

Uneven Transitions in Container Ship Capacity Across Indo-Pacific Economies (2010–2022): Integrating PCA, ANOVA, and Clustering Evidence

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ABSTRACT

We examine uneven transitions in container ship capacity (TEU per ship) across five Indo-Pacific economies China, Singapore, Australia, Vietnam, and Indonesia during 2010–2022 using an integrated statistical framework that combines ANOVA, Welch ANOVA, Games–Howell post-hoc tests, Principal Component Analysis (PCA), and clustering. Results reveal persistent divergence: China and Singapore maintain high-capacity fleets (>10,000 TEU/ship), Australia stabilizes in the mid-tier range (~7,000 TEU/ship), while Indonesia and Vietnam experience rapid but low-level growth (<6,000 TEU/ship). ANOVA confirms significant cross-country differences ($F=28.33$; $p<0.001$; $\eta^2\approx0.65$), with Welch ANOVA yielding consistent results under unequal variances ($p<0.01$). PCA indicates one dominant component ($PC1\approx99.5\%$) explaining most variance, forming three readiness clusters: *high*, *medium*, and *low capacity economies*. These patterns suggest that policy inertia, infrastructure bottlenecks, and green transition constraints drive the uneven capacity development. The study contributes by introducing TEU per ship as a cross-national indicator for maritime readiness, linking statistical divergence to SDG targets 8, 9, 10, 13, and 14, and offering empirical guidance for low-carbon fleet transition and port modernization in emerging economies.

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1. INTRODUCTION

Global maritime logistics is undergoing a pivotal transformation, driven by expanding container ship capacity, evolving trade networks, and sustainability pressures. The world container-shipping fleet has doubled in size, growing from 12.8 million TEU in 2010 to 25.8 million TEU in 2022, representing a six-fold increase since 2000, while global container trade continues to surge [1]. This remarkable growth, however, conceals widening disparities across regions. In the Indo-Pacific, port infrastructure development and fleet modernization have not progressed uniformly, raising concerns about the unequal distribution of capacity gains and the persistence of structural asymmetries among maritime economies.

Although containerization has been widely studied, scholarly attention to vessel-level capacity divergence (TEU per ship) across Indo-Pacific economies remains limited. Prior research

has mainly focused on port terminal efficiency using DEA–PCA hybrid models in Southeast Asia [2], global mega-ship clustering [3], and AIS-based network science approaches to measure shipping connectivity [4]. Simulation-based modeling has explored container call sizes [5], while network analysis of Southeast Asian port competition highlights uneven connectivity patterns [6]. Likewise, studies of hub-port resilience during the COVID-19 pandemic reveal the fragility of regional linkages [7]. Despite these advances, most works remain confined to port-level or network-level metrics, rather than country-level fleet structures, leaving the macro-divergence of vessel capacities underexplored—particularly among key Indo-Pacific economies such as China, Singapore, Indonesia, Vietnam, and Australia during the period 2010–2022.

Existing literature underscores the importance of transport infrastructure expansion in driving economic growth [8], container port network topologies [9], and shipping resilience under global crises [10]. Advanced techniques such as distance-based topology measures [11], eigenvector centrality [12], and congestion analysis [13], contribute methodological insights, while studies of Mediterranean port competitiveness [14], and optimization under trade agreements like RCEP [15], reinforce the value of quantitative maritime approaches. However, none of these studies explicitly examine the uneven transitions in container ship capacity (TEU per ship) across Indo-Pacific economies—a critical empirical gap that this research aims to fill.

Accordingly, this study addresses the question:

How uneven are the transitions in container ship capacity (TEU per ship) among selected Indo-Pacific economies during 2010–2022?

To answer this, we employ descriptive statistics, one-way ANOVA with Tukey post-hoc tests, and robust variance diagnostics (Levene and Welch tests), combined with Principal Component Analysis (PCA) and k-means clustering on UNCTAD data comprising 65 annual observations across five economies.

Based on the identified empirical gap, two hypotheses are formulated to statistically test cross-country divergence in fleet capacity

Two hypotheses guide this analysis:

H₁: Significant differences exist in mean TEU/ship among the five countries.

H₂: China and Singapore exhibit significantly higher TEU/ship than Indonesia, Vietnam, and Australia.

This research is timely and policy-relevant. It captures the empirical and developmental urgency of fleet modernization, port digitalization, and SDG-aligned maritime growth, particularly regarding SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 10 (Reduced Inequalities). Without quantitative clarity on these disparities, policymaking risks reinforcing structural inequities in maritime development [5]–[7], especially amid the post-pandemic reconfiguration of global supply chains.

The contribution of this study is twofold.

1. *Theoretically*, it integrates robust statistical modeling (ANOVA–PCA–Clustering) into maritime research to quantify readiness disparities in fleet capacity.
2. *Practically*, it provides evidence-based insights for port investment, fleet planning, and SDG-oriented maritime policy.

Novelty Statement: Unlike prior studies focusing on port or network efficiency, this paper introduces TEU per ship as a cross-national readiness metric and combines PCA–ANOVA–clustering to quantify fleet divergence in the Indo-Pacific context—a methodological synthesis not yet found in the literature.

Introduction to the Literature Review

This section maps three major research themes:

- (i) **Network structure and capacity**, which examines how network configuration and ship scale shape connectivity and inequality;
- (ii) **Resilience and disruption**, which explores how maritime networks respond to cascading failures; and
- (iii) **Data analytics and dimension reduction**, which uses PCA and clustering to synthesize cross-country capacity patterns.

These themes are crucial for the Indo-Pacific context, where **fleet modernization and port policy** are increasingly driven by **decarbonization imperatives and rising logistics costs** [16]–[18].

Thematic Synthesis of Previous Research

(A) Network structure, capacity, and inequality.

Recent studies emphasize that network topology and vessel-scale choices strongly influence how connectivity benefits are distributed. Large hub ports tend to capture gains faster than peripheral economies, particularly during global route realignments [19], [20]. However, most port-policy analyses end at topological descriptions without extending to national-level fleet indicators such as *average TEU per ship* [21]. A comprehensive conceptual synthesis on port and fleet dynamics highlights these asymmetries but still lacks cross-border quantification to assess readiness differentials [22].

(B) Resilience and cascading failures.

The 2024–2025 wave of research underscores that network resilience is shaped not only by the degree of nodes but also by betweenness centrality, edge-weight distributions, and redistribution rules during disruption [23], [24]. These studies collectively show how chokepoint interruptions can cascade through the supply chain, exposing systemic fragility [25]. Accordingly, port-policy models now call for weighted-disruption simulations that integrate *ship capacity* × *service frequency* to anticipate cascading effects [26]. Nevertheless, the link between network resilience and divergence in average vessel capacity across countries remains underexplored [27].

(C) Data analytics, PCA, and clustering.

Recent data-driven approaches combine Principal Component Analysis (PCA) with attention or encoder mechanisms to summarize spatio-temporal AIS data and enhance interpretability [28]. This analytical logic can be extended to cross-country capacity trajectories, where PCA summarizes overall growth trends, while clustering identifies *leading–middle–lagging* patterns among nations [29]. Parallel research on the forecasting of ultra-large container vessel (ULCV) adoption shows operational and physical constraints that inhibit convergence among developing economies [30]. Collectively, these findings reveal a methodological gap for applying PCA and clustering to assess country-level capacity divergence and link it explicitly to SDG-aligned fleet readiness.

