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Apec textile efficiency drivers: Productivity and equity

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ABSTRACT

This study analyzes efficiency disparities in the textile sector across Asia-Pacific Economic Cooperation (APEC) economies, emphasizing wage gaps and labor conditions. Such inequalities constrain economic development and limit sustainable growth. The research aims to evaluate the relationship between textile sector efficiency and wage levels, identifying factors that explain gaps between developed and developing economies. Data Envelopment Analysis (DEA) was applied through two models: one using the number of employees and the other wages and salaries as primary inputs. Results showed that Hong Kong and Singapore achieved high efficiency in both models, while economies such as Vietnam and Mexico improved their performance when wage variables were considered. The findings suggest that better wage conditions are positively correlated with higher efficiency, underscoring the importance of public policies that balance competitiveness and labor equity within the textile sector. This work contributes evidence for comparative assessments of productive performance and wage equity in international manufacturing contexts and recommends further integration of labor, social, and technological variables. Ultimately, the study provides insights for policymakers aiming to achieve sustainable and inclusive growth in APEC member states, stressing the value of fair labor standards for economic development.

Contribution/ Originality: This study offers an original contribution by comparing the efficiency of the APEC textile sector through DEA models that replace the input "employees" with "wages and salaries," thereby revealing labor equity gaps and shifts in efficiency benchmarks that have not been jointly examined before. Moreover, there is a noticeable scarcity of empirical research explicitly focused on this problem, which makes it a significant area of opportunity to identify structural disparities and to propose policy-oriented solutions for enhancing both efficiency and social welfare in the sector.

1. INTRODUCTION

According to the International Labour Organization (2021), among the various existing sectors, the textile and apparel sector is one of the economic pillars of the Asia-Pacific Economic Cooperation (APEC) economies. It represents a significant share of the global Gross Domestic Product (GDP). Consequently, this sector not only generates millions of jobs but is also vital for the development of global supply chains.

The textile industry experienced an increase in production, reaching 7,180 million dollars in 2022, which represents a growth of 10%. Exports rose by 11.5%, and imports increased by 17.8%. These figures indicate a clear reactivation of trade among international markets, translating into increased economic activity in the textile sector.

According to the latest Fashion Economic Report in Spain, prepared by Modaes.es in collaboration with the Textile and Apparel Information Center (Cityc), the sector now accounts for 2.7% of the country's GDP (Forbes, 2023). The increasing demand for clothing, primarily from developing economies, is expected to drive the annual value of clothing and footwear to reach at least 2.16 trillion dollars (TDD) by 2030 (Global Fashion Agenda & The Boston Consulting Group, 2018).

The textile industry is a key sector for many APEC economies, which include both developed and developing countries. However, there is a considerable disparity in the wages paid to textile workers in these economies. For instance, while economies such as Japan and South Korea offer relatively high wages and regulated working conditions, economies such as Vietnam and Peru still struggle with low wages and precarious working conditions (Fashion Network, 2024).

Some contributing factors include the differences created by inequality in economic development among APEC economies, which contribute to the wage gap. As a result, the more advanced economies have the capacity to pay higher wages to their workers due to their high profit margins and access to international markets (INEGI, 2020). Another factor is the working conditions, since in many developing economies, labor regulations are less stringent, allowing companies to pay their employees lower wages. This results in labor exploitation that perpetuates poverty and limits sustainable economic growth, creating disparities among economies. Consequently, the economic growth derived from the profits generated in this sector does not translate into improved well-being for the population. Therefore, it is important to understand how employment and wages impact the efficiency of the textile sector (Infomercado, 2024).

The wage gap not only affects workers individually but also has broader implications for economic and social development in the region, directly impacting regional well-being. Social inclusion has been declared an objective for APEC; however, the reality shows that many sectors, including the textile sector, have not seen significant improvements. This poses a challenge for policymakers who seek to balance economic growth with social equity (APEC, 2022).

On the other hand, the lack of investment in technology and training in less developed economies limits workers' productivity, which affects their ability to negotiate higher wages (Uddin, 2024).

According to the Lima Chamber of Commerce (2024), digitalization and innovation are areas where more advanced economies excel, creating a gap between developing and developed nations. Some technologies, such as process automation and digitalization, are advancing in sectors like production and logistics within the textile industry. These innovations enable companies to produce faster and more efficiently, as well as to develop smart textiles that are functional within the industry and add value to products. This disparity is evident in more developed economies, while less developed ones continue to rely primarily on traditional production methods.

