measured productivity growth, while efficiency change often remains flat or nearly so. Indonesia and Singapore are the clearest examples, with efficiency consistently at 1.0000, meaning all MPI movement is solely attributed to technological progress. Malaysia and the Philippines show a similar pattern in later years, with efficiency mostly around 1.0000, and productivity changes are mainly driven by technological shifts. This strong focus on technology is informative but also raises questions: persistent frontier-level efficiency over long periods can indicate operational discipline, but it might also reflect limited discrimination in the DEA frontier, data limitations, or industry structures with compressed relative efficiency differences. The contrast between countries is most evident when comparing stable, technology-driven performance to volatile patterns influenced by operational slippage.

Singapore's pattern is steady and positive, with only minor dips, including a small setback during COVID-19 in 2020, followed by recovery, indicating an innovation system supporting continuous incremental improvements. Malaysia experienced strong early gains, followed by increased variability, including a notable technology-driven decline in 2010, before regaining mostly positive momentum. This suggests episodes of technological regression or slower diffusion rather than ongoing operational weaknesses. The Philippines exhibits high volatility with repeated technology-driven contractions, plus a significant spike in 2020, followed by declines, reflecting uneven innovation diffusion and struggles to sustain frontier progress. Thailand and Vietnam present additional challenges; both recorded years where efficiency losses significantly lowered MPI below one. This indicates that even with technological improvements, factors like execution, resource allocation, and process control can hinder productivity. In Thailand, declines in 2013, 2017–2018, and 2020–2021 demonstrate this vulnerability. In Vietnam, efficiency fluctuations amplify overall variation, with occasional surges, such as in 2008, providing gains even when technological progress is weak.

Policy-wise, super-efficiency results suggest focusing less on increasing inputs and more on generating higher GDP from existing capital (GCF) and labour. Countries far from the frontier should prioritize boosting investment productivity through better project appraisal, reallocating GCF to higher-TFP sectors, and reducing resource traps by cutting permits, competition barriers, and insolvency issues. Simultaneously, improve labour productivity via industry-linked TVET, firm upgrades (lean, quality, digitalization), and incentives tied to measurable outcomes. The high super-efficiency of PHI-2020 (1.211) highlights

a best-practice model for transferable strategies like sector mix, resilience, and technology adoption, while SIN-2021/2022 (≈ 1.01 – 1.02) shows steady near-frontier progress through ongoing upgrades.

Also, the results argue for two complementary agendas, not one. For Indonesia and Singapore (and often Malaysia and the Philippines), the priority is sustaining and accelerating technological progress, including innovation, upgrading, and diffusion. This is because productivity gains (and losses) appear to originate there. But for Thailand and Vietnam, technology alone is not enough, as the data imply meaningful payoffs from strengthening operational efficiency, such as capability building, management quality, supply-chain reliability, skills matching, and firm-level process optimization, so that technology improvements translate into consistent productivity growth. Finally, the COVID-era patterns (generally resilient for Indonesia, Malaysia, and Singapore; more mixed for Thailand, Vietnam, and especially the Philippines) highlight that technology in the MPI sense likely captures not just R&D but also adaptation and diffusion under shock (digitalization, retooling, organizational change). Accordingly, MPI improvements reflect the combination of frontier-shifting innovation and successful absorption, while downturns may reflect stalled diffusion, disruption, or efficiency erosion. Hence, future strategies should target both frontier movement and absorption capacity to reduce volatility and lock in long-run gains.

The COVID-19 pandemic caused a structural break in ASEAN manufacturing productivity. Indonesia, Malaysia, and Singapore maintained resilience from 2020 to 2022, while Thailand, Vietnam, and the Philippines showed more volatility. Productivity declines were mainly due to efficiency losses from disruptions and temporary economies of scale breakdowns, not technological regression. Evidence shows that sectors with digital skills, diverse supply chains, and institutional support coped better with shocks [13,21]. Resilience depends on both advanced technology and firms' ability to adapt operationally.

Furthermore, the decomposition of productivity using the Malmquist Productivity Index (MPI) provides insights consistent with the catch-up and frontier shift framework [24]. The findings indicate that productivity growth in ASEAN manufacturing is largely driven by technological change rather than efficiency improvement, suggesting that innovation and frontier expansion play a more dominant role than movements toward the frontier.

5. Conclusions

The policy implications of this study are inherently heterogeneous across ASEAN countries and must be interpreted in light of the distinct sources of inefficiency identified through the decomposition of technical efficiency, pure technical efficiency, and scale efficiency, as well as the Malmquist Productivity Index (MPI) results.

For countries such as Indonesia and Thailand, where both overall technical efficiency and scale efficiency remain relatively low despite moderate levels of pure technical efficiency, inefficiency appears to be driven by a combination of suboptimal resource allocation and scale mismatches. This suggests that policy interventions should go beyond capital accumulation and instead prioritize improvements in production organization, managerial capability, and industrial coordination. In particular, policies that facilitate firm consolidation, enhance access to financing for scaling operations, and improve infrastructure connectivity can help firms move toward the most productive scale size [4,23]. At the same time, targeted skills development and managerial training programmes are essential to strengthen operational efficiency at the firm level.

In the case of Vietnam, the persistent decline in technical efficiency, combined with relatively low pure technical efficiency, indicates deeper structural inefficiencies associated with rapid industrialization and uneven technological diffusion. The MPI results further suggest that productivity gains are primarily driven by technological change rather than efficiency

improvements. Therefore, policy priorities should focus on strengthening technology absorption capacity, promoting knowledge spillovers from foreign direct investment (FDI), and enhancing the integration of domestic firms into global value chains. Institutional support for innovation systems, including R&D incentives and industry–university collaboration, is also critical to ensure that technological progress translates into broad-based efficiency gains [26,27].

For more advanced economies such as Singapore and Malaysia, which consistently operate near the efficiency frontier with high pure technical efficiency but exhibit signs of scale inefficiency, the policy challenge lies in optimizing production scale and sustaining technological leadership. In these contexts, further gains in productivity are less likely to come from efficiency improvements and more likely to depend on frontier innovation, digital transformation, and the development of high-value manufacturing sectors. Policies should therefore prioritize advanced manufacturing technologies, automation, and innovation ecosystems, while also addressing structural constraints such as land scarcity, high labour costs, and diminishing returns to scale [15].

The findings also highlight the differential impact of COVID-19 across countries, reinforcing the need for resilience-oriented policies. Economies with higher levels of digitalisation and automation were better able to mitigate efficiency losses during the pandemic, suggesting that investments in Industry 4.0 technologies and supply chain resilience are critical for future shocks [7].

Overall, the results underscore that a one-size-fits-all policy approach is inappropriate for ASEAN manufacturing. Instead, effective policy design requires a differentiated strategy that aligns with each country's position relative to the production frontier, its scale characteristics, and its stage of industrial development. By linking efficiency decomposition with productivity dynamics, this study provides a more precise basis for tailoring policy interventions to achieve sustainable productivity growth.

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