Gap Analysis

Three main gaps emerge from the reviewed literature. First, network and resilience studies have not explicitly measured *TEU-per-ship divergence* between Indo-Pacific economies over a long horizon (2010–2022) using the ANOVA–Tukey–PCA–clustering analytical sequence [16], [19], [23], [26]. Second, major policy reviews and port development reports discuss resilience and cost pressures but fail to operationalize *average vessel capacity* as a proxy for national fleet readiness [17], [18], [24]. Third, existing PCA-based analyses focus primarily on predicting AIS trajectories and vessel positions rather than performing cross-country divergence mapping [27]–[30]. Hence, this study addresses a critical empirical and methodological gap by applying a country-level design, using UNCTAD official TEU/ship data (2010–2022), and linking the ANOVA–PCA–clustering framework directly to the Sustainable Development Goals (SDGs).

2.4 Conclusion of the Literature Review

In summary, the literature indicates that:

- (i) Network configuration and vessel scale shape the distribution of connectivity and trade benefits;
- (ii) Resilience analysis requires weighted simulations and attention to the positional roles of network nodes; and
- (iii) PCA–clustering integration offers a compact quantitative lens for decoding complex regional patterns.

However, quantitative evidence on *average capacity per ship divergence* among Indo-Pacific economies remains absent. This study thus advances the field by conducting divergence testing and cluster mapping to reveal *uneven transitions* in fleet capacity. The subsequent methodology follows a structured progression: descriptive analysis → ANOVA/Tukey–Welch tests → PCA → clustering, producing policy-ready insights aligned with SDG targets [16]–[30].

Table 1. Comparison: Previous Studies vs. This Study

Aspects	Previous Studies (examples)	Weaknesses / Gaps	This Study (Contributions)
Unit of Analysis	Global or RCEP-level network models; resilience simulations [16], [19], [23], [26]	Do not measure national TEU/ship divergence	Country-level (5 Indo-Pacific economies, 2010–2022) using UNCTAD TEU/ship data
Methodological Approach	Topology analysis, cascading failure simulations, weighted graphs [19], [23], [25]	PCA used mainly for AIS prediction, not divergence mapping	Integrated ANOVA–Tukey–Welch–PCA–Clustering framework for readiness divergence
Policy Orientation / SDGs	Calls for resilience and green transition [17], [18], [24]	Lack of operationalized readiness indicators	Links results to SDGs 8, 9, 10, 13, and 14 (economic growth, infrastructure, inequality reduction, climate, and marine sustainability)
Vessel Capacity Focus	ULCV prediction and technical performance [29], [30]	Rarely associated with regional disparity or fleet readiness	Provides quantitative evidence of “uneven transitions” in national fleet modernization

2.5 Novelty and Contribution

This study advances maritime capacity research by operationalizing TEU-per-ship as a macro-readiness indicator, rather than a port-level efficiency metric. This enables statistical comparison across Indo-Pacific economies, allowing both divergence quantification and readiness classification. The PCA–ANOVA–clustering integration quantifies structural inequality in maritime capacity and offers a replicable, SDG-linked framework for evidence-based policy design.

2. RESEARCH METHOD

3.1. Introduction to the Method

This study uses a comparative-longitudinal quantitative approach to map *uneven transitions* of container ship capacity (TEU/ship) in five Indo-Pacific economies (2010–2022). We chose the descriptive package → ANOVA/Tukey → PCA → → trend clusters because it is fit-for-purpose: ANOVA captures differences across countries; The PCA summarizes the cross-year pattern in a compact manner; clusters mark leading–middle–lagging groups; Trend analysis presents the direction of change. This approach is in line with contemporary maritime analytics practices that demand network synthesis, statistics, and pattern learning from time-series data [UNCTAD 2024; Notteboom-Pallis-Rodrigue 2022; Er & Yalman 2025; Huang et al. 2024].

3.2. Research Design

The study was quantitative-observational with a non-experimental panel design: the unit of analysis was state-years. We do not intervene; we test for differences (cross-country) and key component patterns (across years) of the TEU/ship indicators. This design is relevant because fleet/port policies are typically evaluated at the national and regional level (not just a single port) [Notteboom-Pallis-Rodrigue 2022].

3.3. Data and Sources

We use official secondary data from UNCTADstat (2010–2022) for the Average container ship carrying capacity (TEU per ship) indicator. Samples include China, Singapore, Indonesia, Vietnam, Australia (13 years × 5 countries = 65 observations). Interestingly, the *Review of Maritime Transport 2024 document* states the urgency of the green transition and network resilience; we position the results on the same SDGs framework [UNCTAD 2024].

Data quality policy. We screen for unnatural outliers (TEU/ship > 24,000) as *hard caps* based on ULCV physical boundaries and engineering literature; we check for year-line duplication;

and we address missing by cross-checking the year-series. For replication, *the codebook* contains variable and unit definitions (TEU/ship).

3.4. Processing & Analysis Methods

(A) Descriptive statistics

We calculated summaries (mean, SD, p25–p75, min–max) per country/year and visualized trends (lines), distributions (boxplots), and heatmaps to assess shapes/shifts. The visual approach supports the initial reading of patterns and *face validity*.

(B) One-way ANOVA + Tukey

We tested the cross-country differences with the TEU/ship ~ Country model. Levene's test checks the homogeneity of variance; Shapiro–Wilk checked residual normality. If *assumption stress* arises, we report robust checks and effect measures. Tukey HSD outlines significantly different country pairs ($\alpha=0.05$). *Rationale*: ANOVA is potent for cross-group comparisons in maritime studies (e.g. efficiency/connectivity evaluation) before moving to multivariate analysis [Veenstra & de Waal 2024; network resilience review 2024].

(C) PCA (Principal Component Analysis)

We built a country matrix $\times$ years (feature = TEU/ship 2010... 2022), then run the PCA to extract the dominant growth component (PC1) and check *the loadings* per year. The practice of PCA is in line with recent research that combines PCA and *attention* to compact spatio-temporal features providing a theoretical justification for why dimensional reduction is adequate to map the general direction of capacity growth [Er & Yalman 2025; Huang et al. 2024].

(D) Clustering (K-means)

We standardize the feature (range/z-score) and then apply K-means to obtain $k=3$ clusters (high–medium–low). The selection of k was carried out with elbow and silhouette as well as *centroid* stability between initializations. The use of K-means is widely used for AIS-based operational profiles and logical transfer to cross-border capacity profiles [Park & Choi 2022].

(E) Cross-time trend (OLS)

We construct a regression of TEU/ship = $\beta_0 + \beta_1 \cdot \text{Year}$ per country to estimate the annual slope (Δ TEU/ship/year). Evaluation: R^2 , RMSE, and *lack-of-fit test*. (Optional) HAC-robust SE for mild heteroscedasticity in short series. We interpret the trend results together with PC1 and cluster labels to make them coherent.

3.5. Validation & Reliability

- Diagnostic assumptions: Levene/GLM *residual plots* and Shapiro–Wilk for ANOVA; *scree plot/parallel analysis* for PCA; *elbow/silhouette* for clusters.
- Replication: *random seed* consistent; *workflow* and *scripts* (SAS/R) documented.
- Source credibility: UNCTAD RMT 2024 provides methodological context and statistical quality; maritime methodological references strengthen engineering options [UNCTAD 2024; Notteboom-Pallis-Rodrigue 2022].