Other factors that contribute to innovation include mass customization of products, which allows consumers to design and personalize their own items, and sustainability initiatives driven by technology that reduce waste and improve resource efficiency.

Factors such as e-commerce, digital marketing, data analytics, and artificial intelligence are essential tools that help investigate the latest trends and consumer preferences. Economies that utilize these tools more intensively achieve significant improvements in productivity, product quality, sustainability, and the ability to respond swiftly to market demand. This creates a competitive advantage for those sectors that adopt these technologies, while those that do not may face disadvantages in the evolving market landscape (Lima Chamber of Commerce, 2024).

In this context, the present study aims to analyze the efficiency level of the textile sector within the Asia-Pacific Economic Cooperation (APEC) from 2016 to 2020. It also examines the relationship between sector efficiency and wage remuneration, with a particular focus on best practices and their connection to wage compensation. The study seeks to identify factors that influence productivity and wage levels, providing insights into how industry practices impact economic outcomes in the region (Joshi & Singh, 2020). In addition, the study seeks to identify the factors that contribute to efficiency in the sector, as well as the disparities that exist among different economies (Kao & Liu, 2019).

This analysis will not only provide an evaluation of the current performance of the textile industry in the region but also offer valuable insights that can foster more equitable and sustainable economic growth (Li, Chiu, & Lin, 2021). By examining the interaction between efficiency, working conditions, and wage levels, this research aspires to contribute to the debate on how to balance economic competitiveness with social well-being in a sector that is crucial for APEC economies (Zhang & Wang, 2022).

The study is composed of four sections, in addition to the introduction, which outlines the problem statement and the research objectives. It is followed by a section that describes the methodological approaches used to address the research goal. The third section presents the Data Envelopment Analysis (DEA) methodology. The fourth section discusses the results obtained through the application of this methodology. Finally, the last section provides the conclusions of the investigation.

2. LITERATURE REVIEW

The analysis of efficiency in the textile industry has generated a significant body of research employing various quantitative methodologies. Reviewed studies reveal common patterns regarding the determinants of productivity, while also highlighting regional specificities linked to particular economic contexts. The Data Envelopment Analysis (DEA) technique emerges as the predominant approach in recent literature, particularly in studies evaluating production units within globalized value chains.

Oliveros, García, and Perdomo (2019) demonstrated the usefulness of the DEA Bootstrap in the Colombian case, where technical efficiency showed a positive correlation with firm size and geographical location. Their findings are consistent with those of Goyal, Grover, and Singh (2017) in India, although the latter identified a structural issue of underutilized installed capacity that affected 37% of the plants analyzed. The convergence of these results suggests that emerging economies share similar challenges in productive optimization.

The application of stochastic frontiers has enabled significant methodological advances. Mai, To, Nguyen, and Pham (2020) developed a meta-frontier model that captured technological asymmetries in Vietnam, where foreign-owned firms operated with an efficiency gap 22% smaller than their local counterparts. These findings were partially corroborated by Ayed-Mouelhi and Goaïed (2000) in Tunisia, although in this case, the age of capital proved to be a determining factor. The divergence in estimated coefficients between the two studies may be attributed to differences in the foreign direct investment regimes characteristic of each country.

The literature on developed economies presents distinct nuances. Coll-Serrano and Blasco-Blasco (2011) documented the disruptive impact of trade liberalization in Spain, where the removal of tariff barriers triggered competitive restructuring that particularly penalized small companies. Their results contrast with those of Kouliavtsev, Christopoulos, and Tsionas (2006) in the United States, where sectoral restructuring prior to the 2000s had already shaped an industrial fabric more resilient to external shocks. This comparison suggests that the level of institutional maturity significantly mediates the textile sector's ability to adapt to changes in the competitive environment.

Longitudinal studies offer valuable insights into productivity dynamics. Kapelko, Oude Lansink, and Stefanou (2009) applied the Malmquist index to a pan-European sample, identifying that annual productivity gains fluctuated between 1.2% and 3.7% during the period of 1995 to 2004. These results are consistent with those of Chandra, Cooper, and Shanling (1998) in Canada, though with the important caveat that year-to-year variability was significantly greater in the North American context. Both studies agree that technological improvements accounted for approximately 60% of the total productivity gains.

