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Assessing the Foreign Direct Investment Performance of Middle-Income Countries Using Data Envelopment Analysis with Translation Invariance

Runyu Yang , Youngbok Ryu * and Mikhail V. Oet

College of Professional Studies, Northeastern University, 360 Huntington Ave, Boston, MA 02115, USA; yang.runy@northeastern.edu (R.Y.); m.oet@northeastern.edu (M.V.O.)
* Correspondence: y.ryu@northeastern.edu

Abstract: Foreign direct investment (FDI) is a primary vehicle for manufacturing transfer. Middle-income countries can benefit by effectively utilizing FDI to achieve technological development and economic equality and possibly address the middle-income trap issue. This study assessed the FDI performance of ten middle-income countries and examined the statistical relationships between their performance and their contexts: technological development, economic equality, and during the COVID-19 pandemic. For the former, we employed non-radial data envelopment analysis, taking advantage of its translation invariance property to derive efficiency scores; for the latter, we conducted a series of Kruskal–Wallis tests to examine the statistical relationships. According to the analysis results, we found that (a) most countries, except China and India, showed stable efficiency scores over time, (b) their efficiency scores were statistically significantly associated with the level of technological development (indicated by their technology lifecycle-based sigmoid curves) and economic equality (represented by Gini index and poverty indicator); and (c) their efficiency scores were not associated with the COVID-19 pandemic. The results imply that to improve their foreign direct investment performance, host countries may need to enhance their absorptive capacity in both the technological and economic domains.

Keywords: foreign direct investment; middle-income countries; data envelopment analysis; economic inequality; technological development

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1. Introduction

In the era of a global supply chain, manufacturing transfer is an essential topic, which describes the process of relocating manufacturing operations from one country to another along with the transfer of technical and operation knowledge. It has significant implications for the international economy, especially in middle-income countries (Moran et al. 2005). Manufacturing, as a labor-intensive industry, generally escapes from high-cost home countries with stricter regulations to low-cost host countries with lax regulations to build long-term supply chains so that businesses in home countries can achieve stable profits (Pontrandolfo 1999).

The dominant pathway to manufacturing transfer is foreign direct investment (FDI). In the process of manufacturing transfer, there is significant FDI activity and large capital flows involved. It tends to begin with multinational companies investing in setting up factories for simple processing and assembly, evolving into integrated supply chain clusters, and eventually becoming key players and even regional manufacturing hubs (Andersen 2006). In this expanding and deepening investment process, investors not only gain more margins but also shape the global macroeconomic ecosystem.

Middle-income countries seek to attract FDI because they anticipate that FDI will create a considerable number of jobs, stimulate domestic investment, and promote technological development. The efficient utilization of FDI enables the economy to enjoy a virtuous cycle, leading to long-term growth with the pattern of "manufacturing + export" (Hanson and Robertson 2008), as demonstrated by many middle-income countries like China, Vietnam, and Malaysia (Meyer 2004). However, the lack of a regulatory framework over pollutant emissions in middle-income countries, a considerable portion of which stems from energy-intensive manufacturing, leads to serious environmental issues.

Furthermore, it is concerning that middle-income countries prevent falling into the "middle-income trap" and to achieve continuous growth through the effective utilization of FDI. On the one hand, technology transfer from advanced countries to emerging markets often faces systemic problems, as illustrated by a Korean case study (Yoon 2009). The import of advanced machinery can boost productivity in developing countries, but a persistent technology gap exists compared to developed nations (Navaretti et al. 1998). On the other hand, their absorptive capacity plays a crucial role in technology transfer and innovation for firms in middle-income countries. It enables companies to acquire, assimilate, transform, and exploit knowledge from foreign sources (Latukha 2018; Khan et al. 2019). Firms with a higher absorptive capacity are more likely to benefit from international technology transfer through foreign ownership, supplying multinational enterprises, and exporting (Van Der Heiden et al. 2016). However, many middle-income country firms face challenges in developing absorptive capacity, creating a conundrum where they struggle to access new knowledge without prior upgrading (Khan et al. 2019). While absorptive capacity is crucial for innovation in low-tech companies (Del Carpio Gallegos and Miralles Torner 2018), its importance varies depending on the industry's technological level and the country's stage of development (Mancusi 2008).

Regarding manufacturing transfer, this study focused on FDI as a primary factor in the performance of ten middle-income countries by comprehensively considering multiple aspects, including technology transfer and spillover, domestic investment, poverty reduction, economic growth, and manufacturing pollution. While a large body of studies has sought to investigate FDI and manufacturing transfer using parametric analysis to identify significant factors, there are relatively few studies applying non-parametric analysis to evaluate relative efficiency scores of countries based on identified factors. To fill the gap in the extant literature on non-parametric technique-based macroeconomic research, this study employed an applied mathematical method called data envelopment analysis (DEA). In addressing potential critiques of our approach, we acknowledge the limitations of DEA, particularly regarding its reliance on available input–output data, which may not fully capture all externalities. Since our study period (2015–2022) includes COVID-19 times, some middle-income countries experienced negative FDI net inflow as an economic aftermath of the global pandemic within the study period. To mitigate this, we employed a non-radial DEA model with translation invariance, which allowed us to account for the non-positive values in the dataset. Additionally, the use of a new indicator for technological development—the sigmoid knowledge accumulation based on patent data—provides a more nuanced understanding of technology progress across different countries, which addresses the concerns related to the oversimplification of technological advancements.

This study also contributes to the current literature by testing interesting hypotheses. After a meta efficiency frontier was created based on aggregated data across countries over the study period and the efficiency scores of each country in each year were computed, we examined three hypotheses related to technological development, economic inequality, and global pandemic by applying a series of Kruskal–Wallis tests to different sets of middle-income countries. While we used well-established indicators for the tests (e.g., Gini coefficient for economic inequality), we also propose a new indicator and grouping middle-income countries by their progress in technological development. To that end, we applied the concept of technology lifecycle to generate each country's sigmoid knowledge accumulation, drawing on the number of patents and computed the inflection points of their S curves fitted by logistic functions.

Our research showed that, while most countries displayed stable efficiency levels, China and India experienced efficiency fluctuations associated with the pandemic and internal political aspects. The analysis uncovered correlations between FDI performance and technological development and economic inequality. These findings suggest that advancements in technology and economic equity are critical in enhancing FDI efficiency in middle-income countries.

The remaining sections are organized as follows. Section 2 details a literature survey and presents our research hypotheses. Section 3 describes our methods with a focus on DEA. Section 4 provides our analysis results including the hypothesis testing. Section 5 discusses our empirical results in relation to the extant literature. Section 6 concludes this study along with future extensions.

2. Literature Review and Hypothesis Development

2.1. Theoretical Framework of FDI Performance Analysis

The analysis of FDI performance in middle-income countries sits at the intersection of three theoretical streams: efficiency measurement theory, technology transfer theory, and economic development theory. Data envelopment analysis has emerged as a powerful methodological framework for evaluating complex economic systems where multiple inputs produce multiple outputs (Charnes et al. 1978). Within the context of FDI, this approach enables us to simultaneously consider both the direct economic impacts and indirect spillover effects that characterize foreign investment in manufacturing sectors.

2.2. Evolution of DEA Applications in Economic Performance Assessment

The application of DEA to national and sub-national performance assessments has evolved significantly over the past decades. Early applications focused primarily on technical efficiency in specific sectors (Zaim 2004), but recent studies have expanded to incorporate broader economic and environmental considerations (Sueyoshi and Ryu 2021). These methodological advances have particular relevance for analyzing FDI performance in middle-income countries, where the interplay between economic growth and environmental impact remains a critical concern.

Table 1 summarizes those studies along with the specific methodologies and input and output factors used by them. In terms of economic development performance, for instance, Santana et al. (2017) took BRICS countries as an example to assess the level of sustainable development across the triple bottom line: economic, environmental, and social aspects. Fang et al. (2013) considered employment, investment, consumption, and other factors to evaluate the economic development efficiency of Chinese urban agglomerations.

Another field of macroeconomic research has centered on energy and pollution issues. For example, Matsumoto et al. (2020) explored the European Union's country-level data from 2000 to 2018 and revealed that the 2007–2009 financial crisis had a negative impact on environmental performance. Sueyoshi and Ryu (2021) evaluated the sustainable development performance of the 50 U.S. states and examined the relationship between state-level environmental performance measures and their political and geographical contexts. Zaim (2004) studied the state-level performance of air pollution stemming from the manufacturing sectors in the United States.

Although few DEA studies have focused on FDI, the existing research offers diverse perspectives. Lei et al. (2013) assessed the performance of Chinese provinces in attracting foreign investment. Zhang (2017) focused on the technological spillover effect caused by the inflow of FDI, which further led to the improvement of productivity. Recently, Wanke et al. (2024) investigated the drivers of FDI performance, from an employment perspective, in many countries around the world.

Table 1. Data envelopment analysis applications for foreign direct investment.

Study	Summary	Inputs	Outputs
Santana et al. (2017)	This study used the BCC model to evaluate the sustainable development performance of BRICS countries from three aspects: the economy, environment, and society.	Gross fixed capital formation, employed population, R&D expenditure, gross fixed capital formation, R&D expenditure, gross fixed capital formation, employed population, R&D expenditure	GDP, CO_2 emission, life expectancy
Lei et al. (2013)	This paper established a model to assess the attractiveness of foreign direct investment at the provincial level in China based on data from 1997 to 2008.	Material capital, human capital, energy, degree of openness	FDI performance index, FDI potential index
Matsumoto et al. (2020)	This study assessed the economic–energy–environmental performance of EU countries based on data from 2000 to 2017.	Labor, capital, energy consumption	GDP, CO_2 emissions, $PM_{2.5}$ emissions, waste
Zhang (2017)	The paper focused on the technological spillover effect caused by the inflow of FDI, which further led to the improvement of productivity.	Number of researchers, R&D stock, share of basic research expenses, share of experimental research expenses, FDI stock	Invention patents, utility model, design patent
Fang et al. (2013)	This study combined DEA with macroeconomics to study the input–output efficiency of China's urban agglomerations from a comprehensive perspective.	Total number of employees, net investment in fixed assets, built-up area	GDP, total retail sales in social consumer goods
Sueyoshi et al. (2021)	This study analyzed state-level environmental performance in different political and geographical contexts by employing environmental assessment-oriented DEA models.	Population, government expenditure, energy consumption, patent grants	Gross state product and carbon emissions
Zaim (2004)	Based on the idea that pollution is a major byproduct of manufacturing activity, this study measured and compared manufacturing output and pollution across U.S. states.	Manufacturing employment, capital stock	Gross state product in manufacturing, SOx, NOx, CO
Wanke et al. (2024)	This study used a novel RoCo MCDM model to study the performance drivers of foreign direct investment in countries around the world.	Capital expenditures, FDI amount, incentive per job, incentive per capital expenditure	New jobs, safeguarded jobs, average salary

2.3. *Technological Development and FDI Performance*

There is substantial evidence that many middle-income countries have stagnated, unable to transition to a high-income status (Eichengreen et al. 2013; Pruchnik and Zowczak 2017). The key reasons for this middle-income trap include insufficient investment, inadequate integration of new technologies, and a lack of innovation (Felipe 2012). According to the production function, higher technological levels allow for greater output with the same levels of labor and capital (Bernardes and e Albuquerque 2003). This enables developed countries to achieve sustainable development through investing in technology and transforming production. However, developing countries require external assistance to accelerate the process of technology accumulation to avoid the middle-income trap and achieve sustainable development. Both the Product Life Cycle Theory and the Technology Diffusion Theory support the possibility of accelerating technological development (Michorowska 2008). Investment is crucial for fostering technological development, which in turn enables industries—especially in the manufacturing sector—to effectively absorb and utilize new technologies, thereby contributing to economic efficiency and growth. However, when the integration of these technologies (i.e., infusion) is incomplete or inefficient, countries struggle to achieve the innovation-driven growth needed to escape the middle-income trap (Suh et al. 2010).