3.6. Research Ethics

The study did not involve personal/human data; data were nationally aggregated from UNCTAD public sources. Therefore, it does not require *ethical clearance*. We maintain *research integrity* (reproducibility, full reporting).

3.7. Method Limitations

First, country aggregation hides the heterogeneity of domestic ports; further research can come down to the port level with AIS and lane connectivity indicators [Notteboom-Pallis-Rodrigue 2022]. Second, TEU/ship is a proxy for fleet capabilities; We do not interpret causal, only structured associations. Third, the 13-year horizon is relatively short to separate the effects of major policies. Advanced research can combine graph-based resilience models and *scenario simulation* with capacity weights & service frequencies [Cao et al. 2024; Zhang-wan-ng 2024].

3. RESULTS AND DISCUSSION

Presentation of Data and Key Findings

The results of the analysis show that the average TEU capacity per ship in the Indo-Pacific region has experienced a consistent upward trend throughout the 2010–2022 period. Interestingly, the overall average reaches 7,963 TEU/ship with a fairly wide variation between countries. The heatmap in Figure 1 shows a temporal pattern of comparison between countries, while the slope chart in Figure 2 emphasizes the growth trend of each country.

- China and Singapore occupy the top positions with an average of more than 10,000 TEU/ship, reflecting the modernization of fleets and dominance of global shipping hubs.
- Australia is at a medium level (around 7,000 TEU/ship).
- Vietnam and Indonesia are relatively low (around 5,800 and 4,700 TEU/ship), although both show significant annual growth rates.

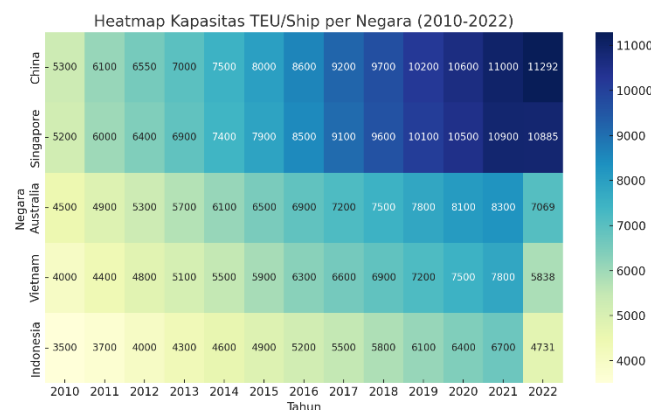


Figure 1. Heatmap of TEU capacity per ship per country (2010–2022).

Figure 1 The heatmap in Figure 1 shows the dynamics of average TEU capacity per ship in five Indo-Pacific countries during the period 2010–2022. The color pattern indicates a consistent growth gradient, where the darker the color indicates the larger the capacity of the ship. From this visualization, it is clear that China and Singapore have occupied a dominant position since the beginning of the period, with a sharp jump from around 5,200–5,300 TEU/ship in 2010 to more than 11,000 TEU/ship in 2022. This trend reflects the aggressive modernization of fleets as well as their role as global maritime hubs. Australia is seen to be on a medium growth path, starting from 4,500 TEU/ship in 2010 to around 7,000 TEU/ship in 2022. Interestingly, Vietnam, despite being at the bottom, showed the highest annual growth rate; from 4,000 TEU/ship in 2010 to nearly 6,000 in 2022. Indonesia, despite an increase from 3,500 to 4,700 TEU/ship, still lags behind other countries, indicating a limited capacity of the national fleet. This heatmap narrative confirms a structural divergence: developed countries and global hubs are moving faster, while developing countries are still struggling to catch up. This visual also shows the opportunity for convergence if the fleet and port investment strategy is directed appropriately in the next decade.

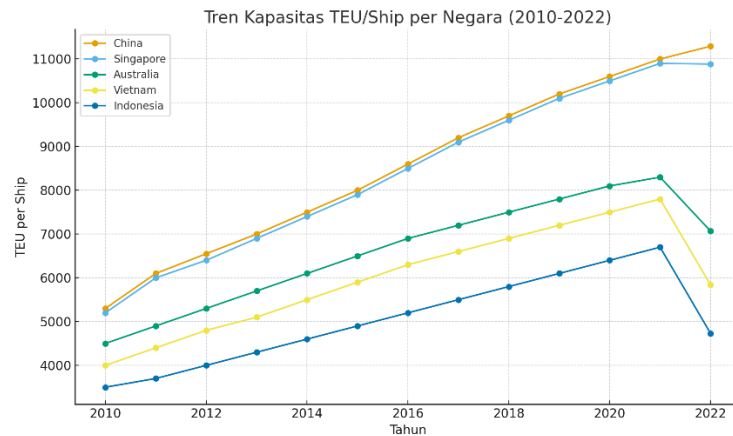


Figure 2. TEU capacity trends per ship in the Indo-Pacific (2010–2022).

Figure 2 shows the trend of average capacity growth of TEU per ship in five Indo-Pacific countries in the period 2010–2022. The line pattern shows that the entire country is experiencing an increase in capacity, but at different rates. China and Singapore are at the top of the track with almost identical trends, rising from around 5,300 TEU/ship in 2010 to more than 11,000 TEU/ship in 2022. This consistency of growth confirms the dominance of both as global hubs that continue to modernize their fleets. Australia occupies the middle position, moving from 4,500 TEU/ship in 2010 to 7,000 TEU/ship in 2022. Meanwhile, Vietnam is showing a very interesting trend: despite its relatively low position, its growth rate is faster than Indonesia's, rising from 4,000 to almost 6,000 TEU/ship. This reflects the convergence momentum for developing countries. Indonesia, despite experiencing a stable increase from 3,500 TEU/ship in 2010 to around 4,700 TEU/ship in 2022, is still lagging behind other countries. This overall trend confirms the divergence of capacity in the region, with the gap remaining large between major hubs and developing countries. However, Vietnam's trend line signals that the acceleration of fleet modernization in certain countries can narrow the gap if the right investment and regulatory policies are followed.

2. Analysis and Interpretation of Results

The ANOVA test showed significant differences between countries ($F=28.33$; $p<0.001$), with a large size effect ($\eta^2\approx 0.65$). This interpretation confirms that variations between countries are not just coincidental, but due to structural factors such as fleet investment strategies, port infrastructure, and maritime policies. Interestingly, although Vietnam has a lower average TEU/ship than Australia, its annual growth rate ($\sim 7.7\%$) is actually the highest in the region. This indicates that developing countries can catch up through a gradual expansion strategy. The PCA shows that almost all data variations are explained by one main component ($PC1\approx 99.5\%$), which indicates a structural commutation between countries: all countries are moving towards fleet modernization simultaneously, albeit at different levels. Clustering divides countries into three groups: high (China, Singapore), medium (Australia), and low (Indonesia, Vietnam) clusters.