The research on operational management has provided particularly relevant findings for business practice. Souza, Lima, and Costa (2014) quantified the impact of visual management tools in a Brazilian plant, documenting an 18%

reduction in cycle times and a 15% increase in capacity utilization. These results were expanded by Gamarra-Alván and Díaz-Muñante (2018) whose two-stage model demonstrated that improvements in quality and innovation have a multiplier effect on operational efficiency. The convergence of these studies underscores the importance of complementing quantitative analyses with qualitative approaches that capture organizational dimensions.

Studies on developing economies have emphasized the particularities of the labor factor. Jaforullah (1999) found that the composition of the workforce (specifically the ratio of male to female labor) explained 12% of the variations in technical efficiency in Bangladesh. These findings were partially replicated by Bhandari and Ray (2023) in India, although in their study, technical training emerged as a key moderating variable. The accumulated evidence suggests that productivity improvement strategies in contexts of incipient industrialization should consider sociocultural variables in addition to traditional productive factors.

Recent literature has begun to incorporate environmental dimensions into efficiency analysis. Battese, Malik, and Gill (2023) developed a stochastic frontier model that internalized carbon costs, revealing that textile plants with environmental certification showed efficiency scores 8–10% higher than the average. These findings, although preliminary, suggest a reconceptualization of productivity paradigms aligned with the Sustainable Development Goals. Future research should explore this area further, especially concerning the measurement of positive externalities.

The recurring methodological limitations in the examined literature include: (1) the heterogeneous treatment of returns to scale, (2) the limited availability of disaggregated data at the plant level, and (3) challenges in international comparability of financial indicators. Coll-Serrano and Blasco-Blasco (2021) partially addressed this last point through a rigorous process of accounting data standardization, setting a valuable precedent for comparative studies.

The synthesis of available evidence suggests three priority areas for future research: first, the analysis of the differential impact of Industry 4.0 on various segments of the textile value chain; second, the evaluation of public policies aimed at reducing technological gaps in developing countries; and third, the integration of sustainability metrics into conventional efficiency measurement frameworks. The development of harmonized regional databases emerges as a fundamental requirement for advancing these research lines.

3. METHODOLOGY

The methods used to estimate efficiency are categorized into two primary groups: parametric, which rely on specific functional forms, and non-parametric, which do not require predefined functional forms. Each approach has its unique characteristics and is selected based on the specific requirements of the study. The key difference between these methods lies in their underlying assumptions. Parametric methods, as noted by Murillo (2002), require a specific functional form, while non-parametric methods, according to Berrio and Muñoz (2005) do not impose this restriction, making them more flexible but also more sensitive to measurement errors.

According to Coll and Blasco (2006), the DEA initially developed by Charnes, Cooper, and Rhodes (1978), is the most widely used non-parametric technique. As highlighted by Cooper, Seiford, and Tone (2007) and Zhu (2009) it has a flexibility that makes it ideal for analyzing multiple inputs and outputs.

Data Envelopment Analysis (DEA) is a non-parametric technique based on linear programming that makes it possible to evaluate the relative efficiency of a set of Decision-Making Units (DMUs). Its theoretical development is primarily attributed to Charnes et al. (1978), who formalized the concepts initially proposed by Farrell (1957) and Debreu (1951) regarding the measurement of technical efficiency.

DEA emerged as an extension of the pioneering works on productive efficiency. As noted by Coll and Blasco (2006) and Farrell (1957) introduced the concept of an efficient frontier, but it was Charnes, Cooper, and Rhodes (1978) who developed a robust mathematical framework through linear programming. According to Álvarez (2001) the first practical precedents go back to Hoffman (1957) and Boles (1966) who applied optimization techniques to estimate production functions.

DEA is characterized by.

1. Not requiring a predefined functional form, unlike parametric methods (Murillo, 2002).
2. Evaluating multiple inputs and outputs simultaneously (Cooper et al., 2007).
3. Constructing an empirical frontier from the most efficient DMUs, considering relative inefficiencies (Coll & Blasco, 2006).