In this vein, many studies have found that one of the key benefits that FDI brings to host countries is the transfer and spillover of technology. These technologies can either be intentionally transferred through formal agreements, such as partnerships or licensing, or they can indirectly spill over to the local firms through the interactions with foreign companies, workforce training, or exposure to advanced technologies. Marasco et al. (2024) showed that high-tech FDI has a strong positive correlation with host country growth, especially in the manufacturing industry. The main mediating factor was whether the foreign capital has technology that can promote productivity, leading to long-term economic growth. The work of Wang (2010) and Fillat and Woerz (2011) supported a positive relationship between FDI and productivity, particularly when high investment is combined with export orientation. Damijan et al. (2003) focused on the critical role of technology transfer in productivity improvement. In particular, for middle-income countries, Tampakoudis et al. (2017) concluded that attracting more FDI helps to avoid falling into the middle-income trap.

Meanwhile, some studies have also noted the challenges of internalizing and absorbing technology induced by FDI while others shed light on the relationship between various determinants in economic growth. Mingyong et al. (2006) argued that enhancing absorptive capability and human capital stocks can contribute to long-term economic growth. Arjun et al. (2020) focused on manufacturing value-added products along with the role of energy, human capital, finance, and technology. Razzaq et al. (2021) indicated that relatively underdeveloped countries find it difficult to internalize FDI spillovers. Alnafrah (2021) emphasized in his study that commercializing knowledge outputs is a challenge faced by BRICS countries. Radosevic and Yoruk (2018)'s study on middle-income countries indicated that FDI offers limited benefits to countries where factors like human capital and institutions fall below certain thresholds.

As a measure to evaluate technology development, patent data have been used since patents are filed and granted to protect research and development outputs under an intellectual property right regime. Chen et al. (2013), for instance, analyzed the fuel cell technology development of leading countries using patent data. Further, Tampubolon and Ramlogan (2004) employed patent analysis to identify the country-level technological change patterns in East Asia and South America. In particular, they used the non-linear sigmoid technology lifecycle concept, often referred to as an S-curve approach.

In this regard, we sought to explore if there is a significant difference in FDI performance between two groups of middle-income countries: one at a leading position in the patent S curve and the other at a lagging position in the curve.

Hypothesis 1. *There is a significant difference in FDI performance between middle-income countries that achieved different levels of technological development.*

H1a. *Countries that have passed their technology lifecycle inflection point by 2022 will demonstrate significantly different FDI performances compared to those that have not.*

The 2022 benchmark provides a contemporary snapshot of technological development, reflecting recent advances in digital transformation and Industry 4.0 capabilities. This hypothesis builds on Radosevic and Yoruk (2018)'s finding that technological capabilities significantly influence FDI benefits in middle-income countries.

H1b. *Countries above the median inflection point in their technology lifecycle curves will show significantly different FDI performances compared to those below the median.*

This alternative hypothesis accounts for the relative positioning of countries in their technological development trajectories, following Lee's (2013) argument that relative technological capabilities matter more than absolute levels in determining development outcomes.

2.4. Economic Inequality and FDI Dynamics

The relationship between FDI and economic inequality presents a complex picture that has evolved over time. Early studies suggested a straightforward relationship between FDI and inequality (Clark et al. 2011), but recent research reveals a more nuanced dynamic. Kaulihowa and Adjasi (2018) identified a U-shaped relationship between FDI and inequality in developing economies, suggesting that initial increases in inequality may eventually reverse as benefits diffuse through the economy.

This temporal dimension of FDI's impact on inequality becomes particularly relevant for middle-income countries, where domestic market development and institutional capacity play crucial mediating roles. Ucal et al. (2016) suggested that FDI has a negative impact on the Gini coefficient based on Turkish data, meaning inequality reduction. In contrast, Clark et al. (2011) indicated that FDI generally increases economic inequality. Majeed (2017), who researched developing countries, argued that the impact of FDI varies across nations. FDI tends to reduce inequality in countries with a high level of economic development, while in those with a low level of economic development, it tends to exacerbate inequality.

Some other studies provided more nuanced trends. Herzer and Nunnenkamp (2011), focusing on European countries, found that FDI has a positive impact on inequality in the short term but a negative one in the long term. Additionally, they suggested a mutual causality, where a reduction in inequality can also lead to increased FDI. Kaulihowa and Adjasi (2018), examining the relationship between FDI and inequality in Africa, described it as a U-shaped curve. FDI can increase inequality in the early stages, but inequality tends to decrease as the benefits of FDI become more widely distributed over time. Deng and Lin (2012) studied FDI based on income classification and found that FDI reduces inequality in low-income countries with poor human capital but exacerbates inequality in middle- and high-income countries with abundant human capital.

In this vein, we sought to investigate if there is a significant difference in FDI performance between two groups of countries: one with higher economic inequality and another with lower economic inequality.

Hypothesis 2. *There is a significant difference in FDI performance between middle-income countries based on their levels of economic inequality.*

H2a. *Countries with higher Gini coefficients will demonstrate significantly different FDI performances compared to those with lower inequality levels.*

This hypothesis builds on Wade (2020)'s argument that inequality affects the institutional and social conditions that influence FDI absorption capacity. The Gini coefficient provides a comprehensive measure of income distribution that captures both top-end and bottom-end inequalities.

H2b. *Countries with higher poverty headcount ratios at USD 3.65 a day will show significantly different FDI performances compared to those with lower poverty levels.*

This hypothesis focuses on bottom-end inequality, following Ravallion (2014)'s emphasis on poverty as a crucial constraint on development capabilities. The USD 3.65 threshold specifically captures vulnerability in middle-income countries.

2.5. Global Pandemic and FDI Resilience

Some diseases have transitioned into an epidemic or pandemic and have become a national or global issue and have wrought havoc in the international economy. For instance, Omoleke et al. (2016) took the example of Ebola Viral Disease in West Africa and presented its economic ramifications including a lower availability of labor, restrictions in business transactions, and disruptions in supply chains. Joo et al. (2019) looked into the economic consequences of a Middle East respiratory syndrome (MERS) outbreak in South Korea, with a focus on the tourism industry. Sueyoshi et al. (2021) explored the relationships between OECD countries' COVID-19 response performance and their socioeconomic systems, with a focus on the transportation and energy sectors.

The COVID-19 pandemic has provided a unique natural experiment for examining the resilience of FDI systems. Previous research on epidemic impacts (Joo et al. 2019) focused primarily on regional effects, but the global nature of COVID-19 allows us to examine systemic responses across multiple economies simultaneously.

Since the COVID-19 became a pandemic in 2020, investment activities have cooled down. Ajide and Osinubi (2020), based on global data, found a positive correlation between COVID-19 cases and deaths and FDI outflows. The primary reasons were the decline in investment due to rising financing costs and decreasing profits, as well as concerns about employee health and safety. Ho and Gan (2021) demonstrated the negative impacts of global health issues on FDI, particularly FDI net inflows in Asia-Pacific countries and emerging economies. Fu et al. (2021) also concluded that the impact of the pandemic on FDI lies in reduced profit margins, affecting host countries. In particular, the service sector's FDI was severely impacted by the pandemic.

In such a background, we sought to examine if there were any significant changes in FDI performance in middle-income countries over time, specifically before and after the COVID-19 pandemic.

Hypothesis 3. *There is a significant difference in FDI performance between middle-income countries before and after the pandemic.*

H3a. *FDI performance will show significant differences between the pre-pandemic (2015–2018) and post-pandemic (2019–2022) periods.*

This hypothesis draws on Kogut and Singh (1988)'s concept of country risk assessment in FDI decisions, suggesting that pandemic experiences may fundamentally alter risk perceptions and investment efficiency patterns.

H3b. *FDI performance will show significant differences during the acute pandemic period (2020–2022) compared to the pre-pandemic period.*

This hypothesis focuses on immediate pandemic impacts, following Contractor (2022)'s argument that crisis periods can reveal underlying strengths and weaknesses in international business systems.

3. Methodology

3.1. Analytic Framework

This study employed DEA with translation invariance at the first stage and conducted a series of Kruskal–Wallis tests at the second stage to verify our research hypotheses. As shown in Figure 1, we computed three types of efficiency scores: the first one under constant returns to scale, the second one under variable returns to scale, and the last one with scale. Then, we applied Kruskal–Wallis tests to examine the statistical differences among various groups of countries in different years depending on their levels of technological development and economic inequality, and on the dynamic changes in public health concerns.