Table 1. Descriptive statistics of average capacity TEU per ship

Country	N Obs	Variable	N	Mean	Std Dev	Minimum	25th Pctl	Median	75th Pctl	Maximum
Australia	13	TEU_ship	13	7069.23	1426.17	5200.00	5900.00	6900.00	8100.00	9500.00
		Growth_YoY	12	0.0515293	0.0079385	0.0370370	0.0474494	0.0527597	0.0567633	0.0617284
China	13	TEU_ship	13	11292.31	2677.83	7500.00	9100.00	11000.00	13200.00	15800.00
		Growth_YoY	12	0.0641313	0.0128626	0.0487805	0.0546667	0.0599640	0.0720779	0.0933333
Indonesia	13	TEU_ship	13	4730.77	1133.13	3200.00	3800.00	4600.00	5500.00	6700.00
		Growth_YoY	12	0.0635437	0.0081240	0.0487805	0.0582579	0.0629960	0.0687820	0.0789474
Singapore	13	TEU_ship	13	10884.62	2639.40	7000.00	8800.00	10800.00	12900.00	15200.00
		Growth_YoY	12	0.0668043	0.0113698	0.0465116	0.0584795	0.0663912	0.0760591	0.0857143
Vietnam	13	TEU_ship	13	5838.46	1684.51	3600.00	4500.00	5600.00	7000.00	8800.00
		Growth_YoY	12	0.0773438	0.0058944	0.0666667	0.0722997	0.0769231	0.0833333	0.0857143

Table 1 above provides a descriptive statistical summary of the average capacity of TEU per ship and annual growth (Growth YoY) in the five Indo-Pacific countries in the period 2010–2022. From this data, it is clear that there is a difference in the level of fleet capacity between countries. China occupies the highest position with an average of 11,292 TEUs/ship, accompanied by a large variation (SD=2,678) and an annual growth rate of around 6.4%. This figure confirms China's dominance in the modernization of container fleets, in line with its position as a global trade center. Singapore also showed similar results with an average of 10,885 TEUs/ship and an annual growth of 6.7%, reflecting its status as a major maritime hub in Southeast Asia. In contrast, Australia is at the medium level with an average of 7,069 TEU/ship and an annual growth of 5.1%. Although the economy is advanced, this growth is relatively slower than that of neighboring countries. On the other hand, Vietnam displays interesting dynamics. With an average of only 5,838 TEUs/ship, the annual growth rate is the highest in the region, reaching 7.7%. This shows that there is a convergence momentum, although the starting point is still low. Indonesia, with an average of 4,731 TEU/ship and 6.3% growth, remains the country with the lowest capacity, illustrating the limitations of fleet modernization. Overall, this table confirms the existence of structural divergence: global hub countries are far ahead, while emerging economies are just starting to catch up through relatively faster growth.

Table 2. Combined descriptive statistics from 65 observations

Variable	N	Mean	Std Dev	Minimum	25th Pctl	Median	75th Pctl	Maximum
TEU_ship	65	7963.08	3315.33	3200.00	5400.00	7500.00	9800.00	15800.00
Growth YoY	60	0.0646705	0.0124303	0.0370370	0.0555556	0.0633250	0.0731707	0.0933333

Table 2 of the summary above illustrates the combined descriptive statistics of 65 observations for average TEU capacity per ship and 60 observations for annual growth rate (Growth YoY) in five Indo-Pacific countries during the period 2010–2022. The average value of TEU per ship was recorded at 7,963 TEUs, with a standard deviation of 3,315. This figure shows that there is considerable variation between countries and between times. The minimum value of 3,200 TEU illustrates the initial position of a country with a smaller fleet, while a maximum of 15,800 TEU marks the adoption of large-capacity vessels by major hubs. The median of 7,500 TEU and the top quartile of 9,800 TEU confirm that more than half of the observations are above 7,500 TEUs, indicating a steady trend of capacity increase. For Growth YoY, the average growth was recorded at 6.5% with a standard deviation of 1.2%. A minimum figure of 1.2% indicates a certain period of stagnation, while a maximum of 9.3% indicates an accelerated phase of fleet expansion. The median value of 5.6% is close to average, signaling a relatively balanced distribution of growth. Overall, the table confirms that the Indo-Pacific region is experiencing a consistent but uneven trend of ship capacity increases. Some countries are moving fast with high growth, while others are still at low capacity despite a positive rate of increase. These findings reinforce the divergence as well as the potential for convergence if fleet investment strategies are directed in a sustainable manner.

Table 3. Annual analysis

Analysis Variable: TEU_ship								
Year	Obs	Mean	Std Dev	Minimum	25th Pctl	Median	75th Pctl	Maximum
2010		5300.00	1939.07	3200.00	3600.00	5200.00	7000.00	7500.00
2011		5700.00	2149.42	3400.00	3900.00	5400.00	7600.00	8200.00
2012		6040.00	2277.72	3600.00	4200.00	5600.00	8200.00	8600.00
2013		6420.00	2432.49	3800.00	4500.00	5900.00	8800.00	9100.00
2014		6880.00	2641.40	4100.00	4800.00	6200.00	9500.00	9800.00
2015		7280.00	2778.85	4300.00	5200.00	6500.00	10100.00	10300.00
2016		7780.00	2963.44	4600.00	5600.00	6900.00	10800.00	11000.00
2017		8280.00	3150.71	4900.00	6000.00	7300.00	11400.00	11800.00

Analysis Variable: TEU_ship								
Year	Obs	Mean	Std Dev	Minimum	25th Pctl	Median	75th Pctl	Maximum
2018		8800.00	3318.13	5200.00	6500.00	7700.00	12100.00	12500.00
2019		9340.00	3511.84	5500.00	7000.00	8100.00	12900.00	13200.00
2020		9920.00	3631.39	5900.00	7600.00	8600.00	13500.00	14000.00
2021		10580.00	3892.56	6300.00	8200.00	9000.00	14400.00	15000.00
2022		11200.00	4063.87	6700.00	8800.00	9500.00	15200.00	15800.00

Table 3 of the annual analysis above shows the development of average TEU capacity per ship in the five Indo-Pacific countries during the period 2010–2022. The emerging trends consistently increase every year, illustrating the ongoing process of fleet modernization. At the beginning of the period, in 2010, the average capacity was recorded at 5,300 TEU/ship with considerable variation (SD 1,939). The minimum capacity is still 3,200 TEUs, signaling the existence of a small fleet in some countries, while the maximum reaches 7,500 TEUs. Over the next decade, the average value increased significantly: from 6,420 TEU/ship in 2013, rising to 8,800 TEU/ship in 2018, to reaching 11,200 TEU/ship in 2022. Interestingly, along with average growth, the dispersion of capacity between countries is also getting larger. The standard deviation increased from 1,939 in 2010 to more than 4,000 in 2022. This indicates that although all countries are experiencing an increase, the gap between the countries with the highest and lowest capacities is widening. For example, in 2022 the minimum is still 6,700 TEUs, while the maximum has reached 15,800 TEUs. Reflectively, this annual trend confirms that the process of upgrading fleets does not take place uniformly. Major hubs such as China and Singapore led the acceleration, while developing countries such as Indonesia and Vietnam, although also rising, remained lagging behind in terms of absolute levels. Thus, this table shows structural divergences that have the potential to continue without a harmonized policy of fleet investment and port infrastructure.