Zhu (2009) and Seijas (2004) highlight that DEA is especially useful in sectors such as textiles, where efficiency depends on multiple interrelated factors.

Classification of DEA Models.

DEA models can be classified according to three key dimensions (Charnes et al., 1978; Coll & Blasco, 2006):

1. Type of efficiency measure
- Radial: Based on proportional reductions in inputs or proportional expansions in outputs (Farrell, 1957).
- Non-radial: Considers non-proportional adjustments, such as the Slacks-Based Measure (SBM) model (Tone, 2001).
2. Model orientation
- Input-oriented: Minimizes resources while maintaining constant production (example: reducing costs without affecting quality).
- Output-oriented: Maximizes output with the same resources (example: increasing production with the same labor force).
3. Returns to scale
- Constant Returns to Scale (CRS): Assumes proportionality between inputs and outputs, as described in the CCR model by (Charnes et al., 1978).
- Variable Returns to Scale (VRS): Allows efficiency evaluation of DMUs of different sizes (BCC model of Banker, Charnes, and Cooper (1984)).

The Variable Returns to Scale (VRS) Model, also known as the BCC model after its creators (Banker et al., 1984), represents a significant evolution of the classical DEA (CCR) model, as it incorporates the possibility of non-proportional returns in production. This theoretical advancement overcame a key limitation of the CCR model: its inability to distinguish between pure technical inefficiency and scale inefficiency (Banker et al., 1984; Coll & Blasco, 2006).

The VRS model arose in response to the need to analyze production units operating at different scales. As Banker et al. (1984) point out, the assumption of constant returns to scale (CRS) in the CCR model proved restrictive for evaluating organizations not operating at their optimal scale. The key innovation of the BCC model was the introduction of a convexity constraint ($\sum\lambda_j = 1$), which allows for the construction of a more flexible production frontier (Coll & Blasco, 2006).

According to Cooper et al. (2007), this modification has important implications:

1. It allows the measurement of pure technical efficiency independently of scale effects.
2. It facilitates the identification of the type of returns to scale (Increasing, decreasing, or constant).
3. It provides more realistic efficiency measures for units of different sizes.

The basic structure of the VRS model maintains DEA's linear programming framework but includes the convexity constraint. As detailed by Coll and Blasco (2006), for input orientation, the model is expressed as:

Minimize $\theta - \varepsilon(\sum s^- + \sum s^+)$

Subject to:

1. $\sum\lambda_j x_{ij} + s^- = \theta x_{i0}$ $(i = 1,\dots,m)$.
2. $\sum\lambda_j y_{rj} - s^+ = y_{r0}$ $(r = 1,\dots,s)$.
3. $\sum\lambda_j = 1$.
4. $\lambda_j, s^-, s^+ \geq 0$.

Where:

- θ represents technical efficiency
- s^- and s^+ are the input and output slacks
- ε it is a non-Archimedean infinitesimal (Charnes et al., 1978).

For output orientation, the formulation is analogous but maximizes the proportional expansion of outputs (Cooper et al., 2007).

3.1. Data Processing and Variable Selection

The study aims to examine the relationship between the efficiency of the textile sector in the major economies that comprise APEC and its connection with employment and wage variables. The objective is to determine whether a differential exists when substituting these variables in input selection. For this analysis, official data extracted from various databases were employed. Below the selected variables for the modeling are detailed. Table 1 presents the variables and data used for this study.

Table 1. Variables and data used.

Variable	Indicator	Unit of Measurement	Source	Year
Human Capital	Employees	INPUT / Units	United Nations Industrial Development Organization, INDSTAT 2 2023, ISIC Revision 3	2023
Human Capital	Wages and Salaries	INPUT / Million USD	United Nations Industrial Development Organization, INDSTAT 2 2023, ISIC Revision 3	2023
Exports	Exports	OUTPUT / Million USD	World Integrated Trade Solution (WITS)	2024
Productivity	Production	OUTPUT / Million USD	United Nations Industrial Development Organization, INDSTAT 2 2023, ISIC Revision 3	2023
Technological Change / Innovation	Value Added	OUTPUT / Million USD	United Nations Industrial Development Organization, INDSTAT 2 2023, ISIC Revision 3; STATSCAN; China Statistical Yearbook; U.S. Bureau of Labor Statistics.	2023
Land	Establishments	INPUT / Units	United Nations Industrial Development Organization, INDSTAT 2 2023, ISIC Revision 3; STATSCAN; China Statistical Yearbook; U.S. Bureau of Labor Statistics	2021

Note: The selection of variables is shown with the source from which the data was obtained for the application of the technological tool that is used.

