ACI Research Paper #08-2026

Comparative Study on the Clean Energy Production Cost Competitiveness Among ASEAN Countries

Jingting LIU

Parag DASS

Yijia HUANG

Bowen YAN

June 2026

Please cite this article as:

Liu, Jingting, Parag Dass, Yijia Huang, and Bowen Yan, "Comparative Study on the Clean Energy Production Cost Competitiveness Among ASEAN Countries", Research Paper #08-2026, *Asia Competitiveness Institute Research Paper Series (June 2026).*

Comparative Study on the Clean Energy Production Cost Competitiveness Among ASEAN Countries

Liu Jingting† Parag Dass‡ Yijia Huang§ Bowen Yan¶

June 2026

Abstract

Supply chain disruptions and surging energy prices resulting from the 2026 Strait of Hormuz crisis underscore the urgent need for energy security in oil and gas import-dependent countries like Singapore. Transitioning to renewable power can be a solution to enhance energy security and sustainability. This study evaluates the cost-competitiveness of ASEAN countries as long-term providers of low-carbon electricity to Singapore. By computing the Levelised Cost of Electricity (LCOE) for hydropower, solar photovoltaic (PV), and wind, we establish a ranking order of candidate countries and technologies. Hydropower emerges as the most cost-competitive, particularly in Malaysia, Indonesia, and Vietnam, followed closely by solar PV power. Conversely, wind power emerges as a comparatively more expensive technology. We then quantify the importance of underlying determinants influencing renewable energy production costs, such as policy support, geographic endowments, and the "learning-by-doing" effect by constructing a Clean Energy Cost Competitiveness Index (CECCI). Finally, as supply chain disruptions and cost volatility may increasingly shape the economic viability of renewable energy deployment, we complement our earlier results with further discussion of the implications of regional supply chains for clean energy equipment and local content requirements (LCR), both of which introduce meaningful upward pressure on renewable energy production costs. This study offers a comprehensive, methodologically rigorous framework to benchmark ASEAN's clean energy supply capacity and inform evidence-based energy security and decarbonisation strategies.

† Jingting: Senior Lecturer at the James Cook University Singapore. Email: cindy.liu@jcu.edu.au.

‡ Parag: Research Analyst at the Asia Competitiveness Institute, Lee Kuan Yew School of Public Policy, National University of Singapore. Email: paragdass@nus.edu.sg.

§ Yijia: Research Analyst at the Asia Competitiveness Institute, Lee Kuan Yew School of Public Policy, National University of Singapore. Email: yjhuang@nus.edu.sg.

¶ Bowen: Research Associate at the Asia Competitiveness Institute, Lee Kuan Yew School of Public Policy, National University of Singapore. Email: yanbowen@nus.edu.sg.

1 Introduction

The importance of clean energy for Singapore lies in three dimensions: enhancing energy security, fulfilling green ambitions and maintaining economic competitiveness in the green economy. The 2026 Strait of Hormuz crisis is a stark reminder of the importance of Singapore's energy security, given its strong oil and gas import dependence, many of which originate from or transit through countries around the Strait of Hormuz. 95% of Singapore's electricity is generated by imported natural gas [31] and 24.8% of its liquefied natural gas (LNG) imports are from the Middle East [110]. To ensure Singapore's long-term energy security, diversifying from LNG-generated power to renewable power is one of the key avenues.

Singapore has seen the importance of clean power in securing its energy supply, mainly by expanding domestic solar power deployment and leveraging the regional power grid to import low-carbon electricity. In terms of domestic solar power expansion, Singapore reached its target to deploy 2 gigawatt-peak (GWp) of solar power in 2025, well ahead of the target year of 2030. The target is then raised to 3 GWp by 2030 [87]. This will meet the annual electricity needs of around 350,000 households [116]. The country's largest solar farm is expected to commence operation by around 2027 and 2028, which will produce 141 megawatt-peak (MWp) of solar capacity by 2030 [126].

Given Singapore's scarcity of renewable energy sources, low-carbon electricity imports are also critical to reduce its strong reliance on LNG-generated power. Singapore raised its low-carbon electricity import target from 4 GW to 6 GW by 2035, meeting one-third of its electricity demand [129]. Table 1 summarises Singapore's current and planned low-carbon electricity import agreements. As of April 2026, Singapore has operated two pilot projects on the regional power grid: 1) the first multilateral cross-border electricity trade project in the Association of Southeast Asian Nations (ASEAN) region to import hydropower from Laos, and 2) renewable electricity from Peninsular Malaysia. These allow for up to 250 MW of low-carbon electricity imports to Singapore. It has also granted Conditional Approvals for 11 large-scale low-carbon electricity import projects from Australia, Cambodia, Malaysia, Indonesia, and Vietnam, mainly solar, hydro and wind power projects. Six Indonesian projects with substantive progress were awarded Conditional Licences.

Beyond energy security, expanding clean power deployment helps fulfil Singapore's green ambitions by decarbonising the carbon-intensive electricity sector. As a signatory of the Paris Agreement, Singapore has committed to reducing emissions to between 45 and 50 million tonnes of carbon dioxide equivalent (MtCO2e) in 2035 and achieving net-zero emissions by 2050. Increasing the adoption of renewable energy is a "national imperative" to achieve these goals [30, 90, 128], as power generation contributed to about 40% of Singapore's carbon emissions [89]. At the ASEAN level, Singapore's expanding adoption of renewable power will also contribute to achieving the target of 45% of the region's total installed capacity being renewable by 2030 [4].

Furthermore, using more low-carbon electricity is critical for Singapore to maintain and improve its attractiveness as a destination for green investment. In 2024, Singapore attracted US$320 million in investment in solar panel manufacturing, accounting for 12% of its private green investment that year [12]. These green investments are driven by global decarbonisation regulations and consumer demand, which incentivise major MNCs to green their supply chains by adopting renewable energy solutions. [1] Furthermore, Singapore's local regulations, notably the carbon tax, which is at $45/tCO2e in 2026, and will further raise it to $50-80/tCO2e by 2030 [128], also motivates companies to reduce their carbon emissions by using clean energy, particularly for the energy-intensive industries, such as data centres, artificial intelligence (AI), semiconductors, and biopharmaceuticals [90, 48].

Recognising the strategic importance of low-carbon electricity imports for Singapore, this paper aims to answer two questions: firstly, which countries and technologies within the ASEAN region offer cost-competitive sources for Singapore's low-carbon electricity imports; secondly, what factors drive the cost variance across these different countries and technologies.

To answer these questions, first, we compute the Levelised Cost of Electricity (LCOE) for hydropower, solar

[1] For example, Facebook partnered with Singaporean utility companies Sembcorp and Sunseap to power its data centre operations with solar power [127].

Table 1: Singapore's Current Power Import Agreements

Source Country	(Expected) Trading Volume	Power Sources	Transmission Lines	Current Status
Import Trials				
Lao–Thailand–Malaysia	200 MW Phase 1: up to 100 MW; Phase 2: up to 200 MW (additional capacity from Malaysia)	Phase 1: renewable hydropower	Existing regional power grid	Pilot programme (commenced on 23 June 2022)
Malaysia (Peninsular)	50 MW	Renewable electricity	Existing interconnectors	Pilot programme (December 2024 – December 2026)
Large-scale Electricity Imports				
Indonesia	3.4 GW (7 projects)	Solar PV power supported by battery energy storage	Subsea cables	Conditional Licences: 3 GW Conditional Approvals: 0.4 GW
Australia	1.75 GW	Solar power	New subsea cables: $\sim$ 4,300 km	Conditional Approval
Vietnam	1.2 GW	Offshore wind Others (potentially)	New subsea cables: $\sim$ 1,000 km	Conditional Approval
Cambodia	1 GW	Solar power; Pumped storage hydropower; Wind power (potentially)	Subsea cables: 1,000+ km Overland (through Malaysia)	Conditional Approval
Malaysia (Sarawak)	1 GW (by 2032)	Hydropower (mainly)	Subsea cables: 700+ km	Conditional Approval

Note: Current status refers to the status as of May 2026.