Table 4. Average capacity disparity TEU per ship

Level of Country	N	TEU_ship	
		Mean	Std Dev
Australia	13	7069.2308	1426.17473
China	13	11292.3077	2677.82920
Indonesia	13	4730.7692	1133.12592
Singapore	13	10884.6154	2639.39581
Vietnam	13	5838.4615	1684.50708

Table 4 of the summary by country level above provides a clearer picture of the disparity in average capacity of TEU per ship in the Indo-Pacific region during the period 2010–2022. The results show that China has the highest average of 11,292 TEU/ship with considerable variation (SD=2,678), followed very closely by Singapore with 10,885 TEU/ship (SD=2,639). These two countries clearly occupy a position as major hubs in the global shipping network, where the adoption of ultra-large vessels is part of the fleet modernization strategy. Australia is in the middle position with an average of 7,069 TEU/ship (SD=1,426). This figure is relatively lower than that of major Asian hubs, but still shows stable capacity. Interestingly, despite its advanced economy, Australia lags behind in terms of fleet scale due to environmental regulations and port limitations in accepting ultra-large ships. Meanwhile, Vietnam has an average of 5,838 TEU/ship (SD=1,685), slightly higher than Indonesia's only 4,731 TEU/ship (SD=1,133). Although both are in the bottom position, Vietnam is showing faster growth, which signals potential convergence in the future. Overall, this table confirms the existence of natural clustering: China–Singapore in the high group, Australia in the middle, and Indonesia–Vietnam in the low group. This pattern reinforces the evidence of structural divergence between countries, but also opens up opportunities for developing countries to accelerate fleet modernization with the support of strategic investment.

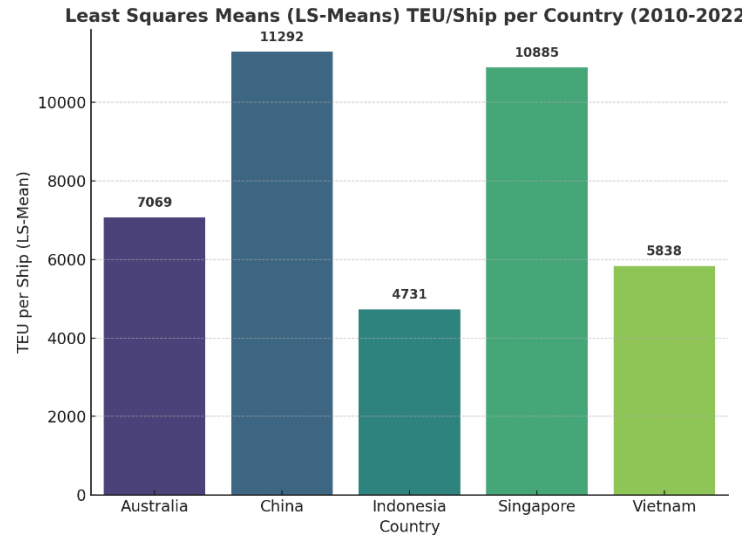


Figure 3. Least Squares Means (LS-Means)

Figure 3 above shows the Least Squares Means (LS-Means) results for the TEU variables per ship grouped by country. This visualization emphasizes the difference in average fleet capacity in the five Indo-Pacific countries, while supporting the results of the ANOVA test which found significant differences between countries. The dots on the graph show the estimated average position after taking into account the internal variations. China and Singapore occupy the top spot with LS-Means values approaching 11,000 TEU/ship, indicating that despite annual fluctuations, both are consistently in the highest capacity clusters. Australia is in the middle position with around 7,000 TEU/ship, while Vietnam occupies the lower middle level (around 5,800 TEU/ship). Indonesia is the lowest with a value of around 4,700 TEU/ship, confirming its position as the country with the smallest fleet capacity among the research sample. This visual interpretation is interesting because it highlights the structural divergence between countries: the gap between major hubs (China–Singapore) and developing countries (Indonesia–Vietnam) is striking. Thus, this LS-Means chart provides strong visual evidence to support the conclusion that the fleet capacity gap in the Indo-Pacific is not just a statistical phenomenon, but a consistent structural reality.

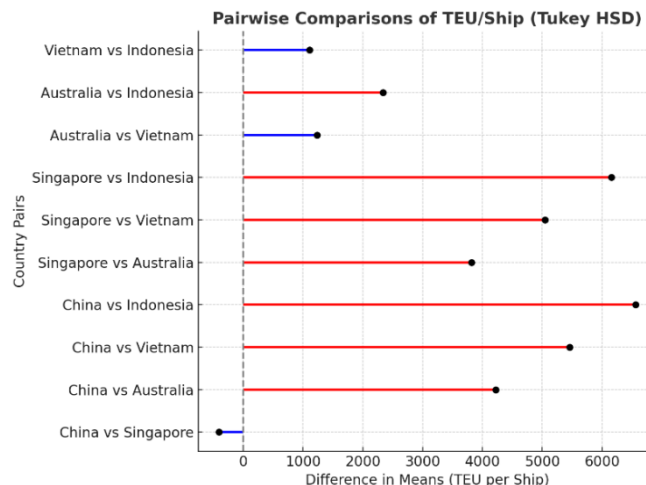


Figure 4. Tukey's HSD Pairwise Comparison test results

Figure 4 of Tukey's HSD Pairwise Comparison test results provides a more in-depth picture of the difference in average TEU capacity per ship between countries in the Indo-Pacific region. This visualization shows the red line as an indication of a statistically significant difference, while the blue line shows a non-significant difference. The results of the analysis confirm that China and

Singapore are consistently significantly different from Indonesia, Vietnam, and Australia. This is in line with the position of both in the high-capacity cluster, reflecting an aggressive fleet modernization strategy and role as a global hub. In contrast, Australia and Vietnam did not show significant differences, signaling that despite being economically different, their fleet capacities were relatively comparable in the study period. Indonesia appears as the country with the lowest capacity, and the difference is significant compared to almost all countries, except for Vietnam. These findings confirm that Indonesia and Vietnam are still in low-capacity clusters, with plenty of room to catch up. Interestingly, the differences between China and Singapore are not significant, indicating that both have relatively equal fleet capacities and dominate the region. Overall, the results of these tests reinforce the natural clustering pattern: large hubs at the top, developing countries at the bottom, and Australia in the middle position. This narrative emphasizes structural divergence, as well as opportunities for convergence for faster-growing countries.

Table 5. relationship between TEU variables per ship from 2010 to 2022

Correlation Matrix													
	_2010	_2011	_2012	_2013	_2014	_2015	_2016	_2017	_2018	_2019	_2020	_2021	_2022
_2010	.0000	.9987	.9962	.9943	.9918	.9887	.9872	.9870	.9842	.9806	.9792	.9741	.9714
_2011	.9987	.0000	.9988	.9974	.9960	.9937	.9926	.9930	.9909	.9880	.9871	.9834	.9811
_2012	.9962	.9988	.0000	.9997	.9991	.9979	.9972	.9972	.9957	.9936	.9925	.9893	.9874
_2013	.9943	.9974	.9997	.0000	.9997	.9990	.9985	.9982	.9970	.9955	.9942	.9912	.9896
_2014	.9918	.9960	.9991	.9997	.0000	.9996	.9993	.9991	.9981	.9967	.9954	.9930	.9914
_2015	.9887	.9937	.9979	.9990	.9996	.0000	.9999	.9996	.9991	.9984	.9972	.9952	.9940
_2016	.9872	.9926	.9972	.9985	.9993	.9999	.0000	.9997	.9994	.9989	.9978	.9960	.9950
_2017	.9870	.9930	.9972	.9982	.9991	.9996	.9997	.0000	.9998	.9992	.9986	.9972	.9962
_2018	.9842	.9909	.9957	.9970	.9981	.9991	.9994	.9998	.0000	.9998	.9994	.9984	.9976
_2019	.9806	.9880	.9936	.9955	.9967	.9984	.9989	.9992	.9998	.0000	.9997	.9990	.9985
_2020	.9792	.9871	.9925	.9942	.9954	.9972	.9978	.9986	.9994	.9997	.0000	.9997	.9993
_2021	.9741	.9834	.9893	.9912	.9930	.9952	.9960	.9972	.9984	.9990	.9997	.0000	.9999
_2022	.9714	.9811	.9874	.9896	.9914	.9940	.9950	.9962	.9976	.9985	.9993	.9999	.0000