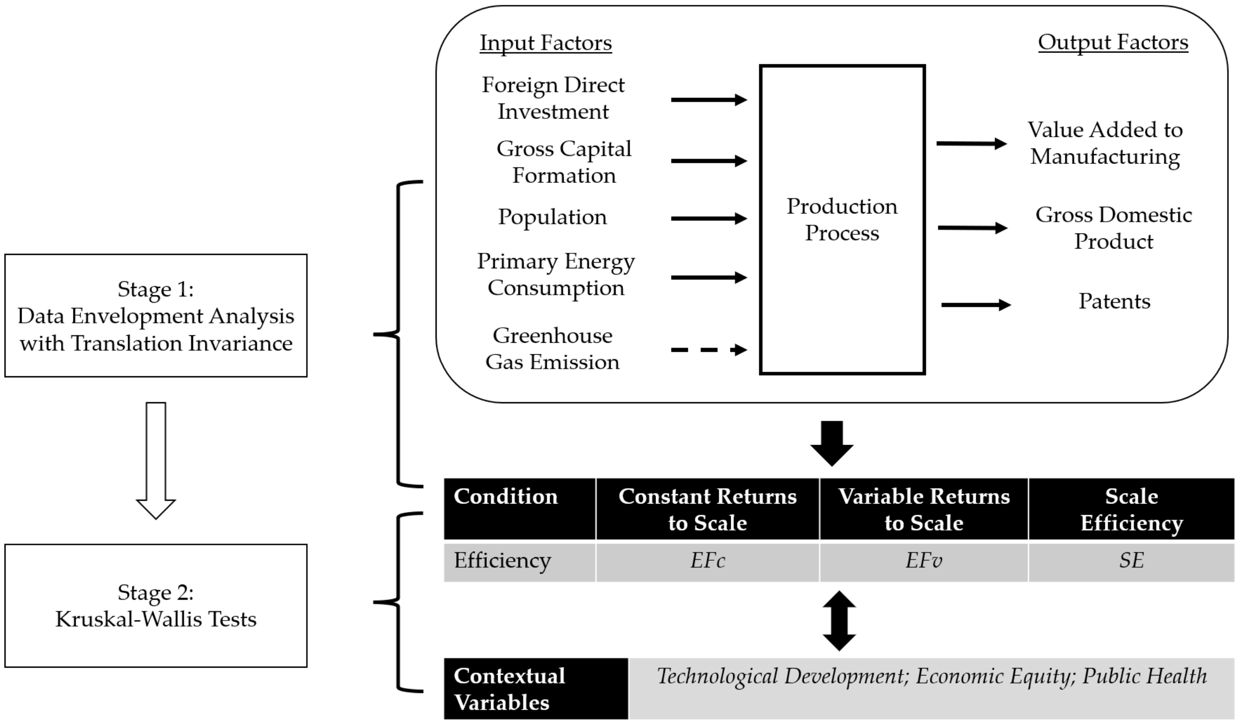

Figure 1. Two stages of analysis.

3.2. Data

This study selected data from 2015 to 2022 from ten typical manufacturing host countries: Brazil, China, India, Indonesia, Malaysia, Mexico, the Philippines, Thailand, and Vietnam. The data sources were the World Bank Database, World Intellectual Property Organization, Emissions Database for Global Atmospheric Research (EDGAR), and Energy Institute. See Appendix A for the raw data.

The selected countries were chosen based on multiple considerations. Firstly, China, India, and Brazil are among the major countries that attract the most FDI and rank in the top three on the GMCI index for Competitiveness in Five Years (Deloitte 2013). We also focused on smaller emerging countries like Vietnam, Thailand, and the Philippines, which have seen varying degrees of growth in manufacturing FDI. From the OECD report and the UNCTAD investment report (UNCTAD 2020), we can find data supporting Malaysia and Indonesia as manufacturing hubs in Southeast Asia. Additionally, Mexico, as part of the North American Free Trade Agreement (NAFTA), has attracted substantial manufacturing FDI from North America.

In our DEA model, we used four inputs and four outputs. The former includes the net inflow of FDI, gross capital formation, population, and primary energy consumption while the latter includes manufacturing value added, GDP, number of patents, and greenhouse gas (GHG) emissions. Since the emission of GHGs, as byproducts of our production process, is an undesirable output, it was transferred to the input side for calculation.

Our selection of input and output variables followed a comprehensive framework that captures both the direct and indirect impacts of FDI on host economies. The input variables reflect both the investment channels and the structural capacity of host economies, while the output variables capture the economic, technological, and environmental dimensions of development outcomes.

For input variables, we incorporated FDI net inflows as our primary measure of foreign investment activity, following the established approach of Wanke et al. (2024). Gross capital formation served as a complementary input that captures domestic investment capacity, which Herzer and Nunnenkamp (2011) identified as crucial for FDI absorption. Population size, as was employed by Sueyoshi and Ryu (2021), represents the human capital base and potential market size of host economies. Primary energy consumption, following Matsumoto et al. (2020), captures the energy infrastructure capacity necessary for manufacturing activities.

Our output selection reflects the multifaceted nature of FDI outcomes in manufacturing-oriented economies. Manufacturing value added, as emphasized by Arjun et al. (2020), directly measures the sector's contribution to the economy. GDP serves as a broader measure of economic impact, consistent with numerous studies including Santana et al. (2017). Patent counts, following Zhang (2017), capture technological development outcomes, which are particularly relevant given FDI's role in technology transfer.

We treated greenhouse gas emissions as an undesirable output, converting it into an input in our DEA model, following the theoretical framework established by Sueyoshi et al. (2020). This treatment acknowledges the environmental challenges accompanying manufacturing growth, which are particularly relevant for middle-income countries where environmental regulations may be less stringent (Zaim 2004). This approach allows us to penalize high-pollution production processes while recognizing their role in the manufacturing ecosystem.

Our variable selection distinguishes itself from previous studies by simultaneously considering technological development (through patents), environmental impact (through emissions), and economic outcomes (through GDP and manufacturing value added). This comprehensive approach enables us to evaluate FDI performance through multiple lenses, providing insights into both the economic benefits and environmental costs of manufacturing-focused FDI in middle-income countries.

The net inflow of FDI, gross capital formation, manufacturing value added, and GDP were measured in billions of USD. The population was measured in millions. The primary energy consumption was measured in exajoules (EJ). The greenhouse gas emissions were measured as millions of tonnes of carbon dioxide equivalent (Mt CO_2eq).

Table 2 shows the average values of the input and output factors over the study period. It is worth noting that China demonstrated much larger values for the production factors than other middle-income countries. On the other hand, Bangladesh, the Philippines, and Thailand showed smaller values for the production factors than other countries.

Table 2. Descriptive statistics of input and output data.

Country	Inputs					Outputs		
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Bangladesh	2.02	104.57	164.57	1.59	269.33	69.08	334.63	0.38
Brazil	64.32	296.39	210.67	12.65	1297.35	192.50	1812.18	25.94
China	222.90	6120.17	1401.25	141.91	14,467.11	3906.65	14,156.46	1433.34
India	39.51	746.29	1106.05	32.27	3026.36	210.60	2402.66	54.55
Indonesia	27.25	444.60	535.47	7.71	1699.75	393.39	1392.51	9.39
Malaysia	17.63	130.94	54.95	4.38	445.80	253.36	560.86	7.33
Mexico	28.58	233.05	101.84	8.08	667.36	76.96	1031.75	16.51
Philippines	8.87	83.46	109.40	1.90	241.54	65.83	354.67	4.05
Thailand	7.68	117.53	71.13	5.12	451.95	127.41	477.90	8.04
Vietnam	14.94	103.15	95.29	3.90	443.15	74.43	317.97	6.77
Max.	222.90	6120.17	1401.25	141.91	14,467.11	3906.65	14,156.46	1433.34
Min.	2.02	83.46	54.95	1.59	241.54	65.83	317.97	0.38

Note: (a) average net inflow of FDI; (b) average gross capital formation; (c) average population; (d) average primary energy consumption; (e) average GHG emissions; (f) average manufacturing value added; (g) average GDP; (h) average number of patents.

3.3. Performance Assessment

This study used DEA as a primary method to evaluate the relative efficiency of decision-making units (DMUs) in a multidimensional manner (Liu et al. 2024). DEA has emerged as a powerful tool for measuring relative efficiency across diverse contexts since its introduction by Charnes et al. (1978). Unlike traditional parametric approaches that require predetermined functional relationships between inputs and outputs, DEA constructs an empirical production frontier based on observed best practices (Cooper et al. 2011). This methodological feature makes DEA particularly valuable for analyzing complex economic systems where the underlying production technology is not well understood or difficult to specify.

The application of DEA to international economic performance assessment has gained significant traction in recent years. For instance, Mandal and Madheswaran (2010) demonstrated DEA's effectiveness in comparing country-level environmental efficiency, while Liu et al. (2024) showcased its utility in evaluating resource management practices across OECD nations. Our study extends this tradition by employing a non-radial DEA model with translation invariance, building on the methodological foundations established by Sueyoshi and Goto (2012).

Our methodological approach offers several distinctive advantages for analyzing FDI performance in middle-income countries. The non-radial measurement framework, as described by Tone (2001), allows us to capture efficiency improvements that may occur non-proportionally across different inputs and outputs. This feature is particularly relevant when examining macroeconomic variables that often exhibit complex interdependencies. Furthermore, the translation invariance property enables us to handle negative values in our dataset, which is particularly important when dealing with FDI net inflows during economic disruptions such as the COVID-19 pandemic (Sueyoshi et al. 2020).

We examined efficiency under both constant returns to scale (CRS) and variable returns to scale (VRS) assumptions. The CRS framework, following Charnes et al. (1978), assumes that changes in inputs lead to proportional changes in outputs regardless of the operational scale. However, as Banker et al. (1984) argued, the VRS assumption often provides a more realistic representation of economic processes, particularly when examining units operating at different scales. By comparing the results under both assumptions, we can derive insights about scale efficiency, offering a more nuanced understanding of FDI performance across our sample countries.

Also, to simplify the treatment of the undesirable output in this model, we placed it (GHG emissions in this study) on the input side so that we could achieve the goal of minimizing the undesirable output. The other difference from conventional DEA models is that this model seeks to measure the level of inefficiency first and compute the level of efficiency by subtracting it from unity.

3.3.1. Efficiency Under Constant Returns to Scale

To assess the performance measured by the degree of efficiency under constant returns to scale (CRS) on the k-th DMU at the t-th period (EFc_t^k), this study used the following formulation to compute the inefficiency (IEc_t^k):

$$\begin{gathered}\text{Maximize } \textstyle\sum_{t=1}^{T}\left(\sum_{i=1}^{m} R_i^x d_{it}^x + \sum_{r=1}^{s} R_r^g d_{rt}^g\right)\\ \text{s.t. } \textstyle\sum_{j=1}^{n} x_{ijt}\lambda_{jt} + d_{it}^x = x_{ikt}\ (i = 1, \ldots, m\ \&\ t = 1, \ldots, T),\\ \textstyle\sum_{j=1}^{n} g_{rjt}\lambda_{jt} - d_{rt}^g = g_{rkt}\ (r = 1, \ldots, s\ \&\ t = 1, \ldots, T),\\ \lambda_{jt} \geq 0\ (j = 1, \ldots, n\ \&\ t = 1, \ldots, T),\end{gathered} \tag{1}$$

$$d_{it}^x \geq 0\ (i = 1, \ldots, m\ \&\ t = 1, \ldots, T)\ \&\ d_{rt}^g \geq 0\ (r = 1, \ldots, s\ \&\ t = 1, \ldots, T).$$

where x_{ijt} is the observed i-th input of the j-th DMU ($i = 1, \ldots, m$ and $j = 1, \ldots, n$) in the t-th period, g_{rjt} is the observed r-th output of the j-th DMU ($r = 1, \ldots, s$ and $j = 1, \ldots, n$) in the t-th period, ξ is a measure of inefficiency, d_{it}^x is an unknown slack variable of the i-th input in the t-th period, d_{rt}^g is an unknown slack variable of the r-th output in the t-th period, λ_{jt} is an unknown intensity variable of the j-th DMU in the t-th period, and ε_s is a prescribed small number.