Source: Authors' compilation based on [28, 26, 27, 88, 107, 115, 111, 21].

photovoltaic (PV), onshore and offshore wind in ASEAN countries. This facilitates a rank-ordering of Country $\times$ Technology pairs to pinpoint the most cost-competitive import sources. We find that hydropower is the most competitive source in the ASEAN region, notably projects in Malaysia, Indonesia, and Vietnam. Solar PV power follows, and the projects in Indonesia, Cambodia and Vietnam have a competitive edge in production cost. Wind power projects are generally more expensive. Accordingly, prioritising hydropower and solar PV, with wind as a secondary focus, will be central to shaping Singapore's import strategy.

Second, as there are indirect factors that shape the variance in the components in the LCOE formula, we construct a novel Clean Energy Cost Competitiveness Index (CECCI). Using regression analysis across both ASEAN and global datasets, we estimate the influence of secondary LCOE determinants, including policy support, renewable deployment scale, geographic factors, import tariff rates, macroeconomic profiles, and innovation and industrial capacity. We find that LCOE is primarily reduced by capacity expansion, effective policy support, favourable macroeconomic conditions that lower investment risk and improve financing accessibility. By integrating the baseline LCOE rankings with this multidimensional index, the study provides a holistic assessment of ASEAN's long-term clean energy supply potential for Singapore.

The remainder of the paper is structured as follows: Section 2 reviews the literature on evaluating clean energy production costs and the structural factors shaping the cost variations. Section 3 details the LCOE calculation methodology and analyses the LCOE components for ASEAN countries, and presents the resulting cost rankings. Section 4 analyses the secondary factors that determine LCOE, presents the global regression results, and details the consequent CECCI. Section 5 discusses about further considerations shaping clean energy cost competitiveness, including supply costs for equipment used in renewable power generation, transmission and storage and the impact of local content requirements, which can potentially raise supply chain costs, and restrict capital acquisition. Finally, Section 6 synthesises the findings and concludes the study.

2 Literature Review

2.1 Gauging Clean Energy Production Costs

LCOE is the most commonly used indicator for comparing the cost competitiveness of various power-generation technologies [121, 37, 130]. Expressed as a discounted cost-per-unit value ($/kWh), LCOE divides the total costs to build and operate a power project by the total electricity generation over the project's lifetime [145]. In practice, LCOE serves as important information for energy generation project developers in power purchase agreements (PPA) negotiations, as the PPA price must exceed LCOE to ensure a project's profitability [83]. For policymakers, LCOE can be used to determine the required subsidies (e.g. Feed-in-Tariff (FiT) policies) to balance the cost difference between renewable energy and other conventional sources [98].

According to the International Renewable Energy Agency (IRENA), the LCOE of renewable energy technologies has experienced remarkable declines in recent years. It is found that 91% of the world's new utility-scale renewable power projects commissioned in 2024 were more cost-effective than any fossil fuel-fired alternative [60]. Nevertheless, the global average may not apply to the reality in ASEAN. Because literature has noted that, when LCOE is applied across very dissimilar geographical locations, or when comparing LCOE results reported by various sources, it could lead to misleading comparisons due to different underlying assumptions [131, 81, 112]. As a result, our study aims to obtain LCOE that accurately reflects the variability within the ASEAN region.

Existing ASEAN LCOE studies remain fragmented in terms of geographic scope, technological coverage, and methodological depth. A study by the ASEAN Centre for Energy (ACE) in 2019 found that the use of conventional energy was still more cost-effective compared to renewable energy technologies during the 2007-2017 period [6]. A 2016 study by the ACE, which informed the mentioned 2019 study, calculated LCOE using project-level data from 64 projects across six ASEAN member states (Indonesia, Malaysia, Laos, Myanmar, Thailand, and Vietnam) for solar PV, biomass, and small hydropower, but relied on a uniform 10% discount rate and relatively small samples for each Country $\times$ Technology pair [5]. A 2015 report by the Asian Development Bank (ADB) focusing on the Greater Mekong Subregion (Cambodia, Thailand, Laos, Vietnam, and Myanmar) applied LCOE to evaluate the economically feasible potential of renewable energy. Although detailed technical considerations were incorporated, such as the degree and intensity of solar irradiation and land area suitability, the assumptions for project costs, discount rates, and operating costs used for LCOE estimation remained standardised across countries [7]. Likewise, a 2020 report by the United States Agency for International Development (USAID) and the National Renewable Energy Laboratory (NREL) used project-level data from 2015–2018 and highly detailed spatial modelling to estimate plant-level capacity availability factors, but often relied on only one project for each Country $\times$ Technology pair [71].

More recent country-specific studies also display trade-offs between technical depth and geographic breadth. Loan et al. (2025) estimated the LCOE of Vietnamese solar PV system and PV system combined with batteries energy storage systems (BESS) using detailed weather, technical, and economic specifications [76]. Vorarat and Tantawat (2023) computed the LCOE of 29 commercial onshore wind energy farms in Thailand based on annual electricity production data derived from project-level installed capacity, while relying on assumptions on key variables like capital costs and capacity factor [140]. Maandal et al. (2021) estimated the LCOE of two types of wind turbines based on the parameters similar to the 25.0372 km^2 offshore wind farm in northern Cagayan, the Philippines. In addition, by building multiple linear regression models, they found that minimum sea depth and plant capacity are highly correlated with the investment costs of the 39 offshore wind farms considered [78].

Despite its popularity among researchers, practitioners, and policymakers, LCOE is far from being a perfect metric. The oversimplification of energy generation costs is a major limitation. According to the International Energy Agency (IEA) [55], the energy supply chain includes power generation by the power plants as well as fuel transportation, electricity transmission, distribution and storage. However, LCOE is calculated at the power plant level without taking into account the costs beyond power generation, and such omission could lead to significant underestimation [52, 81]. Integrating Variable Renewable Energy (VRE) like solar PV and wind compounds this problem. From a cost perspective, energy supply intermittency of VRE introduces additional system costs such as backup capacity, energy storage, grid expansion, and balancing services [133, 91, 40]. From a value perspective, electricity produced during peak demand periods is more valuable than electricity generated during off-peak periods. VRE technologies tend to generate large quantities of electricity during favourable conditions (e.g., midday for solar PV or high wind periods), and significantly less during periods of high demand that do not coincide with these conditions. As VRE penetration increases, this leads to a *value decline* effect, whereby the revenue per unit of electricity decreases due to simultaneous high output during favourable conditions that pushes prices downward, and low output during unfavourable conditions when demand peaks (for instance, night-time) [64, 70, 18, 34, 40].

To address such a limitation, researchers have developed several extensions and alternatives to the traditional LCOE framework [112, 130, 131, 135, 24, 138, 114]. For instance, the levelised cost of storage (LCOS) provides a framework for comparing the costs of different energy storage technologies [39]. In contrast to cost-based metrics, the levelised avoided cost of electricity (LACE) adopts a value-based approach by estimating the revenues or avoided costs associated with electricity generation and ancillary services [135, 138]. A more comprehensive metric, the value-adjusted levelised cost of electricity (VALCOE), developed by the IEA, adjusts traditional cost estimates by the value a plant provides to the electricity system—through its energy, capacity, and flexibility services [45].