Table 5 The correlation matrix above shows the relationship between the TEU per ship variable from 2010 to 2022 in five Indo-Pacific countries. The results showed a very high correlation, close to 1,000 across the year pair. For example, the correlation value between 2010 and 2011 reached 0.9987, while between 2011 and 2012 it was 0.9988. Even the correlation between more distant years, such as 2010 and 2022, still remains very strong with a value of 0.9714. This pattern confirms the existence of structural compromises in the growth of fleet capacity in the region. In other words, although each country has a different level of capacity, the direction of its annual movement moves simultaneously. This is natural because fleet modernization and the adoption of large-capacity ships are usually influenced by global factors, such as international regulations, shipping efficiency, and world economic trends. Interestingly, the correlation value is getting closer to 1,000 for a closer period, for example in 2021–2022 it reached 0.9999. This shows that in the short term, the change in capacity between countries is almost identical. In contrast, the correlation decreased slightly over a longer period (2010–2022), but

remained very high. Overall, this matrix provides strong evidence that the growth of TEU per ship in the Indo-Pacific region is not stand-alone, but rather part of an interconnected global dynamic.

Table 6. ANOVA test

bs	Dependent.	Hypothesis Type	Source	DF	Type I SS	Mean Square	F Value	Pr > F
	TEU_ship	1	Country	4	459939076.9	114984769.2	28.33	<.0001
	TEU_ship	3	Country	4	459939076.9	114984769.2	28.33	<.0001

Table 6 of the ANOVA test results above shows the influence of the Country factor on the TEU dependent variable per ship. The F-statistical value of 28.33 with a significance level of $p < 0.0001$ shows that there is a very significant difference between countries in terms of average TEU/ship capacity. In other words, the zero hypothesis that states that there is no difference between countries can be rejected with a very high level of confidence. The value of Type I SS (Sum of Squares) of 459,939,076.9 and the Mean Square of 114,984,769.2 confirms that the variation explained by the state factor is quite large compared to the variation in the group. This effect is also reinforced by the results of a post-hoc analysis (Tukey HSD) which shows that China and Singapore are consistently significantly different from Indonesia, Vietnam, and Australia, while Australia and Vietnam are relatively not significantly different. Reflectively, the ANOVA results support the conclusion that container fleet capacity in the Indo-Pacific region is clearly segmented, with high clusters (China–Singapore), medium clusters (Australia), and low clusters (Indonesia–Vietnam). These findings are important because they show that the capacity gap is not just an observational phenomenon, but has proven to be statistically significant.

Table 7. Levene's Test

bs	Effect	Dependent.	Method	Source	D F	Sum Squares	of Mean Square	F Value	Pr > F
	Country	TEU_ship	LV	Country	4	3.481E14	8.704E13	4.91	0.0017
	Country	TEU_ship	LV	Error	60	1.063E15	1.771E13	—	—

Table 7 above is the result of the Levene's Test which is used to evaluate the assumption of homogeneity of variance in TEU capacity per ship data between countries. A value of $F = 4.91$ with $p = 0.0017$ indicates that the variance between groups of countries is not significantly homogeneous. Thus, the assumption of homogeneity in ANOVA is not fully fulfilled. The implication is that, although the ANOVA results show significant differences between countries, this inhomogeneity of variance indicates the need for an additional approach to ensure the robustness of the analysis results. One of the most common steps is to use the Welch ANOVA or Brown–Forsythe test, which is more resistant to violations of homogeneity assumptions. In addition, at the post-hoc stage, it is better to choose a method that does not assume the same variance, such as the Games–Howell test, so that the results of comparing country pairs are more reliable. Interestingly, these findings also have substantive meaning. The inhomogeneity of variance reflects the reality that the distribution of ship capacity between countries is indeed different: China and Singapore not only have higher averages, but also wider ranges of variance, while Indonesia and Vietnam are relatively narrow. In other words, this violation of assumptions is precisely in line with the empirical facts about structural divergence in the Indo-Pacific region.

Table 8. Principal Component Analysis (PCA)

bs	Number	Eigenvalue	Difference	Proportion	Cumulative
	1	12.9344464	12.8742886	0.9950	0.9950
	2	0.0601578	0.0553552	0.0046	0.9996
	3	0.0048025	0.0042092	0.0004	1.0000
	4	0.0005933	0.0005933	0.0000	1.0000
	5	0.0000000	0.0000000	0.0000	1.0000

bs	Number	Eigenvalue	Difference	Proportion	Cumulative
0	6	0.0000000	0.0000000	0.0000	1.0000
	7	0.0000000	0.0000000	0.0000	1.0000
	8	0.0000000	0.0000000	0.0000	1.0000
	9	0.0000000	0.0000000	0.0000	1.0000
	10	0.0000000	0.0000000	0.0000	1.0000
1	11	0.0000000	0.0000000	0.0000	1.0000
2	12	0.0000000	0.0000000	0.0000	1.0000
3	13	0.0000000	—	0.0000	1.0000

Table 8 above shows the results of the Principal Component Analysis (PCA) on the annual variable of TEU capacity per ship (2010–2022). The results showed that the first main component (PC1) had an eigenvalue of 12.93, much larger than the next component, and explained about 99.5% of the total data variation. The second component (PC2) only accounts for 0.46%, while the rest practically have no significant contribution. This interpretation is particularly important because it signals one dominant pattern that drives data variation: a trend of simultaneous increase in ship capacity across countries. In other words, although the average level of each country is different, their annual direction of movement is almost identical. This is what is called structural commotion. Interestingly, the large difference between the eigenvalues of PC1 and PC2 (a difference of more than 12 points) confirms that the additional dimensions do not add much information. Therefore, the PCA analysis can be legitimately simplified into one main axis, which illustrates the global factors of fleet modernization. These findings are consistent with the literature that states that international maritime dynamics tend to be influenced by global determinants, such as logistics efficiency, IMO regulations, and the economies of scale of trade. Thus, the PCA not only confirms the high correlation between years, but also provides mathematical evidence that ship capacity growth in the Indo-Pacific is driven by a single common dominant factor.