4. RESULTS

To analyze potential differences in wage distribution and assess the existence of pay gaps, two comparative models were implemented. The first model used the total number of employees as the input variable, whereas in the second model, this variable was replaced by the total amount of wages and salaries. This comparative approach allows for the identification of disparities between labor contribution measured in terms of employees versus total labor costs, which could reveal inequities in the wage structure of the textile sector organization by economy.

Accordingly, as shown in Table 2, the results of the first model indicate that the economies that proved efficient were Hong Kong, New Zealand, Singapore, and the United States for the study period from 2016 to 2020. The economies of Indonesia, with an average value of 0.39; Russia, with an average value of 0.71; Malaysia, with an average value of 0.56 for the 2016–2020 period; and Peru, with an average value of 0.39, did not achieve efficiency. The economies with the lowest values were Vietnam and South Korea, both with an average value of 0.09; the Philippines, with an average value of 0.45; Mexico, with an average of 0.04; Japan, with an average value of 0.30 for the study period; Canada, with an average result of 0.17; and finally Australia, with an average value of 0.11.

Table 2. The comparison of the models using "employees" versus "wages and salaries" as input variables.

Comparison of models without orientation										
Economy	**2016**		**2017**		**2018**		**2019**		**2020**	
	V. employees	**V. wages and salaries**	**V. employees**	**V. wages and salaries**	**V. employees**	**V. wages and salaries**	**V. employees**	**V. wages and salaries**	**V. employees**	**V. wages and salaries**
Australia	0.12	0.32	0.12	0.38	0.11	0.43	0.1	0.38	0.11	0.34
Canada	0.22	0.52	0.18	0.54	0.17	0.61	0.14	0.63	0.15	0.53
China	0	**1**	0	**1**	0	**1**	0	**1**	0	**1**
Hong-Kong	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
Indonesia	0.49	0.89	0.49	0.92	0.35	**1**	0.32	**1**	0.28	**1**
Japan	0.31	**1**	0.32	**1**	0.31	**1**	0.3	**1**	0.28	**1**
Malaysia	0.54	0.69	0.58	0.71	0.54	0.75	0.54	0.72	0.59	0.74
Mexico	0.06	0.84	0.07	0.87	0	0.99	0.01	0.98	0.04	0.91
New Zealand	**1**	0.28	**1**	0.32	**1**	0.35	**1**	0.34	**1**	0.29
Peru	0.09	0.81	0.01	0.97	0.58	0.83	0.62	0.65	0.62	0.65
Philippines	0.34	0.37	0.24	0.44	0.6	0.54	0.54	0.73	0.53	0.45
South Korea	0.12	0.49	0.1	0.48	0.08	0.5	0.08	0.49	0.08	0.48
Russia	0.74	0.51	0.71	0.62	0.72	0.62	0.68	0.66	0.68	0.57
Singapore	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
United States	**1**	0.94	**1**	0.85	**1**	0.96	**1**	0.88	**1**	0.81
Vietnam	0.19	0.67	0.13	**1**	0.11	**1**	0	**1**	0.01	**1**

Note: The comparison of models was carried out for the years 2016 to 2020.

Meanwhile, in the second model performed, the economies that proved efficient throughout the entire period were China, Hong Kong, Japan, and Singapore, while economies such as Vietnam and Indonesia achieved efficiency in almost all years within the studied period. Continuing with the results, the economies that most closely approached the value of 1 were Mexico with an average result of 0.92, Malaysia registering an average of 0.72, the United States with an average value of 0.89, and Peru with an average of 0.72, followed by Russia, averaging a value of 0.60. Canada had an average value of 0.57 during the period, the Philippines registered an average of 0.51, South Korea 0.47, Australia 0.37 on average, and New Zealand 0.32 (see Table 2).