Additionally, we specified the following data ranges for inputs (X) and outputs (G) to avoid an occurrence of zero in dual variables.

R_i^x is a data range for the i-th input, which was specified as follows:

$$R_i^x = (m + s)^{-1}\{max_{jt}(x_{ijt}|all\ j\ \&\ all\ t) - min_{jt}(x_{ijt}|all\ j\ \&\ all\ t)\}^{-1} \quad (2)$$

R_r^g is a data range for the r-th desirable output, which was specified as follows:

$$R_r^g = (m + s)^{-1}\{max_{jt}(g_{ijt}|all\ j\ \&\ all\ t) - min_{jt}(g_{ijt}|all\ j\ \&\ all\ t)\}^{-1} \quad (3)$$

Then, we measured the degree of efficiency of the k-th DMU in the t-th period:

$$EFc_t^k = 1 - IEc_t^k = 1 - \varepsilon_s\left(\sum_{i=1}^{m} R_i^x d_{it}^{x\,*} + \sum_{r=1}^{s} R_r^g d_{rt}^{g\,*}\right) \quad (4)$$

where the inefficiency score (IEc_t^k) and all slack variables were determined based on the optimality of Model (1). Thus, the equation within the parenthesis on the right-hand side was obtained from the optimality of Model (1).

3.3.2. Efficiency Under Variable Returns to Scale and Scale Efficiency

To compute the degree of inefficiency under variable returns to scale (VRS) on the k-th DMU in the t-th period (IEv_t^k), we added $\sum_{i=1}^{m} \lambda_{jt} = 1$ $(t = 1, \ldots, T)$ to the constraint of Model (1).

We measured the degree of efficiency on the k-th DMU in the t-th period using

$$EFv_t^k = 1 - IEv_t^k = 1 - \varepsilon_s(\sum_{i=1}^{m} R_i^x d_{it}^{x\,*} + \sum_{r=1}^{s} R_r^g d_{rt}^{g\,*}) \quad (5)$$

where the inefficiency score (IEv_t^k) and all slack variables were determined based on the optimality of Model (1) plus the additional constraint.

Moreover, the degree of scale efficiency (SE) of the k-th DMU in the t-th period (SE_t^k) was measured using

$$SE_t^k = \frac{EFc_t^k}{EFv_t^k} \quad (6)$$

It is worth noting that this study used a non-radial DEA approach, which is different from conventional DEA models. First, Model (1) addresses the multiple projection issue, which often occurs in conventional models, by incorporating the direction for maximization. For instance, Model (1) incorporates the direction g_{rkt} for maximization, given the observed g_{rkt}. The models do not have such a direction for optimal projection. Second, we assessed the performance of the k-th DMU, one of many (J_t) in the t-th period. This approach can handle datasets with negative or zero values, in conjunction with the translation invariance property.

3.3.3. Translation Invariance

The property of translation invariance enables us to handle zero or negative values in a dataset by proving that a data shift will lead to the same results. Data shifts of all the DMUs (j = 1, . . ., n) were specified by

$$\overline{x}_{ijt} = x_{ijt} + \alpha_{it}\ (i = 1, \ldots, m)\ and\ \overline{g}_{rjt} = g_{rjt} + \beta_{it}\ (r = 1, \ldots, s) \quad (7)$$

where x_{ijt} and g_{rjt} are the original data points for the input and output, respectively; α_{it} and β_{rt} are arbitrary positive numbers that make all the original zero or negative values positive; and $\overline{x}_{ijt}$ and $\overline{g}_{rjt}$ are shifted data points.

With the data shifts, all production factors of the j-th DMU become $\overline{x}_{ijt} > 0$ (i = 1, . . ., m) and $\overline{g}_{rjt} > 0$ and constraints in Model (1) are transformed to

$$\sum_{j=1}^{n} \left(x_{ijt} + \alpha_{it}\right)\lambda_{jt} + d_{it}^{x} = x_{ikt} + \alpha_{it}\ (i = 1,\ \ldots,\ m)\ and\ \sum_{j=1}^{n} \left(g_{rjt} + \beta_{rt}\right)\lambda_{jt} - d_{rt}^{g} = g_{rkt} + \beta_{rt}\ (r = 1,\ \ldots,\ s) \tag{8}$$

under the condition that $\sum_{j=1}^{n} \lambda_{jt} = 1$, $\sum_{j=1}^{n} \alpha_{it}\lambda_{jt} = \alpha_{it}$, and $\sum_{j=1}^{n} \beta_{rt}\lambda_{jt} = \beta_{rt}$. By canceling out α_{it} and β_{rt} on both sides of the two constraints in Equations (8),

$$\sum_{j=1}^{n} x_{ijk}\lambda_{jt} + d_{it}^{x} = x_{ikt}\ (i = 1, \ldots, m)\ \text{and} \sum_{j=1}^{n} g_{rjk}\lambda_{jt} - d_{rt}^{g} = g_{rkt}\ (r = 1, \ldots, s) \tag{9}$$

which are the same as the constraints in Model (1). Thus, the data shift did not actually change the constraints of Model (1).

Reflecting the data shift in the objective function of Model (1), it transforms the two types of slacks, but it does not actually change the objective function, as shown below:

$$\begin{aligned} &\sum_{i=1}^{m} R_i^x \left[(x_{ikt} + \alpha_{it}) - \sum_{i=1}^{n} \left(x_{ijt} + \alpha_{it}\right)\lambda_{jt}\right] = \sum_{j=1}^{m} R_i^x \left(x_{ikt} - \sum_{j=1}^{n} x_{ijt}\lambda_{jt}\right) = \sum_{j=1}^{m} R_i^x d_{it}^x \text{ and} \\ &\sum_{r=1}^{s} R_r^g \left[\sum_{j=1}^{n} \left(g_{rjt} + \beta_{rt}\right)\lambda_{jt} - \left(g_{rkt} + \beta_{rt}\right)\right] = \sum_{r=1}^{s} R_r^g \left(\sum_{j=1}^{n} g_{rjt}\lambda_{jt} - g_{rkt}\right) = \sum_{r=1}^{s} R_r^g d_{rt}^g \end{aligned} \tag{10}$$

Equation (10) verifies the translation invariance by showing that the objective value and constraints of Model (1) do not change. As a consequence, Model (1) can handle zero or negative values in a dataset (e.g., negative net FDI inflow in this study).

3.4. Technological Context Evaluation

While we used standard indicators, such as the Gini index, for socioeconomic context evaluation, we proposed employing the concept of technology lifecycle, visualized as a sigmoid or S curve. To fit the S curve into the data (the cumulative number of patents in this study), we used the following logistic function:

$$S_t = \frac{\gamma N_t}{1 + \exp(-\beta(t - \tau))} \tag{11}$$

where S_t = the number of accumulated patents at time t; γN_t = saturation level of accumulated patents; γ = fraction; N_t = total population; τ = inflection point; and $\beta/2$ = maximum growth rate.

Considering the relationship between FDI and technological development in middle-income countries, we categorized the countries into different groups based on their technological development level. To measure the level of technological progress, we focused on each country's inflection point (τ) and used 2022 or the median inflection point as the reference year. The year 2022 was selected to reflect post-pandemic recovery trends, providing a meaningful benchmark for evaluating the impact of recent global disruptions on technological advancement and patent activity.

4. Results

4.1. DEA Results

Using the model and data presented in Section 3, we assessed the FDI performance of ten middle-income countries by computing their efficiency scores under CRS and VRS conditions along with their SE scores. The CRS model represents a linear proportionality between inputs and outputs, regardless of the size of a country's economy. The VRS model allows countries of different sizes to exhibit varying FDI efficiencies. It builds upon the CRS model by incorporating the possibility of increasing or decreasing returns to scale, which can flexibly reflect the impact of different countries' development scales and stages on their FDI performance.

4.1.1. Results of CRS Model

The CRS model-based efficiency scores of FDI performance of the 10 countries from 2015 to 2022 are presented in Table 3 and Figure 2. In particular, Figure 2 shows that the efficiency scores of most countries were stable, while those of China and India fluctuated. With the emergence of COVID-19, China had a dip in its efficiency scores. India's slump in its efficiency scores started in 2017 along with its political/economic turmoil such as the presidential election, widespread farmer protests, and the implementation of the Goods and Services Tax (GST).

Table 3. Efficiency scores of CRS model.

Country	2015	2016	2017	2018	2019	2020	2021	2022
Bangladesh	0.984	0.986	0.988	0.989	0.991	0.994	0.997	1.000
Brazil	0.989	1.000	1.000	0.990	0.991	1.000	0.985	0.986
China	0.895	1.000	1.000	1.000	0.962	0.959	0.938	1.000
India	0.957	0.964	0.857	0.851	0.850	0.846	0.855	0.855
Indonesia	0.953	1.000	0.991	0.988	0.979	0.986	1.000	0.987
Malaysia	1.000	0.995	0.999	1.000	1.000	1.000	0.996	1.000
Mexico	1.000	0.995	0.992	0.994	1.000	0.994	1.000	1.000
Philippines	0.993	0.991	0.990	0.991	0.992	1.000	0.992	0.992
Thailand	0.991	0.994	0.993	0.992	0.997	1.000	0.991	0.992
Vietnam	0.985	0.985	0.985	0.984	0.984	0.984	0.984	0.984

Figure 2. Efficiency scores of CRS model.

4.1.2. Results of VRS Model

The VRS model results are presented in Table 4 and Figure 3. In general, the results of the VRS model are similar to those of the CRS model. However, one major difference in the results of two models is India's rebound after 2021.

Table 4. Efficiency scores of VRS model.

Country	2015	2016	2017	2018	2019	2020	2021	2022
Bangladesh	1.000	1.000	1.000	0.999	0.999	1.000	1.000	1.000
Brazil	0.990	1.000	1.000	0.991	0.992	1.000	0.988	0.988
China	1.000	1.000	1.000	1.000	0.962	0.959	1.000	1.000
India	0.957	0.964	0.909	0.860	0.871	0.857	0.978	1.000
Indonesia	0.969	1.000	0.991	0.989	0.979	0.986	1.000	1.000
Malaysia	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000
Mexico	1.000	1.000	0.992	0.994	1.000	0.994	1.000	1.000
Philippines	1.000	0.998	0.997	0.997	0.999	1.000	1.000	0.999
Thailand	0.992	0.994	0.993	0.992	0.997	1.000	0.992	0.993
Vietnam	0.991	0.99	0.989	0.986	0.985	0.985	0.986	0.985

Figure 3. Efficiency scores of VRS model.