This study contributes to the ASEAN LCOE literature by providing stronger empirical grounding through the use of 218 projects across multiple Country × Technology pairs. Although due to the data availability constraint, the study continues to rely on the conventional LCOE formula without taking into account the cost of storage or value-adjusted costs, most of our model assumptions are generally more detailed and country-specific than those employed in parts of the existing literature.

2.2 Factors Influencing Clean Energy Production Costs

Theoretically, every component included in the LCOE formula contributes to the result variation. Yet, great ambiguities still exist in the cost-changing mechanism across technology, geographic region, and time [145, 131, 14]. In the literature, there has been discussion on various factors that directly or indirectly influence the costs of electricity generation technologies. In the subsection below, we categorised these factors into five categories, namely, geographic factors, input costs, technological improvement and R&D, learning-by-doing and experience curves, and policy instruments, which are adapted from Samadi's literature review framework [108].

2.2.1 Geographic Factors

The availability of solar, hydro and wind power depends on natural resource attributes, yet the immediate impact of such environment-related factors on power generation costs is rarely discussed in the literature [97, 145]. Literature discusses that climate change may alter the spatial distribution and temporal variability of natural resources, but whether it poses upward or downward pressure on the energy supply and generation costs is highly uncertain [35].

Weather conditions determine the operating efficiency of power systems at the site, which is closely related to the capacity factor in the LCOE equation. Examples include solar irradiance, ambient temperature, relative humidity, wind speed, river flow, and reservoir storage [113, 97, 145]. In addition, resource endowment can also limit the availability of suitable sites for energy production plants and their capacity. The scarcity of suitable sites in a country can affect the power plants' deployment and operation costs. Take Singapore as an example. The country's limited land area poses a serious constraint on large-scale domestic solar PV deployment. Even though energy imports remain a viable solution, the power generated overseas must be transmitted via long-distance submarine power cables, which are much more expensive than overhead or underground cables. Consequently, the required capital expenditure rise sharply as the distance between the offshore location and Singapore increases. Comparing offshore wind farms in Singapore and those in Malaysia, estimates based on simulations show that the capital cost jumps from 2,400 $/kW to nearly 12,000 $/kW [94].

2.2.2 Input Costs

Equipment used in renewable power generation revolves around manufacturing technology, and its dominant cost is the initial capital for manufacturing and installing the equipment [102]. The costs incurred at the utility infrastructure construction stage, including materials' costs and field workers' wages, could offset the cost reductions from technological improvements and economies of scale gained from manufacturing capacity expansion, as seen in a study of US wind energy prices [14].

Since 2020, the importance of manufactured component costs has received renewed attention with the rising commodity prices [54]. As documented by IEA, the international prices of the leading critical minerals and metals have soared. For example, the price of copper, nickel and aluminium rose by around 25% to 40% from 2020 to 2021 [53]. This poses significant trade-related risks to manufacturers using imported minerals, given the high level of geographic concentration in global supply chains. A study focusing on the solar PV industry in ASEAN shows that such trade-related risks are particularly relevant given regional producers' heavy reliance on extra-regional materials for renewable energy technologies [43].

Besides external disruptions, some countries impose substantial import tariffs that effectively make renewable technologies less affordable, extending project timelines and slowing clean energy adoption [96, 100, 54]. According to UN Conference on Trade and Development (UNCTAD)'s calculations, Asia's average tariffs on goods along solar and wind energy technology value chains reached 2.5%, and tariffs on intermediate goods were the highest among all product groups [134].

2.2.3 Technological Improvement and Research and Development (R&D)

Technological improvement is a primary driver of long-term cost reductions in renewable energy, operating independently of immediate supply chain fluctuations. Facilitated by public and private R&D investment, fundamental breakthroughs in materials science and energy conversion efficiency are the leading drivers of rapid cost reductions in clean energy [32, 66, 124, 137, 101]. Increased module efficiency, reductions in non-silicon materials, and targeted R&D investment were all found to contribute significantly to cost declines for solar PV. Wind energy exhibits similar patterns: sustained reductions in manufacturing costs rely on a combination of deployment-driven learning and targeted R&D, with public R&D being particularly crucial during the early, less mature phases of technology [67, 118, 22]. Yet, results from expert elicitations showed that the cost-reducing impact of R&D investments is heterogeneous across technologies, and that there are decreasing returns to scale for R&D investments [136].

In the context of ASEAN, the impact of R&D differs from that of the global leaders. Many regional countries currently lag behind in both the volume and the type of R&D, focusing more on technology transfer and adaptation than on frontier innovation. These findings imply that for Southeast Asia to achieve meaningful cost reductions and scale renewable deployment, strategies must combine R&D support with mechanisms for bolstering the absorptive capacity of local firms to integrate global knowledge into local manufacturing and deployment systems.

2.2.4 Learning-by-Doing and Experience Curves

Apart from R&D expenditure, technological innovation theory has identified a number of cost-reducing mechanisms, comprising learning-by-doing, learning-by-using, economies of scale at the manufacturing or project level, relocating manufacturing to lower-cost locations, and knowledge spillover [103, 108]. Specifically, learning-by-doing describes a process in which the accumulation of experience in manufacturing, installation, and operation reduces unit costs. In empirical research, the relationship between experience and cost is typically modelled using a learning curve (or experience curve). It is derived from a function relating the unit cost of technology to its cumulative installed capacity or output [61, 106]. A study found that joint learning from technology adoption and learning-by-doing (of both manufacturers and project developers) through cumulative installed capacity is among the most significant driving factors of the price reduction in China's wind power [104].

2.2.5 Policy Instruments

Even with the recent technological cost reduction, the renewable energy market is still, to a large extent, policy-driven [23]. The design and implementation of policy instruments play a key role in shaping the development and cost trajectory of renewable energy. In the existing literature, there are various classifications of renewable energy policy instruments [121, 72, 75, 73].

Among all policy tools, the most common ones are price-based instruments, in particular Feed-in-Tariffs (FiTs), which guarantee a fixed price per unit of renewable electricity sales from the power plant to the grid [72]. Governments utilise such instruments to establish favourable price regimes for renewable energy relative to conventional fossil fuel energy sources, stimulating market demand, investment and R&D activity, thus accelerating the experience accumulation and further cost reduction [23, 102, 11, 121, 20, 74]. Within ASEAN, Indonesia, Malaysia, the Philippines, Thailand and Vietnam implemented FiTs for different renewable energy technologies, and their impact on promoting investment into solar energy was found to be significant [10].

Although FiTs may lead to expanding renewable power production and thereby higher penetration of renewable energy in the short run, they appear to preclude the possibility of price competition among renewable developers, and the transmission investments required to interconnect renewable generation tend to be large. As a result, the literature cautions against prolonged reliance on price-support policies [1]. Some argued that gradually degressing FiTs could be an alternative solution, because they create predictable downward pressure on costs by incentivising firms to innovate continuously, and simultaneously avoid abruptly disrupting investment cycles [77].