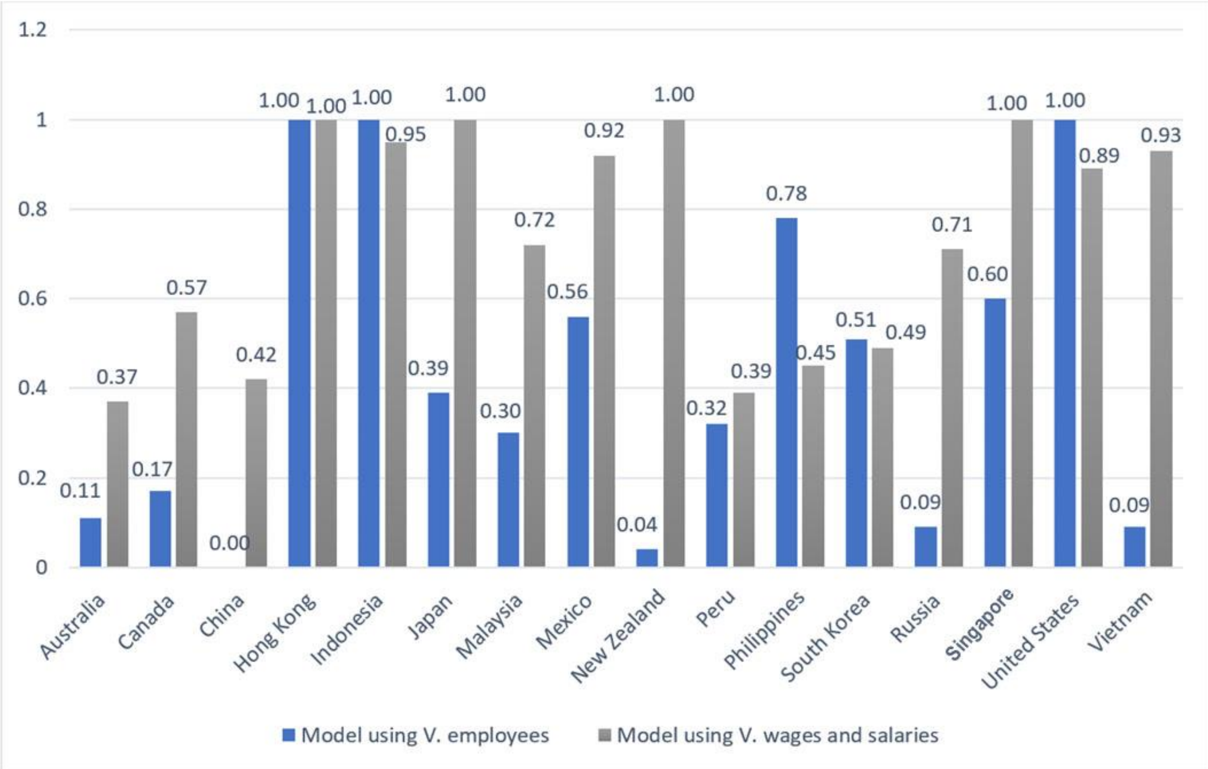

Figure 1. Comparison between the model employing the “employees” variable and the model using the “wages and salaries” variable.

Note: The comparative analysis presented corresponds to the last year under review. The blue bar denotes the model that incorporates the variable "employees" as an input, while the gray bar represents the model that incorporates the variable "wages and salaries" as an input.

As evidenced by the comparison of efficiency scores obtained from both models (see Figure 1 and Table 2), the economies of Hong Kong and Singapore were the only ones that achieved efficiency across both specifications. Nevertheless, within the model employing wages and salaries as an input, the economies of China, Japan, and Vietnam also achieved efficiency, whereas in the model using employees as an input, the United States and New Zealand were identified as efficient.

Furthermore, the economies of Australia, Canada, Indonesia, Malaysia, Mexico, Peru, the Philippines, and South Korea demonstrated higher efficiency under the model that incorporated wages and salaries as inputs.

4.1. Benchmarking

Benchmarking is a systematic process for identifying, understanding, and adapting best practices from other organizations to enhance one's own performance (Camp, 1989). Within the context of Data Envelopment Analysis (DEA), benchmarking involves comparing the relative efficiency of different decision-making units (DMUs) to identify those that operate most efficiently. These units serve as benchmarks or models to be emulated, providing valuable insights for performance improvement and strategic decision-making (Charnes et al., 1978). DEA enables the identification of DMUs positioned on the efficiency frontier, namely those that utilize the minimum quantity of inputs to produce a given amount of outputs or that generate the maximum quantity of outputs with a given amount of inputs (Cook & Seiford, 2009). These efficient DMUs become the benchmarks for others, which can learn from their practices and strategies to improve their own efficiency performance (Dyson et al., 2001).