4.1.3. Scale Efficiency

By comparing the efficiency scores under CRS with that under VRS, the SE was calculated, which can tell whether the current scale is optimal. If the SE is 1, the current scale is optimal, otherwise, the scale can be changed to further improve efficiency. The results of the ten countries' scale efficiency scores are presented in Table 5 and Figure 4. Like the operational efficiency scores under the CRS and VRS conditions, most countries showed stable patterns, but China and India showed fluctuating patterns. In particular, India's scale efficiency scores tended to decrease over time.

Compared to the CRS model, the VRS model was better able to capture scale-related changes. Fluctuations can have different impacts on economies of varying scales. Larger economies find it more difficult to consistently remain at a good scale efficiency. When it comes to macroeconomics, fluctuations in scale efficiency or diseconomies of scale may stem from the following: structural economic changes caused by political interventions; market economic activities, such as market expansion and industrial upgrading; and scale inefficiencies in particular sectors that spread, leading to poor overall scale efficiency in the economy.

Table 5. Scale efficiency.

Country	2015	2016	2017	2018	2019	2020	2021	2022
Bangladesh	0.984	0.986	0.988	0.990	0.992	0.994	0.997	1.000
Brazil	0.999	1.000	1.000	0.999	0.999	1.000	0.997	0.998
China	0.895	1.000	1.000	1.000	1.000	1.000	0.938	1.000
India	1.000	1.000	0.943	0.990	0.976	0.987	0.874	0.855
Indonesia	0.983	1.000	1.000	0.999	1.000	1.000	1.000	0.987
Malaysia	1.000	1.000	0.999	1.000	1.000	1.000	0.996	1.000
Mexico	1.000	0.995	1.000	1.000	1.000	1.000	1.000	1.000
Philippines	0.993	0.993	0.993	0.994	0.993	1.000	0.992	0.993
Thailand	0.999	1.000	1.000	1.000	1.000	1.000	0.999	0.999
Vietnam	0.994	0.995	0.996	0.998	0.999	0.999	0.998	0.999

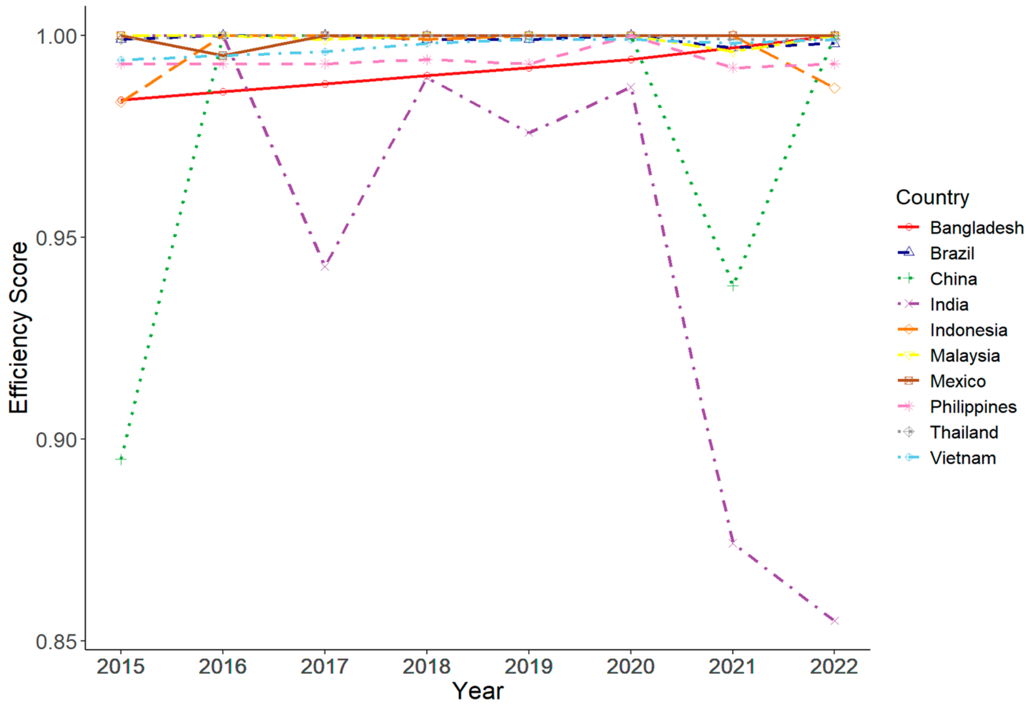

Figure 4. Scale efficiency.

4.1.4. Result Analysis

Table 6 presents the average and standard deviation values of the two operational efficiency scores and scale efficiency scores for the ten countries. The varying patterns observed under the CRS and VRS models reveal important insights into the nature of FDI efficiency in different economic contexts. While the average efficiency scores showed broad similarities across both models, several countries, particularly India, exhibited notable differences that merit careful examination.

The CRS model, which assumes a linear relationship between inputs and outputs regardless of operational scale, showed India maintaining the lowest average efficiency (0.879) with the highest volatility (standard deviation of 0.0502). However, under the VRS model, which accounts for scale-dependent variations in efficiency, India demonstrated a markedly different pattern, which was particularly evident in its post-2021 recovery (rising from 0.857 in 2020 to 1.000 in 2022). This divergence between the CRS and VRS results suggests that India's FDI efficiency is significantly influenced by scale effects, a finding consistent with Banker et al. (1984)'s theoretical framework on scale-dependent efficiency measurements.

Table 6. Descriptive statistics of DEA results.

Country	CRS—Average	CRS—Sd	VRS—Average	VRS—Sd	SE—Average	SE—Sd
Bangladesh	0.991	0.0055	1.000	0.0005	0.991	0.0055
Brazil	0.993	0.0064	0.994	0.0054	0.999	0.0011
China	0.969	0.0386	0.990	0.0183	0.979	0.0403
India	0.879	0.0502	0.925	0.0573	0.953	0.0578
Indonesia	0.986	0.0149	0.989	0.0112	0.996	0.0068
Malaysia	0.999	0.0021	0.999	0.0018	0.999	0.0014
Mexico	0.997	0.0034	0.998	0.0035	0.999	0.0018
Philippines	0.993	0.0031	0.999	0.0013	0.994	0.0025
Thailand	0.994	0.0032	0.994	0.0029	1.000	0.0005
Vietnam	0.984	0.0005	0.987	0.0025	0.997	0.0020

The scale efficiency analysis further illuminated these differences. Thailand achieved optimal scale efficiency (1.000), indicating that its operational scale aligns well with its technological capabilities. In contrast, India's lower scale efficiency (0.953) suggests that its FDI operations may be operating at a suboptimal scale. This pattern aligns with Ray and Das (2010)'s findings on scale effects in emerging economies, where rapid growth can lead to temporary mismatches between operational scale and technical efficiency.

Large economies like China and India showed more pronounced fluctuations in both models, but with different patterns. China's efficiency scores demonstrated greater stability under VRS (average 0.990) compared to CRS (average 0.969), suggesting that when scale effects are considered, its FDI utilization appears more efficient. This finding resonates with Margono and Sharma (2006)'s observations about scale economies in large manufacturing sectors, where the benefits of scale can partially offset other inefficiencies.

The differing patterns between the CRS and VRS results can be attributed to several factors. First, the VRS model's ability to account for scale-dependent efficiencies is particularly relevant for economies experiencing rapid structural changes. For instance, India's improved performance under VRS post-2021 suggests that its FDI efficiency gains were partly masked by scale-related factors in the CRS model.

Second, countries with more stable efficiency scores across both models (such as Malaysia and Thailand) likely operate at scales closer to their optimal efficiency frontiers. This stability indicates that their FDI operations have achieved a better alignment between scale and technical efficiency, consistent with Tone and Tsutsui (2014)'s findings on efficiency stability in mature manufacturing economies.

Third, the temporal patterns in both models reveal how external shocks, such as the COVID-19 pandemic, affect efficiency through different channels. The VRS model's results suggest that some efficiency losses attributed to scale effects in the CRS model were actually due to temporary disruptions in operational scale rather than fundamental efficiency declines.

4.2. Technology Lifecycles of Ten Middle-Income Countries

Table 7 describes the three parameters of the ten countries' S curves fitted by Model (11) as well as their R^2 values for the goodness of fit and other simple statistics. On average, the saturation level was expected to be approximately 6 million patents while the maximum growth rate was estimated to be 5.6%. China surpassed other countries in the saturation level and maximum growth rate. The mean of the inflection points was predicted to be the year 2062. As of 2024, only three countries (Bangladesh, Brazil, and China) passed the inflection points of their S curves. The R^2 values were relatively high, all of which were greater than 96%, implying that Model (11) fit the data well. See Appendix B for the 10 countries' S curves based on the number of accumulated patents (actual and fitted by logistic function curves) over time.

Table 7. Descriptive statistics of ten countries' S curves.

Country	Saturation Level	Max. Growth Rate	Inflection Year	R-Squared Value
Bangladesh	2815	0.041	2011	0.996
Brazil	242,473	0.041	2016	1.000
China	20,701,734	0.138	2019	1.000
Indonesia	197,172	0.072	2037	0.993
India	6,809,312	0.054	2052	0.999
Mexico	3,852,296	0.024	2121	0.997
Malaysia	6,136,042	0.047	2080	0.978
Philippines	5,202,870	0.033	2118	0.991
Thailand	7,729,580	0.041	2092	0.963
Vietnam	9,490,702	0.065	2074	0.998
Mean	6,036,500	0.056	2062	0.992
Max.	20,701,734	0.138	2121	1.000
Min.	2815	0.024	2011	0.963
SD	6,146,488	0.032	41	0.012

In addition to technology advances (reflected by an increase in the number of patents) as an output, this study used manufacturing value added as another output. Technological advancements can shift manufacturing from low value added to high value added. Superior technology clearly aids decision-making units in achieving higher efficiency scores. According to the *World Investment Report 2019*, the inflow of technology-intensive FDI grew significantly, accounting for over 40% of global FDI. Among them, technologically advanced economies like China attracted a substantial amount of high-tech FDI, mainly due to its technological and innovation capabilities (UNCTAD 2019). China is a typical representative of the sustainable cycle, where policies attract FDI, technological advancements, manufacturing shifts to add higher value, and economic growth.