Empirical evidence consistently shows that coordinated policy mixes could be more effective than isolated pricing interventions [144, 62]. Empirical evidence from China shows that combining FiT with direct R&D support and deployment subsidies catalysed both large-scale deployment and technological upgrading, improving firm performance, innovation, and market responsiveness [147, 38]. Furthermore, simply subsidising renewable energy deployment through pricing adjustment does not automatically reduce vulnerabilities and dependencies, as technological advances in materials science, manufacturing engineering, and systems integration become increasingly vital for the energy sector. Consequently, many countries have introduced tax credits for local manufacturing and local content requirements (LCRs), which are frequently imposed as a precondition for accessing renewable energy FiT programs [102].

3 Levelised Cost of Electricity of ASEAN Countries

This section calculates and analyses the Levelised Cost of Electricity (LCOE) of clean energy technologies across ASEAN countries, using project-level CAPEX data and technology-specific assumptions on capacity availability, discount rates, economic lifetimes, and fixed operation and maintenance costs. Section 3.1 introduces the LCOE methodological framework. Section 3.2 summarises the main data sources used to calculate the LCOE figures. Section 3.3 presents the main LCOE ranking across Country $\times$ Technology pairs. Section 3.3.2 examines how

LCOE estimates vary under different CAPEX assumptions and discusses cost dispersion across Country × Technology pairs. Section 3.4 compares the calculated LCOE values with observed bidding prices to explain possible divergences.

3.1 Methodology

Specifically, the total costs to build and operate a power project can be broken down into capital costs (ACC), fixed and variable operation & maintenance (O&M) costs ($FOMC$ and $VOMC$), and fuel costs (FC).

$$LCOE = ACC + FOMC + VOMC + FC \tag{1}$$

The first input variable ACC is expressed as:

$$ACC = \frac{OC \times CRF \times 1000}{CAF \times 24 \times 365} \tag{2}$$

It refers to the annualised overnight construction cost (OC) expressed in terms of capacity ($/kW). CRF is the capital recovery factor constructed by the discount rate (r) and the economic life (n) of a plant following this formula:

$$CRF = \frac{r(1+r)^n}{(1+r)^n - 1} \tag{3}$$

CAF stands for the capacity availability factor, a ratio between the actual electrical energy and the theoretical maximum electrical energy output in a year if the capacity operates 24 hours a day and 365 days. With CAF, we can account for the quality of generation resources (e.g., availability of wind or solar) and other technological characteristics [131, 130].

The construction of $FOMC$ follows this equation:

$$FOMC = \frac{FXC \times 1000}{CAF \times 24 \times 365} \tag{4}$$

FXC represents fixed costs, which cover costs associated with operating the project that are proportional to generation system size, but not annual energy output costs for labour, equipment, parts and other costs associated with operating the project that are proportional to generation system size [71].

Because most O&M costs from renewable energy systems are $FOMC$, it is safe to assume $VOMC$ to be zero when estimating the LCOE of clean energy in ASEAN [132, 71]. In addition, although a typical LCOE equation includes fuel FC, they don't apply to renewable energy technologies other than biomass [131]. Therefore, both $VOMC$ and FC are excluded from Equation 1.

By the formula construction, the LCOE calculation results can be very sensitive to the change in the input variables of Equation 1, which would alter the cost of energy generation. For renewable technologies, CAPEX, which represents the OC component in Equation 2, generally contributes to the majority of their LCOE [131]. In addition, sensitivity studies show that different renewables exhibit different patterns in their CAPEX elasticities of LCOE [114]. The LCOE of solar PV are the most sensitive, while the LCOE of onshore wind and hydropower have more gradual slopes. Offshore wind projects might even decrease in slope as more upfront investments are made, since projects with higher capital expenditure tend to have higher capacity utilisation factors after a certain threshold. This is similar in concept to previously understood natural gas technologies, where increased capital expenditure brought greater thermal efficiency [131].

What causes changes in CAPEX is not only the economic drivers like increased economies of scale through large size of equipment manufacturing plants or power generation plants, learning-by-doing, and R&D efforts, but also technology-level differences. This includes the production technology of solar PV modules (crystalline vs amorphous silicon), or the improved module efficiency within these technology types through factors like increased wafer area [141, 66]. For wind energy, especially offshore wind, turbine equipment cost (including blades, tower and transformer is the primary contributor to CAPEX, and it is also sensitive to price increases in commodities like copper and steel [58]. The wind turbine foundations (i.e. tower) are also considerably expensive, depending on both the water depth and the chosen construction principle. Based on evidence from Danish wind projects, while constructing onshore wind projects on the ground comprises 4-6% of the total project cost, doing the same in deep water is over 21% of the total project cost [15].

Given the determinative role of CAPEX in the LCOE for renewable technologies, Section 3.3 presents estimated LCOE results based on three distinct methods for computing the CAPEX component. These three methods provide a holistic assessment of each Country × Technology pair's cost-competitiveness without relying on a single metric that might distort the results.

Method 1, Section 3.3.1, utilises the national average CAPEX from 2009 to 2025 to calculate LCOE values, offering a straightforward, aggregated comparison across countries and technologies. However, estimates based on mean values are highly sensitive to outlier projects. For instance, if a country's high average LCOE is skewed upward by a few projects with high CAPEX, while the middle 50% of projects sit within a much lower interquartile range (IQR), treating the entire country's electricity generation costs as uncompetitive would be misleading.

If policy-making only considers average LCOE figures, there could be risks of overlooking a viable import source or overestimating the cost competitiveness of an immature market. Avoiding these pitfalls requires granular assessments to isolate project-specific anomalies. To resolve such distortion, Method 2, Section 3.3.2, calculates the LCOE from minimum, 25th percentile, median, 75th percentile, and maximum CAPEX data points, as computed from BMI project-level data for each Country × Technology pair. By evaluating both the IQR and the absolute cost extremes, Singapore can gauge both typical costs of prospective import sources and best- and worst-case cost scenarios.

Finally, because a single historical horizon can obscure cost competitiveness shifts, and technology maturation occurs over time, Method 3, Section 3.3.3, models the temporal trajectory of LCOE using periodic CAPEX averages. By dividing the timeline into three phases, this method identifies the most cost-competitive technology and countries in different periods. Synthesising the results from these three complementary methodologies ensures a holistic evaluation of the cost-competitiveness of Singapore's potential renewable power import sources.

3.2 Data Sources

Table 2 summarises the primary data sources used to compute the LCOE across ASEAN member states and technologies. Project-level specifications, including renewable technology type, investment value (USD), capacity (MW), and construction timelines, are sourced from the Business Monitor International (BMI) database. To ensure the calculation of robust average overnight construction costs, the sample is restricted to projects with complete cost and capacity data. To maintain temporal consistency across all LCOE components, the analysis covers the period between 2009 and 2025. For all components of LCOE calculation, we filter and report only those Country × Technology pairs for which $CAPEX$ data is available from the BMI database.

Parameters for discount rates (r) and the economic life (n) of power plants are sourced from the IRENA [60], providing full coverage for all ASEAN Country × Technology pairs.[2]

CAF are primarily derived from the ACE [3]. For instances where country-specific CAF data is unavailable (e.g., onshore wind in Indonesia), figures were sourced from IRENA [60]. In cases where both primary sources lacked specific entries, technology-specific ASEAN regional averages were employed as proxies to ensure model completeness. For Vietnam, where offshore-specific data were limited, the CAF of wind was utilised as a proxy for both onshore and offshore wind.

$FOMC$ are synthesised from ACE and USAID. Annualised FOMC data for solar PV and onshore wind are sourced from [71], but the USAID lacks the data for hydropower and offshore wind. We thereby obtained FXC

[2] For discount rate, we sourced the data for weighted average cost of capital (WACC) from IRENA, which is a commonly used proxy of the discount rate. See [63].

of hydropower and offshore wind from ACE [3] and annualised the data by dividing by CAF and time to ensure cross-technology comparability.