For the first model, which employs the variable "employees" as an input, the economies of Australia, Canada, Hong Kong, Malaysia, Mexico, New Zealand, Peru, and South Korea lead the rankings as those demonstrating the greatest similarities with other economies. Meanwhile, Indonesia, Japan, the Philippines, and Russia exhibit moderate efficiency levels. Singapore and the United States continue to display low efficiency levels, and China does not demonstrate similar behavior patterns with any other economy (see Figure 2).

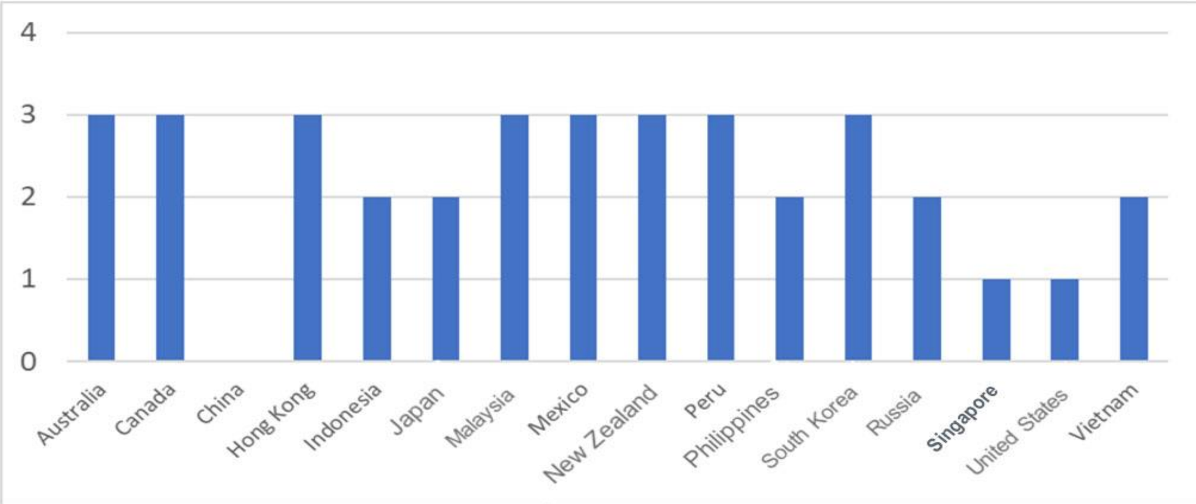

Figure 2. Benchmarking results for the model with the variable "employees".

Note: Economies that were efficient in the model employing the variable "employees" as an input, along with the number of times they were used as a reference for the inefficient economies, using the variables considered.

For the second model (the model that employs the variable "wages and salaries" as an input), as shown in Figure 3, three economies have not presented results: China, Indonesia, and South Korea. The strongest economies in this model are Hong Kong and Malaysia.