4.3. Hypothesis Testing

Next, the three hypotheses along with the six sub-hypotheses were tested. Based on the CRS and VRS scores obtained, we used a series of Kruskal–Wallis tests across the different groups of middle-income countries to test the different hypotheses. The test results are summarized in Table 8.

Table 8. Kruskal–Wallis test results.

		Hypothesis 1		Hypothesis 2		Hypothesis 3	
		H1a	H1b	H2a	H2b	H3a	H3b
CRS	Group 1 Mean	0.984	0.964	0.995	0.962	0.981	0.980
	Group 2 Mean	0.976	0.993	0.967	0.989	0.976	0.977
	Chi-Squared Statistic	0.095	7.973	18.069	7.965	0.023	0.327
	p-Value	0.758	0.005 ***	0.000 ***	0.005 ***	0.880	0.567
VRS	Group 1 Mean	0.995	0.979	0.997	0.978	0.988	0.986
	Group 2 Mean	0.984	0.995	0.981	0.994	0.987	0.990
	Chi-Squared Statistic	4.187	0.913	9.074	0.509	0.033	1.258
	p-Value	0.041 **	0.339	0.003 ***	0.476	0.856	0.262
SE	Group 1 Mean	0.990	0.984	0.998	0.984	0.993	0.993
	Group 2 Mean	0.991	0.998	0.986	0.996	0.989	0.987
	Chi-Squared Statistic	0.280	2.824	3.382	16.601	0.021	0.010
	p-Value	0.597	0.093 *	0.066 *	0.000 ***	0.884	0.921

Note: *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Hypothesis 1 was concerned with whether there was a significant difference in FDI performance between middle-income countries that achieved different levels of technological development. When grouping countries by the inflection points of their cumulative number of patents-based S curves, we used the year 2022 as the divider and formed two groups (H1a). Group 1 included Bangladesh, Brazil, and China, while group 2 included Indonesia, India, Mexico, Malaysia, the Philippines, Thailand, and Vietnam. The sub-hypothesis was supported at the 5% significance level in the VRS model. When grouping countries by the median inflection point of their S curves (H1b), two groups were formed. Group 1 included Bangladesh, Brazil, China, Indonesia, and India, while group 2 included Mexico, Malaysia, the Philippines, Thailand, and Vietnam. This sub-hypothesis was supported at the 1% significance in the CRS model and at the 10% significance level for SE.

Hypothesis 2 was concerned with whether there was a significant difference in FDI performance between middle-income countries that achieved different levels of economic inequality. When grouping countries by their Gini coefficient (H2a), two groups were formed. Group 1 with a Gini coefficient above 0.4 included Brazil, Malaysia, Mexico, and the Philippines, while group 2 with a Gini coefficient below 0.4 included Bangladesh, China, Indonesia, India, Thailand, and Vietnam. The sub-hypothesis was supported in both the CRS and VRS models at the 1% significance level and at the 10% level for SE. When evaluating economic inequality using a poverty headcount ratio of USD 3.65 a day (H2b), two groups were formed. Group 1 with a ratio above 10% included Bangladesh, India, Indonesia, and the Philippines, while group 2 with a ratio below 10% included Brazil, China, Malaysia, Thailand, and Vietnam. This sub-hypothesis was supported at the 1% significance level in the CRS model and at 1% for SE.

Hypothesis 3 was concerned with whether there was a significant difference in FDI performance between middle-income countries before and after the COVID-19 pandemic. The groups for testing H3a were divided into two time windows: 2015–2018 and 2019–2022, split equally by time. The groups for testing H3b were divided into another two time windows, 2015–2019 and 2020–2022, with a time lag between the occurrence of the global pandemic and realized economic consequences. Both sub-hypotheses were not significant in either the CRS or VRS model.

5. Discussion

The DEA results showed several interesting points for discussion. Our results tended to show higher efficiency scores than other studies. Wanke et al. (2024), for instance, demonstrated FDI performance scores as low as 0.37 while our scores were over 0.85. This significant difference stemmed primarily from the study sample and industry sectors. Wanke et al. (2024) included not only developing countries but also developed and underdeveloped ones, which dragged the performance score down. Moreover, they considered overall industries, including low-tech and low value-added ones, which decreased the performance score further. In contrast, our study included an elite group of middle-income countries that tend to receive the benefit of substantial amounts of FDI. Also, our study focused on the manufacturing sector, which tends to be high tech and high value, so our performance scores were relatively high.

Additionally, it is worth adding more context to the performance scores of two large economies—China and India—considering their significant contribution to the global economy. In the CRS model, 2015 stood out as an unusual year for China, with an efficiency score lower than normal. In fact, China's economy experienced a slowdown in 2015, dropping to below 7% for the first time since 1991 (Magnier 2016). Investor confidence in the economic growth of China declined under the background of overcapacity in the manufacturing sector (Xu and Liu 2018). In the CRS model, India's efficiency scores for 2015–2016 were higher than usual. India's economy grew rapidly due to reforms implemented by the Modi government (Echeverri-Gent et al. 2021), surpassing China to become the fastest-growing major economy (Bellman 2016). In general, sizable events such as the shock of a pandemic with strict lockdowns, economic recessions, or reforms by a new government, which can impact the entire economy, tend to cause significant fluctuations in efficiency scores. Miniscule events such as a temporary increase in pollution, mild pandemic containment measures, or short-term political fluctuations, which can only affect parts of the economy, lead to a moderate change in efficiency scores.

China was the only country whose FDI efficiency performance was significantly impacted by the COVID-19 pandemic among the 10 middle-income countries. The manufacturing sector was sluggish in 2020 due to the strict zero-COVID policy. The blow to confidence from the pandemic continued to keep consumption, employment, and the real estate market depressed in 2021 (Qian 2023), resulting in a drop in GDP growth to 3% (National Bureau of Statistics of China 2023). In SE, China and India, as large countries, showed a need for further adjustments to achieve an optimal scale. This implies that it may be more challenging for large countries to sustain an optimal scale.

The hypothesis test results also offer food for thought. There have already been many studies indicating that the spillover effects of FDI can promote technological progress in host countries. This study also supports the relationship between FDI performance and technological development. While most extant literature used parametric methods to examine the relationship between FDI, technology, and other factors, this study employed non-parametric methods to derive efficiency scores based on multiple economic factors and applied the technology lifecycle concept to take into account the accumulative characteristics of technological development.

Another aspect of the hypothesis testing results concerned the relationship between FDI performance and economic inequality. The current evidence for this relationship is inconclusive. Some studies suggested that FDI is associated with high inequality, while others argued the opposite. This study examined two aspects of economic inequality: the wealth gap and poverty. We offer a more thorough understanding by analyzing the simultaneous phenomena of a widening wealth gap and the reduction in poverty. When it comes to economic inequality, both regional inequality and income inequality were considered. On the one hand, FDI tends to favor coastal and port cities, as well as the tax-free zones and free trade areas. While this may exacerbate regional inequality (Wei et al. 2009), it may be beneficial for overall economic development as the more developed regions can spread growth to less developed regions (Huang and Wei 2016). On the other hand, FDI business activities make business owners wealthier. In our literature review, some studies that tracked long-term changes in economic inequality showed a dynamic process where inequality first widens and then narrows (Herzer and Nunnenkamp 2011; Kaulihowa and Adjasi 2018). The countries we studied are developing nations with middle incomes, which are still in the early stages of a dynamic shift, characterized by significant economic inequality. The future reduction in economic inequality may be driven by domestic reinvestment that will benefit other non-wealthy groups and regions. Combining the statistic results of hypotheses H2a and H2b, FDI was found to have a poverty reduction effect (Magombeyi and Odhiambo 2017), showing that even if the gap between the rich and the poor widens, the poorest group will still benefit.

The insignificant relationship between FDI performance and the COVID-19 pandemic in our analysis presents an intriguing contrast to studies focused on absolute FDI flows. While authors such as Evenett (2020) and Fu et al. (2021) documented substantial declines in global FDI volumes during the pandemic, our efficiency-based analysis reveals a more nuanced picture of FDI performance during this period.

Several factors help explain this paradox. First, the efficiency measures in our DEA framework capture the relationship between inputs and outputs rather than absolute values. While both FDI inflows (input) and manufacturing output (output) declined proportionally during the lockdowns, the efficiency scores remained relatively stable. This finding aligns with Kalotay and Sass (2021)'s observation that manufacturing firms adapted their operations to maintain productivity despite the reduced scale.

Second, the temporal pattern of the pandemic impacts varied significantly across our sample countries. China, for instance, experienced efficiency fluctuations during its strict zero-COVID policy implementation, which was particularly evident in the 2020–2021 period. However, other countries in our sample maintained relatively stable efficiency scores despite experiencing significant absolute declines in FDI. This heterogeneity in responses aligns with Pascariu et al. (2021)'s finding that country-specific institutional factors significantly influenced pandemic resilience.

Third, our analysis reveals an important distinction between short-term shocks to FDI volumes and the underlying efficiency in FDI utilization. While the pandemic disrupted global investment flows, the fundamental capabilities of countries to efficiently utilize FDI remained largely intact. This observation supports Gereffi (2020)'s argument that the pandemic accelerated existing trends rather than fundamentally altering the efficiency of global production networks.

Lastly, this study investigated a leading group of middle-income countries, which are more resilient in terms of FDI performance, rather than a middle or lagging group, which can be more vulnerable to external shocks such the pandemic. The stability of efficiency scores during the pandemic period may reflect the adaptive capacity of manufacturing sectors in middle-income countries. As noted by Sofic et al. (2022), many manufacturing firms in developing economies demonstrated remarkable resilience through the rapid adoption of digital technologies and the reorganization of production processes. This adaptation helped maintain operational efficiency even as absolute production volumes fluctuated.

The insignificance of our results, which rebuts the pandemic-related hypotheses (H3a and H3b), should therefore not be interpreted as evidence that COVID-19 had no impact on FDI systems. Rather, it suggests that efficiency measures capture aspects of economic performance that are different from traditional volume-based metrics. This finding has important implications for policy makers: while strategies to restore FDI volumes post-pandemic are important, maintaining and improving the efficiency of FDI utilization may be equally crucial for long-term economic recovery.

6. Conclusions

This study assessed the FDI performance of 10 middle-income countries in their specific contexts, with a focus on technological development, economic inequality, and performance during the global pandemic. In the first stage, we employed the non-radial DEA model with its translation invariance property to address the negative net inflow of FDI. In the model, we used five inputs—the net inflow of FDI, gross capital formation, population, primary energy consumption, and greenhouse gas pollution (as an undesirable output)—and three outputs—manufacturing value added, GDP, and number of patents. After calculating the operational efficiency scores under the CRS and VRS conditions, the SE was obtained as well. In the CRS model, Malaysia had the highest average efficiency score for FDI performance. In the VRS model, Bangladesh outperformed the other countries. India showed the lowest average efficiency in both the CRS and VRS models, with the largest standard deviation. As for SE, Thailand demonstrated an optimal scale, while there was room for improvement for India who needs to adjust its scale to the optimal level.