A summary of statistics for individual components of LCOE, including $CAPEX$, CAF, CRF, and $FOMC$ can be found in Tables A.1-A.4 in the Appendix.

Table 2: Data Sources of LCOE Computation for ASEAN Countries

LCOE Components	**Data Source**
Project-level Overnight Construction Cost (CAPEX)	Business Monitor International (BMI)
Discount Rate & Economic Life of Plant (CRF)	International Renewable Energy Agency (IRENA)
Capacity Availability Factor (CAF)	ASEAN Centre for Energy (ACE) IRENA
Fixed O&M Costs (FOMC)	ASEAN Centre for Energy United States Agency for International Development (USAID)

3.3 LCOE by Country and Technology in ASEAN Countries

3.3.1 LCOE Estimates Derived from Average CAPEX (2009–2025)

As shown in Table 3, hydropower is the most cost-competitive option in the ASEAN region, among the four clean energy technologies assessed. Hydro projects in Malaysia, Indonesia, and Vietnam have the lowest LCOE values. However, the cost variance among these top three nations is marginal—the LCOE for Vietnamese hydropower is merely 0.0043 USD/kWh (9.7%) higher than that of Malaysia, the regional leader. Because generation costs among top competitors are so similar, Singapore can shift its focus to factors beyond the average LCOE when selecting suppliers, such as export capability and willingness, as well as the costs and risks of transmission. Assessing these LCOE findings against Singapore's existing power import agreements, we find that Singapore's clean power import strategy does not purely follow cost advantages. Among the cost-competitive hydropower sources, only Malaysian hydropower features (Table 1). Whilst Singapore has granted a Conditional Approval for Vietnamese imports, this focuses on offshore wind, a much more expensive technology than its hydropower. Conversely, Singapore has a pilot programme to import hydropower from Laos, whose LCOE is much higher.

Solar PV closely follows hydropower as a highly cost-competitive alternative. Indonesia and Laos have the lowest LCOE values, closely followed by competitive projects in Cambodia and Vietnam. The cost variance between the top three sources, Indonesia, Laos and Cambodia, is larger than that of hydropower. The LCOE of Cambodian solar PV is 0.0182 USD/kWh (27.2%) higher than that of Indonesia. Availability of CAPEX data is a relevant concern when estimating solar PV LCOE for these countries, and these differences may vary in reality. Therefore, this ranking should be considered as an early indication of differences in solar PV cost competitiveness, rather than enduring, exhaustive differences. Singapore has granted conditional licenses and approvals for solar PV power import from Indonesia and a Conditional Approval from Cambodia. Vietnam's LCOE is only 0.0038 USD/kWh (4.6%) higher than Cambodia's but its solar PV power has yet to be considered in Singapore's power import agreements (Table 1).

Wind power is structurally more expensive. While onshore wind is notably cheaper than offshore wind, its LCOE still remains above hydropower and solar PV across most countries. Indonesia, Vietnam, and Thailand are the most competitive locations for onshore wind but Singapore has yet to have any import agreements with them. Offshore wind is the least cost-competitive technology, driven by higher capital expenditure compared to other technologies. Vietnam is the only country in the sample, reflecting that the technology is at an early-stage deployment in the ASEAN region. Although Vietnam's offshore wind is 0.0663 USD/kWh (58.1%) more expensive than its onshore wind, it has been granted Conditional Approval by Singapore (Table 1).

While Singapore has technology-specific PPAs with several of these countries, it has also signalled broader ambitions through MoUs on cross-border electricity trade—notably with Vietnam, Indonesia, and other ASEAN partners. These MoUs suggest that Country × Technology pairs without current PPAs can be included in the future. As APG interconnections expand, domestic grids deepen, and regional demand grows, cost-competitive sources that are today inaccessible may become viable import options for Singapore. This analysis thus provides a reference point for identifying where new PPAs could be pursued.

Table 3: Ranking of LCOE Across Country × Technology Pairs based on Average CAPEX (USD/kWh)

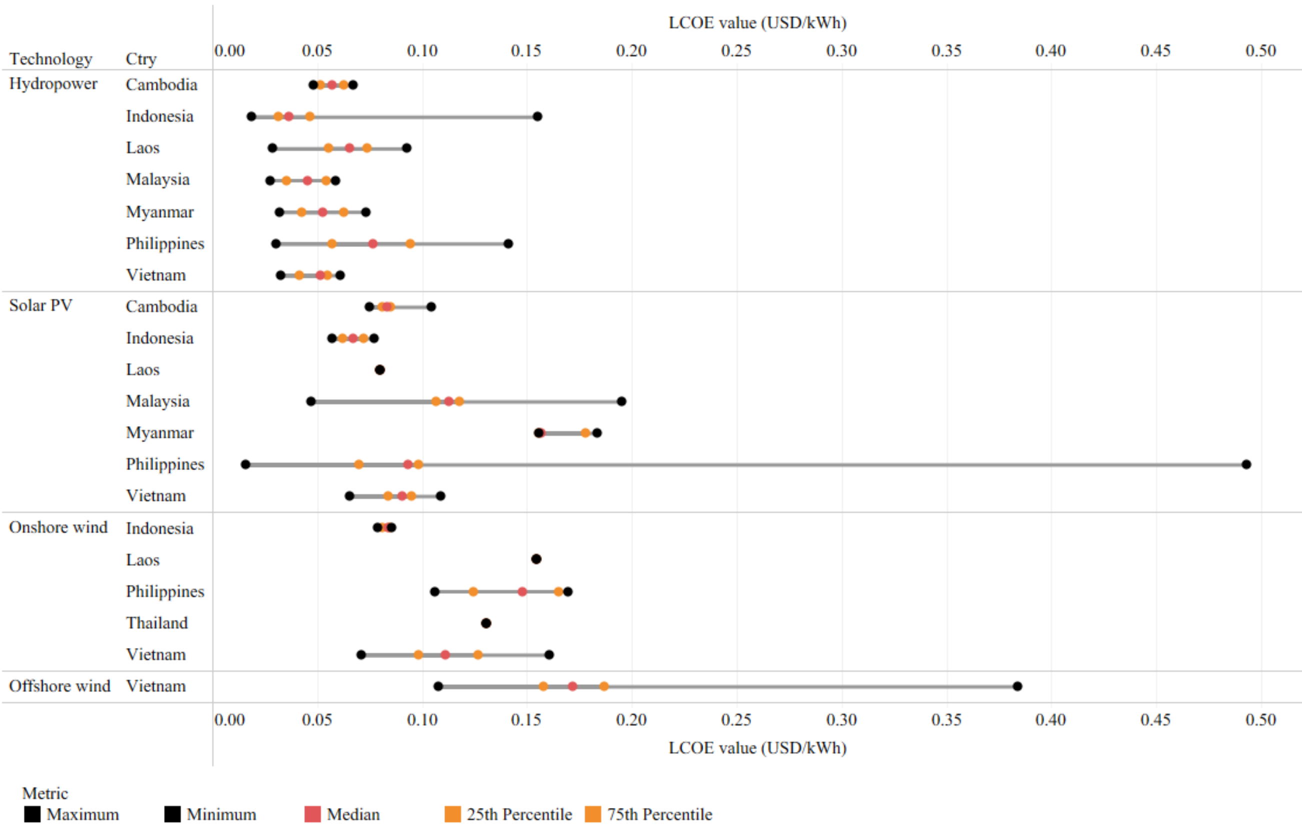
Country	Technology	No. of CAPEX Entries	LCOE (USD/kWh)
MYS	Hydropower	4	0.0442
IDN	Hydropower	12	0.0480
VNM	Hydropower	14	0.0485
MMR	Hydropower	2	0.0526
KHM	Hydropower	4	0.0572
LAO	Hydropower	27	0.0639
IDN	Solar PV	2	0.0670
PHL	Hydropower	16	0.0771
LAO	Solar PV	1	0.0800
IDN	Onshore wind	3	0.0825
KHM	Solar PV	6	0.0852
VNM	Solar PV	18	0.0891
PHL	Solar PV	46	0.0955
VNM	Onshore wind	23	0.1141
MYS	Solar PV	7	0.1148
THA	Onshore wind	2	0.1306
PHL	Onshore wind	10	0.1426
LAO	Onshore wind	1	0.1546
MMR	Solar PV	5	0.1657
VNM	Offshore wind	15	0.1804

Source: Authors' calculations based on [33, 60, 3, 71].