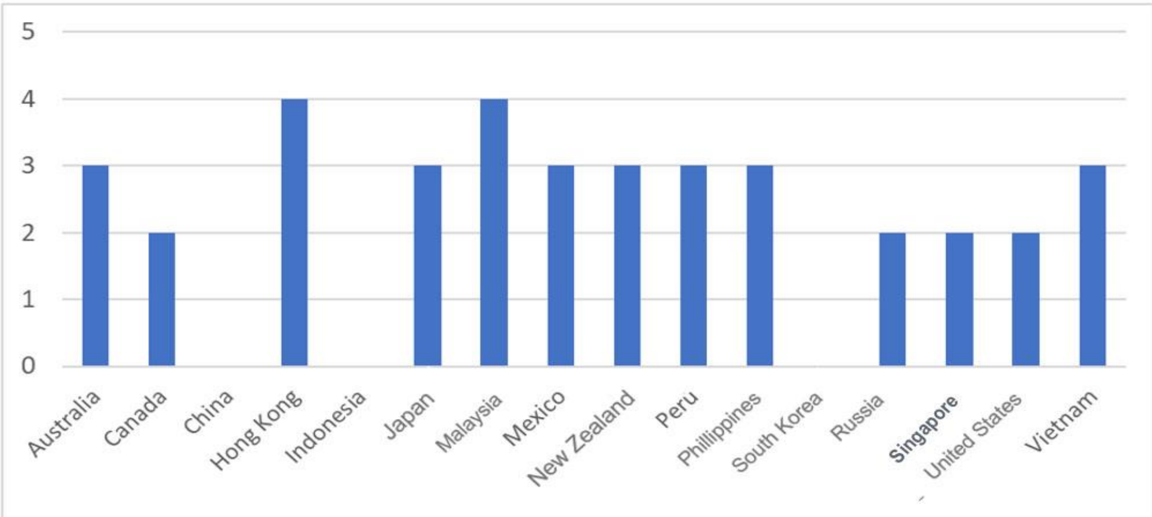

Figure 3. Benchmarking results for the model with the variable "wages and salaries".

Note: The economies that were efficient in the model employing the variable "wages and salaries" as an input, along with the number of times they were referenced by the inefficient economies, using the variables considered.

5. CONCLUSIONS

It can be observed that within the activities faced by the textile sector, there is a pronounced disparity regarding the wage gap. This disparity requires the consideration of country-specific factors, since standardized measures are not equally effective across all economies due to their inherent differences. First, the research confirms the existence of significant disparities in productive efficiency within the textile sector among the economies that comprise the Asia-Pacific Economic Cooperation (APEC). The DEA model employed proved effective in identifying and quantifying these variations, revealing that certain economies exhibit more favorable conditions for maintaining fair wage remuneration, while in others, such conditions are not applied in the same manner. A central finding of the study is the complex relationship between wages and salaries and productive efficiency. Although there is an observed correlation between higher wages, more developed economies, and better working conditions, the DEA results indicate that greater efficiency does not necessarily ensure fair wage remuneration. Developing economies within APEC face specific challenges that constrain efficiency in the textile sector, such as lower capital investment, less advanced technology, and a greater reliance on labor-intensive processes. These factors result in lower efficiency scores compared to developed economies, in addition to generating differences in wage conditions.

Trade also plays a crucial role in the efficiency of the textile sector. Economies with higher export volumes tend to demonstrate greater efficiency, suggesting that access to international markets fosters productivity and stimulates innovation. These findings carry important policy implications for APEC member economies, indicating that governments should prioritize policies that encourage technological investment, promote skills development, and improve infrastructure in order to enhance efficiency in the textile sector.

It is essential to strike a balance between economic competitiveness and fair labor standards. While low wages may provide a short-term cost advantage, they can also undermine productivity and contribute to social and economic inequalities. The integration of sustainability considerations in the textile sector—such as the promotion of environmentally responsible production practices and the responsible sourcing of materials—is equally important.

It is also necessary to acknowledge the limitations of this study, particularly regarding data availability, and to suggest avenues for future research that extend the scope of analysis by incorporating additional variables, such as environmental performance or social indicators. The role of APEC in promoting regional integration is crucial for the textile sector, as it can reduce trade barriers, harmonize regulations, and facilitate technology transfer.

The efficiency level in the textile sector depends on the conditions prevailing in each member economy of the Asia-Pacific Economic Cooperation (APEC). Based on the results obtained from various models, it is possible to identify economies with higher efficiency, including China, Hong Kong, Singapore, Vietnam, the United States, and New Zealand. These economies are predominantly developed, consistent with their structural characteristics. Conversely, other APEC members such as Malaysia, the Philippines, Indonesia, and Peru are classified as developing economies. Consequently, it can be concluded that the efficiency of each economy is influenced by factors such as value added, wage levels, the number of employees, the number of establishments, production capacity, and export performance. These variables serve as determinants that can either bring an economy closer to or further away from achieving optimal efficiency. The wages and salaries are directly related to efficiency. Based on the results obtained, it can be concluded that better wage and salary conditions enable greater efficiency, as it can be inferred that employee satisfaction contributes to increased productivity and performance in their activities.

Ultimately, enhancing efficiency in the textile sector requires an approach that takes into account economic, social, and environmental factors. By integrating these considerations into policy design and business strategies, APEC member economies can achieve sustainable and inclusive growth within this critical industry.

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