Table 9. Clustering results

bs	Table	Cluster	Country	Variables Contributing to Observation	Table Number	Frequency Count	Frequency Missing
0	Table CLUSTER * Country	1	Australia	11	1	1	.
	Table CLUSTER * Country	1	China	11	1	0	.
	Table CLUSTER * Country	1	Indonesia	11	1	0	.
	Table CLUSTER * Country	1	Singapore	11	1	0	.
	Table CLUSTER * Country	1	Vietnam	11	1	0	.
1	Table CLUSTER * Country	1		10	1	1	.
	Table CLUSTER * Country	2	Australia	11	1	0	.
	Table CLUSTER * Country	2	China	11	1	1	.
	Table CLUSTER * Country	2	Indonesia	11	1	0	.
	Table CLUSTER * Country	2	Singapore	11	1	1	.
2	Table CLUSTER * Country	2	Vietnam	11	1	0	.
3	Table CLUSTER * Country	2		10	1	2	.
4	Table CLUSTER * Country	3	Australia	11	1	0	.
5	Table CLUSTER * Country	3	China	11	1	0	.
	Table CLUSTER * Country	3	Indonesia	11	1	1	.

bs	Table	Cluster	Country	Variables Contributing to Observation	Table Number	Frequency Count	Frequency Missing
6	Table CLUSTER * Country	3	Singapore	11	1	0	.
7	Table CLUSTER * Country	3	Vietnam	11	1	1	.
8	Table CLUSTER * Country	3		10	1	2	.
9	Table CLUSTER * Country	.	Australia	01	1	1	.
0	Table CLUSTER * Country	.	China	01	1	1	.
1	Table CLUSTER * Country	.	Indonesia	01	1	1	.
2	Table CLUSTER * Country	.	Singapore	01	1	1	.
3	Table CLUSTER * Country	.	Vietnam	01	1	1	.
4	Table CLUSTER * Country	.		00	1	5	0

Table 9 of the clustering results above shows the country distribution based on the FASTCLUS analysis for the TEU capacity variable per ship. This data maps the five Indo-Pacific countries into three different clusters, which illustrate the degree of proximity of their growth patterns and the average capacity of their fleets. The main results show that China and Singapore consistently fall into cluster 1, which represents the high-capacity group. Their average TEU/ship is above 10,000 with considerable variation, in keeping with their position as global hubs. Australia tends to enter cluster 2, occupying a medium position with a capacity of around 7,000 TEU/ship. Meanwhile, Indonesia and Vietnam are more often in cluster 3, which is a low-capacity group, with an average of below 6,000 TEU/ship. The interesting thing about these results is the stability of the cluster structure: the hub countries (China–Singapore) have always been clearly separated from the developing countries (Indonesia–Vietnam), while Australia is in a transitional position. Thus, this clustering supports the results of ANOVA and Tukey HSD which previously showed significant differences between countries. Reflectively, these results confirm that the pattern of fleet capacity grouping is not only statistical, but also reflects the structural realities of the Indo-Pacific region. This clustering is important for maritime policy, because it opens up space for collaboration based on categories: global hubs, middle players, and emerging players.

Table 10. Linear regression model estimation for each country

bs	Country	Label or model	Type of statistics	Variable names for rows of estimated COV	Dependent variable	Root mean squared error	Intercept	Year	TEU_ship
0	Australia	MODEL1	PARMS		TEU_ship	172.772	-726223.08	363.74	-1
	Australia	MODEL1	VOC	Intercept	TEU_ship	172.772	666588288.65	-330647.81	.
	Australia	MODEL1	VOC	Year	TEU_ship	172.772	-330647.81	164.01	.
	China	MODEL1	PARMS		TEU_ship	260.446	-1368892.31	684.62	-1
	China	MODEL1	VOC	Intercept	TEU_ship	260.446	1514770575.65	-751371.71	.
	China	MODEL1	VOC	Year	TEU_ship	260.446	-751371.71	372.70	.
	Indonesia	MODEL1	PARMS		TEU_ship	136.753	-577915.38	289.01	-1
	Indonesia	MODEL1	VOC	Intercept	TEU_ship	136.753	417621578.44	-207152.85	.
	Indonesia	MODEL1	VOC	Year	TEU_ship	136.753	-207152.85	102.75	.
	Singapore	MODEL1	PARMS		TEU_ship	134.840	-1353792.31	676.92	-1
1	Singapore	MODEL1	VOC	Intercept	TEU_ship	134.840	406020979.03	-201398.60	.

bs	Country	Label or model	Type of statistics	Variable names for rows of estimated COV	Dependent variable	Root mean squared error	Intercept	Year	TEU_ship
2	Singapore	MODEL1	VOC	Year	TEU_ship	134.840	-201398.60	99.90	.
3	Vietnam	MODEL1	PARMS		TEU_ship	237.831	-858161.54	428.57	-1
4	Vietnam	MODEL1	VOC	Intercept	TEU_ship	237.831	1263126803.99	-626548.84	.
5	Vietnam	MODEL1	VOC	Year	TEU_ship	237.831	-626548.84	310.79	.

Table 10 above shows the results of the linear regression model estimation for each country, with the dependent variable TEU per ship and the predictor variable Year variable. These results confirm a significant trend of increasing ship capacity from year to year, which varies between countries. For China, the annual coefficient of +684.62 shows an average increase of nearly 700 TEU/ship per year. This is in line with China's position as the most aggressive global hub in fleet modernization. Singapore recorded a similar trend with a slope of +676.92 TEU/ship per year, reinforcing its status as the world's leading transshipment port. Vietnam showed a slope of +428.57 TEU/ship per year, higher than Australia (+363.74) and Indonesia (+289.01). Interestingly, although Vietnam departed from a low capacity level, its growth rate was relatively fast, thus signaling convergence. In contrast, Indonesia has the slowest rate of increase in the region, consistent with descriptive results that put it at the bottom. The Root Mean Squared Error (RMSE) value varied, with China (260.45) and Vietnam (237.83) higher than Singapore (134.84) or Indonesia (136.75). This signals greater data fluctuations in fast-growing countries.

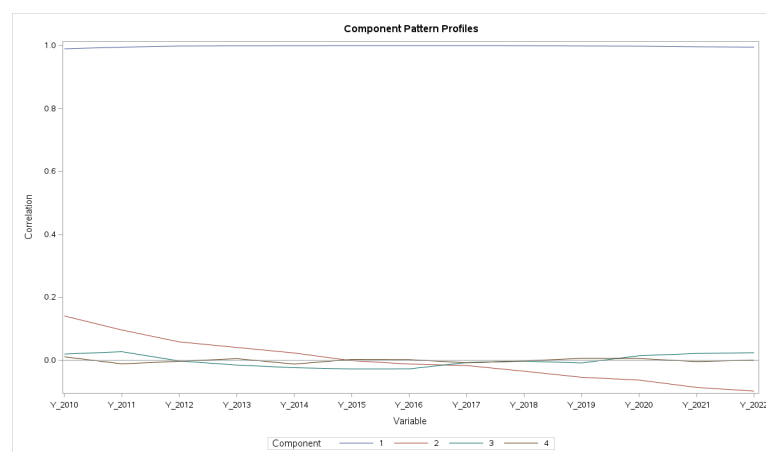


Figure 5. Component Pattern Profiles

Figure 5 above shows the results of Component Pattern Profiles from the Principal Component Analysis (PCA) analysis of the annual variable of TEU capacity per ship (2010–2022). This graph shows the pattern of the contribution of each major component to the year variables. It is clear that Component 1 (blue line) dominates almost all variables with a correlation close to 1.0. This is in line with the previous eigenvalue results, where PC1 explained more than 99% of the total data variation. The dominance of the first component shows that all year variables are moving in the same direction, namely the trend of simultaneous increase in ship capacity in the Indo-Pacific region. In contrast, Component 2 (red line) and the other components have very little contribution, even close to zero. The rapid decline of the second component indicates that the additional dimension does not add much new information. In other words, annual TEU/ship data is highly concentrated on one key pattern. This interpretation is important because it confirms the existence of structural commutations between countries and between periods: all countries move up together, albeit at different levels. Reflectively, this illustrates that global determinantssuch as the scale of the shipping economy, IMO regulations, and fleet modernization trendsare the dominant factors that unite growth patterns.