3.3.2 LCOE Distribution Analysis Based on CAPEX Sensitivity

When selecting cost-competitive import sources, an ideal Country × Technology pair should exhibit not only a low average LCOE but also a narrow inter-quartile range (IQR), which indicates highly mature and standardised

Figure 1: LCOE by Technology and Country: Distribution Based on Varying CAPEX Values



Note: A full table including summary statistics of LCOE calculated based on varying CAPEX values (average, median, 25 percentile, 75 percentile, minimum, and maximum) can be found in Table A.5 in the Appendix.

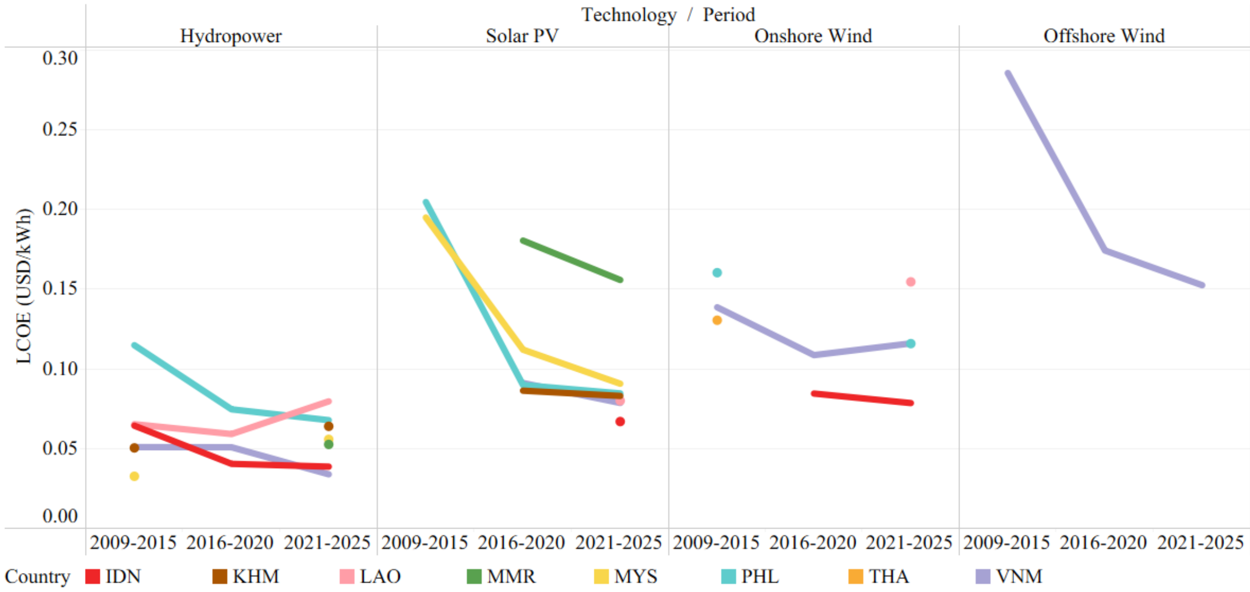
Source: Authors' calculations based on [33, 60, 3, 71].

technology deployment. Figure 1 shows the LCOE distributions based on varying CAPEX values by Country × Technology pair: median, 25th percentile, 75th percentile, minimum, and maximum.

Hydropower remains the most cost-competitive technology in the ASEAN region, as the IQR for its LCOE sits relatively lower on the cost spectrum compared to other technologies (see Figure 1). This low core cost profile suggests high regional maturity for deployment. Among the cost-competitive countries identified in Section 3.3.1, Indonesia's IQR occupies the lowest cost bracket of the seven assessed countries, making it reliably cost competitive as a hydropower source. However, Indonesia exhibits the region's widest range at 0.14, suggesting that both the cheapest and most expensive hydropower projects in the region are located in Indonesia. This underscores the necessity of evaluating more granular, location-specific cost determinants when selecting which plant to import power from. Conversely, while the IQRs for Malaysia and Vietnam sit at slightly higher cost levels than Indonesia's, their ranges are narrower. This tight clustering indicates that cost variance for typical projects in these countries is marginal, reflecting highly predictable and mature technology deployment.

While the IQR for solar PV sits slightly higher on the LCOE scale than that of hydropower, the technology generally exhibits tighter cost clustering across most countries, albeit with a few distinct outliers driving overall dispersion. Among the most cost-competitive countries identified in Section 3.3.1, Indonesia, Laos, and Cambodia, cost dispersion appears remarkably low, with absolute LCOE ranges situated at the lower end of

Figure 2: LCOE by Technology, Country, and Period (2009-2015, 2016-2020, 2021-2025)



Source: Authors' calculations based on [33, 60, 3, 71]

the spectrum. However, this perceived stability likely reflects limited sample sizes and should be treated as an early indication of cost competitiveness rather than a more enduring and exhaustive marker. This is especially true for Laos whose sample contains merely one project. In contrast, Vietnam, which has a larger data sample, demonstrates an IQR positioned marginally above these top three countries. Crucially, its narrow IQR confirms a highly stable and predictable project cost profile that is not merely a consequence of limited data.

Wind power IQRs, both onshore and offshore, sit higher on the LCOE scale than hydro and solar PV, reflecting that regional wind deployment is still in its early stages. For onshore wind, Vietnam, which was previously identified as the second-most cost-competitive source for onshore wind in Section 3.3.1, records the largest range (0.09). Countries like Indonesia, Lao PDR, and Thailand each have lower ranges compared to Vietnam, however this may be due to their low sample sizes, each having fewer than five projects. A comparison between Vietnam and the Philippines, the two countries with substantial sample sizes, reveals distinct profiles. The Philippines has a narrower absolute range but a wider IQR (0.04 versus 0.03), with its 75th percentile (0.16) sitting just below its maximum (0.17), indicating a heavy concentration of projects at the higher end of the cost spectrum. Vietnam's wider overall range, by contrast, is driven by a few high-cost outliers: its 75th percentile sits well below its maximum, confirming that most projects remain tightly clustered at competitive cost levels.

For offshore wind, Vietnam exhibits a wide overall range (0.28) but a low IQR (0.03) and moderate 75th percentile (0.19). The bulk of projects are tightly clustered; the wide range is driven by a small number of high-cost outliers rather than systemic variance.