In the second stage, we conducted Kruskal–Wallis tests to examine three hypotheses, composed of six sub-hypotheses, using both the CRS and VRS models. Among them, five hypotheses were supported with statistically significant results. There was a significant difference in FDI performance between middle-income countries that achieved different levels of technological development. When grouped by inflection points of cumulative number of patent curves with 2022 as the divider, a significant difference was observed in the VRS model. When grouped by the median value of inflection points as the divider, a significant difference was observed in the CRS model. We suggest that the reason for this lies in the virtuous cycle between FDI and technological development. FDI can bring about technology spillovers and transfers at first. After internalization, it can lead to industry upgrading in the host country from low tech to high tech. In turn, a higher technology level helps attract higher value-added manufacturing FDI, further benefiting economic development.

There was a significant difference in FDI performance between the middle-income countries that have achieved different levels of economic inequality. When evaluating economic inequality using the Gini coefficient, a significant difference was observed in both the CRS and VRS models. When evaluating economic inequality using the poverty headcount ratio of USD 3.65 a day, a significant difference was observed in the CRS model. We suggest that the inequality brought by FDI is natural in the early stages, but through reinvestment and other trickle-down effects, it can ultimately promote economic growth.

While this paper contributes to the extant literature by exploring the FDI issue during the pandemic period and by applying non-radial DEA with a translation invariance property, it has some limitations. We attempted to use validated input and output factors by drawing on an extensive literature review, but there is a possibility that a better set of factors exists to measure FDI performance. Similarly, there is a possibility that the inclusion of a lagging group of developing countries, which are not resilient in terms of FDI performance, may lead to statistically significant results.

In terms of data limitations, the data used in this study came from secondary sources provided by international organizations, including the World Bank Database, the World Intellectual Property Organization, EDGAR, and the Energy Institute. They were not customized to our study, which may bring in imperfect measures. Another issue was the time window between the input and output factors. It may take years to add value to manufacturing, increase GDP, and increase the number of patents from FDI inflow. To take that into account, it may be better to use output data with time lags, but to the best of our knowledge, there is little research on the identification of appropriate time lags. Also, there may be heterogeneity in time lags among different output factors. In our future studies, we hope to have better information about the time lags and incorporate them into the DEA model.

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Appendix A

Table A1 presents the raw data used for our DEA model.

Table A1. Raw data for inputs and outputs.

		Inputs					Outputs		
Year	**Country**	**I 1**	**I 2**	**I 3**	**I 4**	**I 5**	**O 1**	**O 2**	**O 3**
2015	Bangladesh	2.83	56.35	157.83	1.39	248.09	32.75	195.08	0.34
2015	Brazil	64.74	313.79	205.19	12.66	1307.97	189.61	1802.21	30.22
2015	China	242.49	4782.45	1379.86	126.49	13,479.88	3202.51	11,061.60	1101.86
2015	India	19.78	293.23	259.09	28.52	961.41	180.66	860.85	45.66
2015	Indonesia	44.01	675.60	1322.87	6.78	3389.88	327.82	2103.59	9.15
2015	Malaysia	36.25	287.99	120.15	4.01	790.36	240.52	1213.29	7.73
2015	Mexico	9.86	76.62	31.07	7.93	321.31	67.18	301.36	18.07
2015	Philippines	5.64	65.40	103.03	1.60	210.10	61.07	306.45	3.73
2015	Thailand	8.93	89.71	70.29	4.98	447.45	109.85	401.30	7.93
2015	Vietnam	11.80	76.82	92.19	2.99	358.06	50.15	239.26	5.03

Table A1. *Cont.*

Year	Country	Inputs I 1	I 2	I 3	I 4	I 5	Outputs O 1	O 2	O 3
2016	Bangladesh	2.33	80.21	159.78	1.39	255.68	53.97	265.24	0.34
2016	Brazil	74.29	268.81	206.86	12.36	1285.09	193.69	1795.69	28.01
2016	China	174.75	4788.92	1387.79	127.00	13,447.14	3153.13	11,233.30	1338.50
2016	India	4.54	315.52	261.85	29.80	956.68	191.25	931.88	45.06
2016	Indonesia	44.46	692.40	1338.64	6.80	3443.29	347.94	2294.80	8.54
2016	Malaysia	38.90	270.76	121.52	4.22	799.05	220.99	1112.23	7.24
2016	Mexico	13.47	78.31	31.53	8.11	318.39	65.66	301.26	17.41
2016	Philippines	8.28	78.44	104.88	1.75	221.04	62.42	318.63	3.42
2016	Thailand	3.49	87.24	70.61	5.08	449.92	112.21	413.37	7.82
2016	Vietnam	12.60	81.56	93.13	3.24	379.76	55.25	257.10	5.23
2017	Bangladesh	1.81	90.91	161.79	1.45	268.20	58.97	293.76	0.30
2017	Brazil	68.89	301.80	208.51	12.47	1298.02	221.24	2063.51	25.66
2017	China	166.08	5295.15	1396.22	131.94	13,710.10	3460.35	12,310.50	1381.59
2017	India	39.97	821.48	1354.20	30.94	3590.03	204.75	2651.47	46.58
2017	Indonesia	20.51	342.37	264.50	7.04	1019.78	398.21	1015.62	9.30
2017	Malaysia	9.37	81.52	31.98	4.28	307.93	240.07	319.11	7.07
2017	Mexico	33.11	284.49	122.84	8.26	802.74	69.71	1190.72	17.18
2017	Philippines	10.26	83.96	106.74	1.92	239.39	64.05	328.48	3.40
2017	Thailand	8.29	104.66	70.90	5.17	449.46	123.28	456.36	7.87
2017	Vietnam	14.10	90.89	94.03	3.48	386.34	63.66	281.35	5.38
2018	Bangladesh	2.42	102.27	163.68	1.55	278.91	66.85	321.38	0.37
2018	Brazil	78.16	289.36	210.17	12.51	1274.95	201.82	1916.93	24.86
2018	China	235.37	6085.06	1402.76	138.30	14,296.57	3868.48	13,894.90	1542.00
2018	India	42.12	874.21	1369.00	32.69	3754.62	207.03	2702.93	50.06
2018	Indonesia	18.91	360.32	267.07	7.72	1109.64	402.24	1042.27	9.75
2018	Malaysia	8.30	85.74	32.40	4.35	326.31	253.64	358.79	7.30
2018	Mexico	37.86	294.95	124.01	8.16	780.82	77.24	1256.30	16.42
2018	Philippines	9.95	94.17	108.57	1.97	246.03	66.24	346.84	4.30
2018	Thailand	13.75	127.80	71.13	5.33	446.29	135.37	506.75	8.15
2018	Vietnam	15.50	99.29	94.91	3.91	441.91	72.46	310.11	6.07
2019	Bangladesh	1.91	113.15	165.52	1.74	276.85	74.49	351.24	0.41
2019	Brazil	69.17	290.67	211.78	12.72	1281.46	193.56	1873.29	25.40
2019	China	187.17	6176.24	1407.75	144.74	14,606.13	3823.42	14,280.00	1400.66
2019	India	50.61	853.41	1383.11	33.52	3731.12	220.50	2835.61	53.63
2019	Indonesia	24.99	378.03	269.58	8.22	1161.78	381.55	1119.10	11.48
2019	Malaysia	9.15	76.86	32.80	4.47	329.67	258.99	365.18	7.55
2019	Mexico	29.95	288.59	125.09	8.06	791.00	78.18	1305.21	15.94
2019	Philippines	8.67	99.49	110.38	2.03	253.39	69.77	376.82	4.38
2019	Thailand	5.52	129.55	71.31	5.34	453.57	139.38	543.98	8.17
2019	Vietnam	16.12	106.93	95.78	4.34	493.76	79.53	334.37	7.52
2020	Bangladesh	1.53	117.06	167.42	1.65	269.03	77.02	373.90	0.40
2020	Brazil	38.27	237.89	213.20	12.22	1277.69	157.84	1476.11	24.34
2020	China	253.10	6369.59	1411.10	149.45	14,879.56	3860.70	14,687.70	1497.16
2020	India	64.36	768.15	1396.39	31.76	3519.12	210.40	2671.60	56.77
2020	Indonesia	19.18	342.53	271.86	7.61	1104.71	377.35	1059.05	8.16
2020	Malaysia	4.06	66.34	33.20	4.30	324.52	224.32	337.46	6.83
2020	Mexico	31.52	226.40	126.00	7.43	739.32	75.02	1120.74	14.31
2020	Philippines	6.82	63.07	112.19	1.84	242.64	63.88	361.75	3.99
2020	Thailand	−4.95	118.80	71.48	4.97	449.40	127.89	500.46	7.53
2020	Vietnam	15.80	110.63	96.65	4.34	499.45	83.00	346.62	7.70
2021	Bangladesh	1.72	129.12	169.36	1.73	276.80	88.40	416.27	0.45
2021	Brazil	46.44	320.44	214.33	12.85	1343.14	168.64	1649.62	24.23
2021	China	344.08	7687.80	1412.36	157.94	15,632.90	4909.01	17,820.50	1585.66
2021	India	44.73	983.70	1407.56	34.51	3754.63	228.33	3150.31	61.57
2021	Indonesia	21.21	373.14	273.75	7.76	1128.06	455.91	1186.51	8.80
2021	Malaysia	20.25	82.64	33.57	4.58	334.67	273.64	373.83	7.53
2021	Mexico	33.75	281.61	126.71	7.99	765.46	87.44	1312.56	16.16