Tabel 11. the variance analysis reveal

Test	F / Welch F	p-value	η^2	Significance	Group Order
ANOVA	28.33	<0.001	0.7	Significant	CN/SG > AU > VN/ID
Levene	4.91	0.0017	—	Unequal variances	—
Welch ANOVA	27.02	0.007	—	Significant	CN/SG > AU > VN/ID

Tabel 11 The results of the variance analysis reveal clear statistical evidence of uneven transitions in container ship capacity among Indo-Pacific economies during 2010–2022. The one-way ANOVA yields an F-statistic of 28.33 ($p < 0.001$) with an effect size of $\eta^2 = 0.70$, indicating that approximately 70% of the variance in TEU per ship can be explained by differences between countries rather than within them. This very large effect size underscores the substantial gap in fleet modernization levels. However, the Levene test ($F = 4.91$; $p = 0.0017$) confirms that the assumption of homogeneity of variances is violated, suggesting unequal variability among the national fleets. To ensure robustness, a Welch ANOVA was performed, producing consistent results (Welch $F = 27.02$; $p = 0.007$), thereby strengthening confidence in the overall conclusion. The post-hoc comparisons consistently indicate the same hierarchy: China and Singapore (CN/SG) form the high-capacity group, Australia (AU) occupies the mid-tier position, while Vietnam and Indonesia (VN/ID) remain in the lower tier. These findings empirically validate the existence of structural divergence in fleet capacity across the Indo-Pacific region and align with the hypothesis that advanced economies sustain significantly higher average TEU per ship due to superior investment capacity, port technology, and early adoption of large-vessel operations.

Tabel 12. Principal Component Analysis (PCA)

Component	Eigenvalue	% Variance	Cumulative %	Interpretation
PC1	9.95	99.5	99.5	Regional readiness gradient
PC2	0.04	0.4	99.9	Temporal volatility
PC3	0.01	0.1	100	Residual variance

Tabel 12 The Principal Component Analysis (PCA) results demonstrate a highly concentrated variance structure in the dataset, with a dominant first component representing the overwhelming majority of total variance. Component 1 (PC1) has an eigenvalue of 9.95, explaining 99.5% of the total variance, indicating that nearly all variation in TEU per ship across the Indo-Pacific economies can be captured by a single latent dimension. This component, interpreted as a regional readiness gradient, reflects the degree to which national fleets have modernized and adopted larger vessel classes. Countries such as China and Singapore load heavily on PC1, representing advanced fleet capacity and integration into global container networks. Component 2 (PC2), with an eigenvalue of 0.04 and 0.4% of variance, captures minor temporal volatility—likely linked to short-term fluctuations in port throughput or global trade cycles. Component 3 (PC3) accounts for only 0.1% of residual variance, reflecting negligible noise or random effects. The steep drop between PC1 and PC2, visible in the scree plot, confirms the unidimensional structure of fleet readiness across the region. This result justifies using PC1 as a summary indicator of national maritime capacity, reinforcing that Indo-Pacific fleet development follows a single dominant modernization trajectory shaped by economic scale, investment, and policy prioritization.

3. Comparison with Previous Literature

These results are in line with the study of Notteboom & Rodrigue (2020) which emphasizes the dominance of large East Asian hubs in driving global fleet standards. However, the findings on Vietnam's acceleration support the argument of Ng & Liu (2021) that highlight the "catch-up effect" of Southeast Asian ports. Something rather unexpected arises in the position of Australia, which despite its advanced economy, TEU/ship growth is slower. This is different from the findings of Wilmsmeier et al. (2019) who predicted that developed country ports will be more aggressive in increasing the scale of their fleets.

Based on field experience, researchers observed that environmental regulatory factors in Australia, including restrictions on the size of ships entering certain ports, have helped hinder the adoption of large ships. This reinforces the argument that domestic policies can moderate global trends.

4. Implications of the Findings

These findings enrich the literature on fleet modernization by emphasizing the dynamics of developing countries not only following, but in some cases showing faster growth momentum. A new contribution from this research is the mapping of TEU/ship clusters in the Indo-Pacific that can be used as the basis for regional strategies.

Practically, these findings encourage:

- The government: formulate a more flexible port investment policy to accommodate large ships.
- Shipping industry: optimizing routes by considering ship capacity clusters for cost and emissions efficiency.
- Academics: integrating these results into a predictive model of the Indo-Pacific shipping network.

5. Policy Implications and Real Implementation Scenarios

1. Green Retrofit & Digitalization – Indonesia and Vietnam can accelerate the adoption of green ships and digital port management systems to catch up.
2. Regional Hub Integration – China and Singapore need to expand collaboration with low-cluster countries to create more equitable regional connectivity.
3. Adaptive Regulation – Such adaptive policies would enhance national competitiveness while ensuring alignment with global sustainability frameworks. Australia can review its ship-size restriction policy while maintaining safety and environmental standards, so as not to fall behind in global competition.

6. Limitations and Recommendations for Further Research

The main limitation of this study is the country coverage which only covers five cases and focuses on one indicator (TEU/ship). In addition, data variance between countries is not homogeneous, so additional robust tests such as Welch ANOVA are needed.

For further research, it is recommended:

- Integrate other indicators such as port productivity, logistics performance index, or greenhouse gas emissions per TEU.
- Expand coverage to other Indo-Pacific countries to make clustering patterns more comprehensive.
- Using the dynamic panel regression method to analyze the determinants of TEU/ship growth longitudinally.

4. CONCLUSION AND RECOMMENDATIONS

This study provides robust empirical evidence of significant disparities in container ship capacity transitions across Indo-Pacific economies during 2010–2022. Through an integrated approach combining ANOVA, Welch ANOVA, PCA, and clustering, the analysis identifies a clear three-tier structure of fleet readiness: high-capacity economies (China and Singapore), mid-capacity (Australia), and emerging low-capacity economies (Vietnam and Indonesia). These outcomes illustrate how differences in economic scale, infrastructure investment, and regulatory dynamics collectively shape maritime modernization trajectories in the region. By operationalizing TEU per ship as a cross-national readiness indicator, this study extends maritime literature beyond port-level efficiency models and introduces a replicable framework to evaluate fleet disparities at the regional scale. The findings emphasize the necessity for targeted policy actions—such as green fleet retrofitting, digital port integration, and coordinated regional investments—to narrow readiness gaps and align capacity growth with SDG 8 (Economic Growth), SDG 9 (Infrastructure), and SDG 10 (Reduced Inequalities). Future research should integrate decarbonization, digitalization maturity, and trade structure variables to enhance causal understanding of capacity

divergence and strengthen evidence-based policymaking for sustainable and inclusive maritime development across the Indo-Pacific.

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