3.3.3 Evolution of LCOE over Time

Across three periods, 2009-2015, 2016-2020, and 2021-2025, a general downward trajectory is observed in the LCOE across all four assessed clean power technologies, indicating steadily improving cost-competitiveness across the region, as exhibited in Figure 2. In most assessed countries, hydropower remains the most cost-competitive technology across the three periods, followed by solar PV, onshore and offshore wind power, consistent with our findings in the previous two sections.

The LCOE calculations by time period for Country × Technology pairs can be found in A.6.

Indonesia and Vietnam consistently rank among the top three most cost-competitive hydropower sources and their competitiveness has been strengthened significantly over time. From the periods of 2009-2015 to 2021-2025, LCOEs of the two countries have consistently declined, with Indonesia's declining from 0.0644 to 0.0387 USD/kWh (39.9%), and Vietnam's declining from 0.0509 to 0.0339 USD/kWh (33.4%). However, it is important to note that Vietnam's sample is clustered within the 2009-2015 period, indicating that the real LCOE aggregates in the later periods may vary.

Conversely, as the most cost-competitive source in the first period, Malaysia's LCOE almost doubled from 0.0326 USD/kWh in the period of 2009-2015 to 0.0558 USD/kWh during 2021-2025. This indicates that its strong overall cost-competitiveness, as identified in Section 3.3.1, is primarily driven by exceptionally low costs during the initial period. Although it remained cost-uncompetitive in the last period, the Philippines recorded the most significant LCOE reduction, from 0.1149 to 0.0673 USD/kWh (41.4%).

It is noteworthy that the LCOE of Laos' hydropower decreased in the first two periods but increased during 2021-2025. A potential reason is the uneven number of projects across periods. There was only one hydropower project recorded in Laos between 2021 and 2025, and the project had a high CAPEX per MW, which was likely driven by its remote and mountainous location, as suggested by the literature that projects in difficult terrain in upland areas are much less cost effective [117].

The cost-competitiveness landscape for solar PV power changed significantly over the three periods. During 2021-2025, Indonesia and Laos emerged as cost-competitive solar power generators in the ASEAN region, which significantly contributed to their overall cost-competitiveness identified in Section 3.3.1. Yet, these results require cautious interpretation as their CAPEX data is only available in the last period, with limited data points. This is especially true for Laos, whose LCOE is derived from only 1 solar PV project. Vietnam's solar PV power has been cost-competitive in the second and third period, with a moderate reduction in LCOE from 0.0911 to 0.0786 USD/kWh (13.72%). However, the Vietnam's sample is the last period includes only 3 solar PV projects, indicating that real cost reductions may vary. The LCOE for the Philippines and Malaysia registered the sharpest reductions, reaching 0.0843 USD/kWh (58.7%) and 0.0907 USD/kWh (53.5%), respectively. However, the sample for Philippines is disproportionately clustered within 2021-2025, indicating that the real aggregates in earlier periods may vary. That said, later comers like Indonesia and Vietnam still emerge more cost-competitive than Malaysia and Philippines in the final period.

For onshore wind, Indonesia's LCOE becomes the lowest since its emergence during the periods of 2016-2020 and 2021-2025, significantly contributing to its overall cost-competitiveness exhibited in Table 3. Its LCOE reduces from 0.0845 to 0.0786 USD/kWh (6.98%). However, this should be interpreted with caution given the limited number of projects with CAPEX data availability, only three projects across two periods. Vietnam's LCOE, the second-lowest overall (Table 3), also declined substantially from 0.1387 USD/kWh in 2009-2015 to 0.1160 USD/kWh in 2021-2025 (16.4%). Cost reductions are most evident in the Philippines, with LCOE going from 0.1604 USD/kWh in 2009-15 to 0.1159 USD/kWh in the final period (27.7%), ranking it among the top three cost-competitive countries. While recent data for Thailand is unavailable, a similar downward trend is expected, consistent with regional capacity expansion, with 435 GW of onshore wind projects in its pipeline [3] and associated learning effects.

For offshore wind, Vietnam, the only country with available data, exhibits a substantial decline in LCOE, from 0.2857 to 0.1525 USD/kWh between 2009-2015 to 2021-2025 (46.6%), reflecting early-stage cost compression as capacity scales.

3.3.4 Summary of LCOE Results

Synthesising findings across the three analytical lenses — average LCOE, distributional analysis based on CAPEX sensitivity, and evolution of LCOE over time — a clear hierarchy of cost-competitive Country × Technology pairs emerges for Singapore's electricity import requirements. Hydropower is consistently the most cost-competitive clean energy technology in ASEAN, closely followed by solar PV. Wind energy remains structurally more expensive, reflecting the early stage of regional deployment.

[3] Data source: Global Energy Monitor database.

Within hydropower, Malaysia records the lowest average LCOE, driven by projects in East Malaysia, though more recent projects carry higher costs, so import preference should be given to earlier projects from the 2009–2015 period. Indonesia and Vietnam follow closely and are the stronger long-run candidates: both exhibit narrow IQRs, confirming that low average costs reflect mature, stable deployment, and have recorded consistent LCOE declines across all three periods.

Solar PV from Indonesia, Cambodia, and Vietnam constitutes the next priority tier.[4] Distributional and temporal analysis, however, introduces important nuance. Indonesia's apparent competitiveness rests on very limited data concentrated in the most recent period, warranting caution. Cambodia's sample, while also limited, spans two periods, suggesting a declining cost profile. Vietnam, despite ranking slightly lower on average LCOE, is the most robust candidate: it is supported by a larger sample, a narrow IQR, and a consistent downward cost trend.

For onshore wind, Indonesia, Vietnam, and Thailand record the lowest average LCOEs. Indonesia's ranking is constrained by limited data, while Vietnam's distributional profile is more reliable, with most projects clustered at competitive cost levels despite a wide overall range. Thailand's data is sparse, but its average LCOE remains competitive in the regional mix, and its cost profile is expected to improve given that it holds the second-highest onshore wind installed capacity in the region and associated learning effects.

Offshore wind from Vietnam, the only country with existing installed capacity in ASEAN, records the highest average LCOE across all assessed pairs and should be the lowest priority on pure cost grounds. Its sharp temporal decline, however, signals improving future competitiveness as the sector scales.

3.4 Understanding the Difference Between LCOE and Electricity Bidding Price

As mentioned earlier, LCOE effectively serves as the technical benchmark for developers of energy generation projects to make PPA bids. Theoretically, it helps assess the alignment between project-level cost structures and current market expectations. Comparing the LCOE values derived from our analysis in Section 3 with the range of electricity bidding prices submitted by project developers in selected countries, certain differences emerge where bids tend to be even lower than calculated LCOE figures.

Table 4: Comparison of Calculated LCOE and Observed Bidding Prices for Selected ASEAN Solar PV Auctions

Country	Technology	LCOE (USD/kWh)	Bidding Price (USD/kWh)
Malaysia	Solar PV	0.1148	0.035–0.066 (2021–22)
Cambodia	Solar PV	0.0852	0.0387 (2019)
Philippines	Solar PV	0.095	0.071–0.092 (2023 and 2026)

Source: Authors' compilation based on [122, 123, 125, 79, 19]

For instance, Malaysia's average Solar PV LCOE is estimated at 0.1148 USD/kWh. However, bidding prices for large-scale solar PV (LSSPV) was 0.035–0.066 USD/kWh in 2021-2022 [122, 123]. These values are substantially below the calculated average LCOE. Similarly, Cambodian Solar PV PPAs were agreed at rates as low as 0.0387 USD/kWh in 2019, a record low in the ASEAN region at the time [125]. This is well below the estimated average LCOE of 0.0852 USD/kWh. Even the LCOE limited to the 2021-2025 period in Malaysia (0.0907 USD/kWh) and Cambodia (0.0830 USD/kWh) is higher than the submitted bidding prices in those periods. One plausible explanation is the limited number of project-level observations for Malaysia (7 projects, only 3 in 2021-2025) and Cambodia (6 projects, only 2 in 2021-2025).