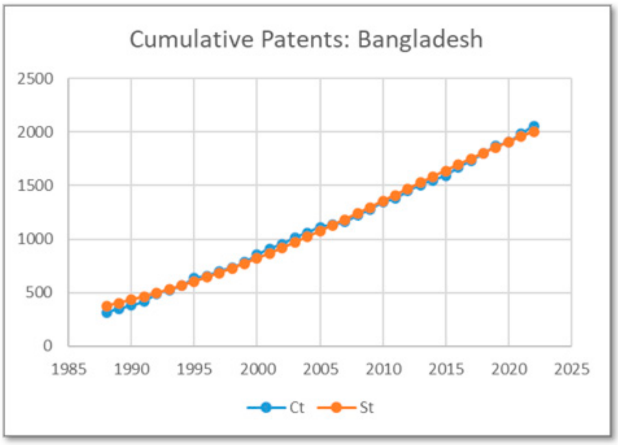
Table A1. *Cont.*

Year	Country	Inputs I 1	I 2	I 3	I 4	I 5	Outputs O 1	O 2	O 3
2021	Philippines	11.98	83.31	113.88	1.96	254.43	69.52	394.09	4.39
2021	Thailand	15.16	144.73	71.60	5.01	455.67	137.40	505.57	8.24
2021	Vietnam	15.66	122.54	97.47	4.34	496.73	90.13	366.14	8.53
2022	Bangladesh	1.63	147.48	171.19	1.79	281.08	100.16	460.20	0.42
2022	Brazil	74.61	348.37	215.31	13.41	1310.50	213.56	1920.10	24.76
2022	China	180.17	7776.13	1412.18	159.39	15,684.63	4975.61	17,963.20	1619.27
2022	India	49.94	1060.58	1417.17	36.44	3943.26	241.87	3416.65	77.07
2022	Indonesia	24.70	392.37	275.50	9.77	1240.83	456.06	1319.10	9.97
2022	Malaysia	14.73	95.68	33.94	4.84	353.92	314.70	407.03	7.37
2022	Mexico	39.10	333.41	127.50	8.73	819.87	95.22	1465.85	16.61
2022	Philippines	9.37	99.85	115.56	2.11	265.30	69.70	404.28	4.77
2022	Thailand	11.23	137.76	71.67	5.06	463.87	133.87	495.42	8.61
2022	Vietnam	17.90	136.57	98.19	4.59	489.16	101.22	408.80	8.71

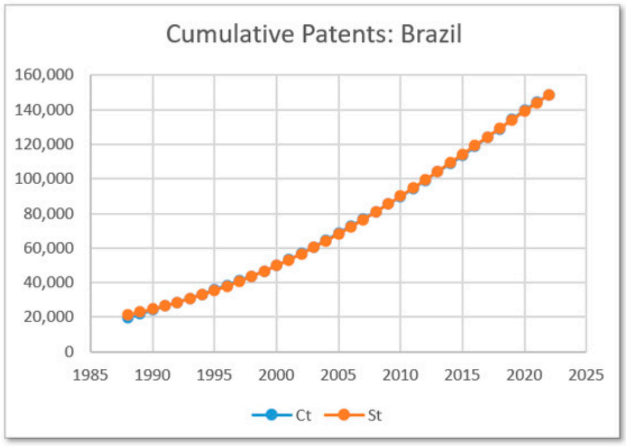
Note: I 1 = net inflow of FDI; I 2 = gross capital formation; I 3 = population; I 4 = primary energy consumption; I 5 = GHG emissions; O 1 = manufacturing value added; O 2 = GDP; O 3 = number of patents.

Appendix B

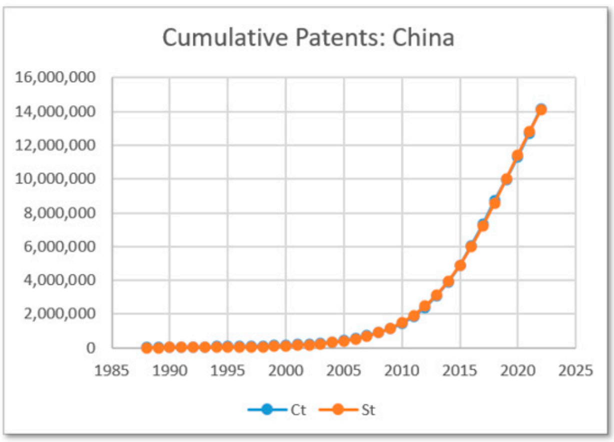
Figure A1 presents a panel of the 10 countries' S curves based on the number of accumulated patents (actual and fitted by logistic function curves) over time.



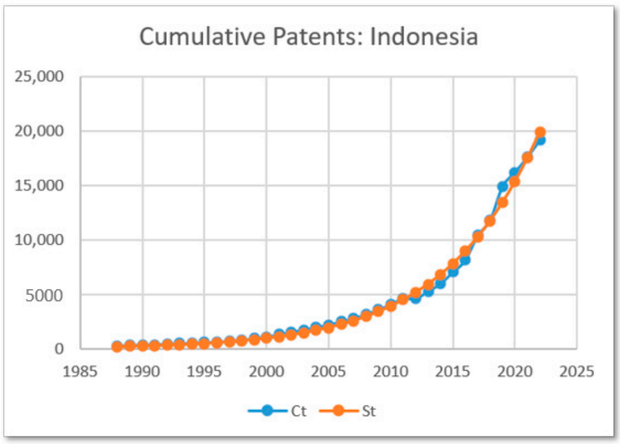
(**a**)



(**b**)

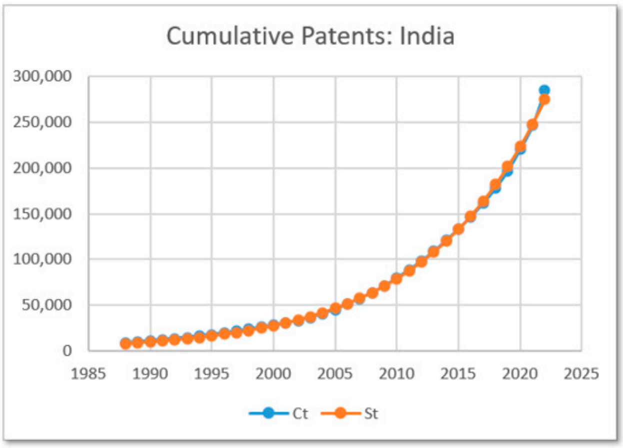


(**c**)

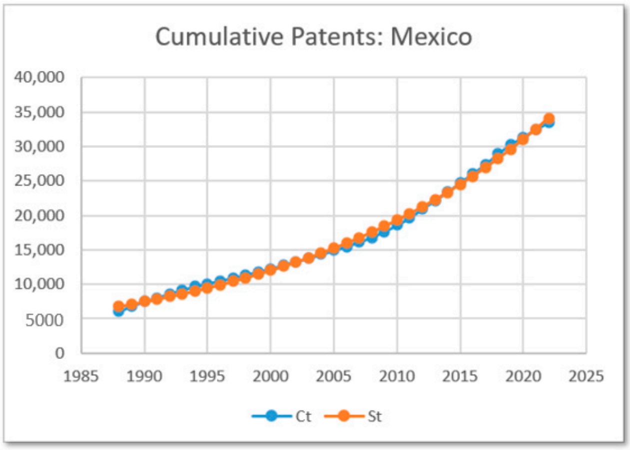


(**d**)

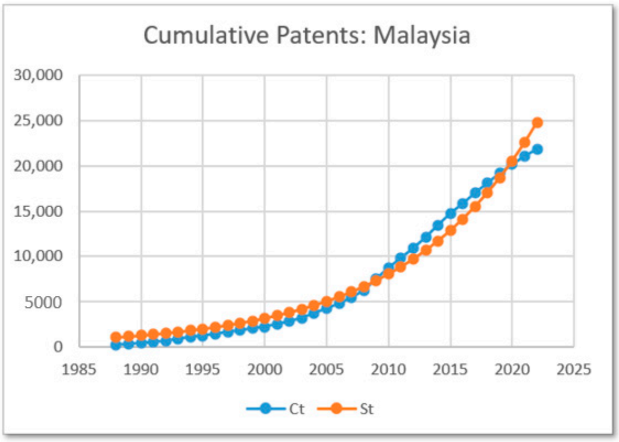
Figure A1. *Cont.*



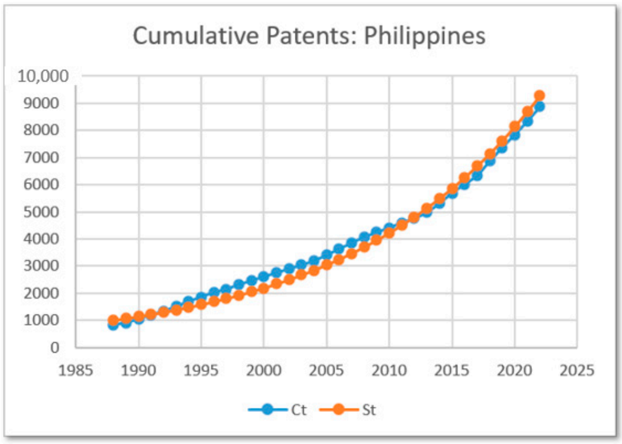
(**e**)



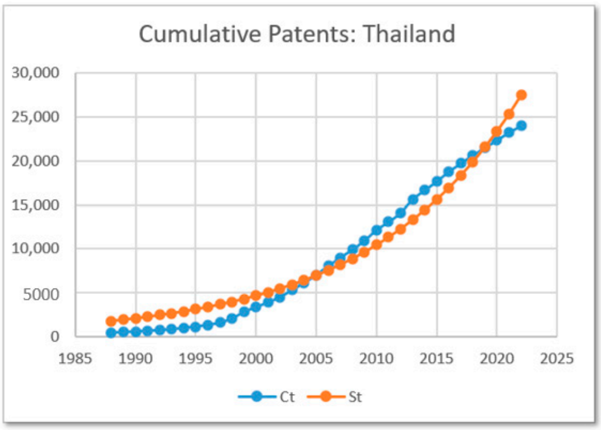
(**f**)



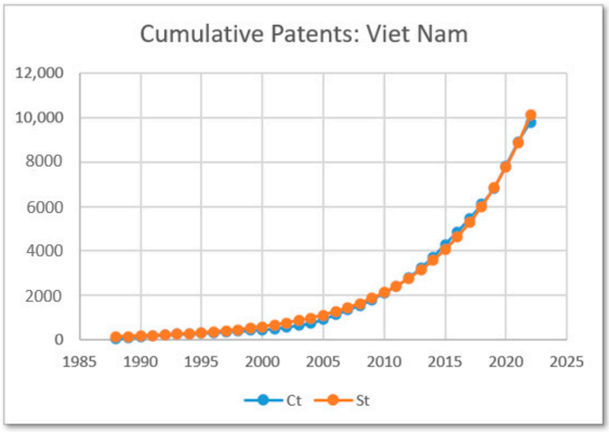
(**g**)



(**h**)



(**i**)



(**j**)

Figure A1. Patent-based S curves of ten middle-income countries. Note: C_t = cumulative number of patents (actual); S_t = cumulative number of patents (fitted by logistics function). (**a**) Bangladesh; (**b**) Brazil; (**c**) China; (**d**) Indonesia; (**e**) India; (**f**) Mexico; (**g**) Malaysia; (**h**) the Philippines; (**i**) Thailand; and (**j**) Vietnam.

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