[4] Laos has a competitive LCOE but it is derived from only one project. Combined with the country's low installed solar PV capacity, it cannot be reliably included among cost-competitive producers at this time.

A similar but more moderate pattern is observed in the Philippines, where data coverage is more complete (46 projects). In Green Energy Auction (GEA) rounds 2 through 4, ground-mounted Solar PV tariffs ranged from PhP 4.4043 to 5.6833 (0.071–0.092 USD/kWh) [79, 19]. While still below the estimated LCOE of 0.095 USD/kWh (0.0846 USD/kWh when limited to the 2021-2025 period), the gap is considerably narrower compared to Malaysia and Cambodia.

The extant literature has consistently highlighted this divergence between LCOE and observed bidding prices, suggesting that LCOE is not a perfect predictor of actual bid prices. In practice, bidding outcomes are strongly influenced by access to low-cost financing, reliance on indirect revenue streams and government incentives, and strategic underbidding based on expectations of future cost reductions.

First, LCOE is highly sensitive to the discount rate, or cost of capital. For instance, in representative solar PV or onshore wind projects analysed by IRENA, LCOE increases by 80% when the cost of capital rises from 2% to 10%.[5] Across countries, these rates vary widely, from as low as 1.1% (e.g., German onshore wind) to above 10% in higher-risk markets such as Ukraine [59]. Within ASEAN, Myanmar exhibits particularly high discount rates exceeding 16%, resulting in relatively higher LCOE across technologies (Table 3). More broadly, cost of capital tends to be lower in mature markets such as China, Europe, and North America (3–5%) compared to emerging economies (6–9%), with substantial variation even within countries [59], thus driving significant differences in projects whose lower cost representatives may be better suited to bid lower.

Second, renewable energy auctions themselves have intensified competition, compressing profit margins, driving down bids, and increasing firms' exposure to risk and uncertainty [119].IEA analysed that some developers' aggressive bidding strategies to gain market shares could also widen the difference between LCOEs and announced bid prices [51]. Even in mature markets such as Denmark, concerns have been raised regarding the feasibility of delivering projects at aggressively low bid prices under realistic financing conditions [80].

Third, strategic underbidding plays a critical role. Firms may submit low bids based on expectations of future cost declines, particularly where contractual arrangements and auction design allow flexibility in project execution (e.g., grace periods, optionality in delivery, pay-as-you-bid or uniform pricing mechanisms) [82]. Additional advantages, such as access to high-quality resource sites with superior capacity factors, favourable regulatory environments, and government incentives, further enable bids below current LCOE estimates [143].

4 Clean Energy Cost Competitiveness Index

This section develops the CECCI, which complements the LCOE analysis in Section 3 by examining the broader structural factors, including macroeconomic, policy, geographic, and industrial capability, that shape clean energy production costs across countries. Section 4.1 outlines the three-step methodology framework used to construct the CECCI. Section 4.2 summarises the datasets used to construct the variables, including policy instruments, import-weighted tariffs, installed power capacity, geographic endowments, macroeconomic indicators, and innovation and industrial capacity. Section 4.3 presents the global regression results and assesses how policy support, installed power capacity, import tariffs, geographic endowments, macroeconomic conditions, financing costs, manufacturing wages, and R&D intensity are associated with the LCOE of solar PV and onshore wind. Section 4.4 presents the CECCI trends for ASEAN countries and discusses the structural factors underlying country-level differences in clean energy cost competitiveness.

4.1 Methodology

While the LCOE is traditionally viewed through the lens of project-specific capital expenditures, a rigorous analysis of cross-country cost disparities requires an examination of broader exogenous factors beyond the LCOE formula. In this section, we construct the CECCI to capture ASEAN countries' disparities in clean energy production costs. To this end, we first utilise a global panel dataset to discern statistically generalisable

[5] Solar PV installed cost is assumed 700 USD/kW and onshore wind installed cost is assumed USD 1300 USD/kW. Capacity factors are assumed 18% for Solar PV and 38% for Onshore wind [59].

mechanisms that drive renewable energy cost differences, then map these global structural patterns back to the ASEAN context. While we acknowledge that no single econometric model can perfectly capture the nuances of country-level cost differences, our choice of determinants reflects a balance between data availability and the fundamental drivers necessary for a comprehensive comparison.

A three-step methodological framework is designed to operationalise the analysis. The first stage involves a global regression analysis. As summarised by Equation 5, the dependent variable is $LCOE_{it}^{k}$ (USD/mWh), where i, k, and t represent, country, technology and year, respectively. At this step, the regressions are only run for solar PV and onshore wind [6].

The explanatory variables, which are selected from a series of most commonly mentioned factors shaping the clean power production cost in the literature (see Section 2.2), are captured by $\boldsymbol{X}_{it}^{k}$. By estimating the weights (β) for each underlying factor in determining the LCOE for a given technology k, we are able to measure the impact of each factor on a global scale. Table 5 summarises the data sources used to construct the explanatory variables comprising $\boldsymbol{X}_{it}^{k}$ in Equation 5.

$$LCOE_{it}^{k} = \alpha^{k} + \boldsymbol{\beta}\boldsymbol{X}_{it}^{k} + \epsilon \tag{5}$$

With the presence of cumulative variables, such as Policy_{it} and $\log(\text{Capacity})_{it}^{k}$, that inherently grow over time, year fixed effects are included in the regressions to absorb such variation. More details on data sources and variable construction methods will be explained in Section 4.2.

In the second stage, these globally derived weights β are applied to ASEAN-specific data $\boldsymbol{X}_{it}^{k}$, where $i \in$ ASEAN countries, to generate a predicted $L\hat{CO}E_{it}^{k}$, as seen from Equation 6. It is important to distinguish this predicted value from the observed LCOE in Section 3.3 which is derived from project-level CAPEX data. This predicted $L\hat{CO}E_{it}^{k}$ reflects the expected cost based on a country's underlying structural conditions, as informed by our global regression conducted in the first stage.

$$L\hat{CO}E_{it}^{k} = \hat{\alpha}^{k} + \hat{\boldsymbol{\beta}}\,\boldsymbol{X}_{it}^{k} \text{ , where } i \in \text{ ASEAN countries} \tag{6}$$

The final stage of the methodology involves taking the inverse of the predicted LCOE values. The resulting $CECCI_{it}^{k}$ provides a comparative metric where a higher index value signifies that the country i has a better cost-competitiveness in a specific technology k in year t, based on exogenous factors that are beyond the scope of standard LCOE calculations.

$$CECCI_{it}^{k} = \frac{1}{L\hat{CO}E_{it}^{k}} \tag{7}$$

4.2 Variables

This section expands on how we construct the explanatory variables that are used in our global regression analysis.

Economic Policy Instruments: Government policies could affect the LCOE of a technology by shaping regulatory environments, changing market signals, and reducing uncertainty in investments. To quantify the impact of policy instruments on LCOE, we counted the cumulative number of renewable energy policies in ASEAN countries, based on the Climate Policy Database. Among all policies supporting renewable energy development, economic policy instruments are selected, as they are proven to have a stronger impact on investments [75]. We classified economic policy instruments into two categories, "Revenue" and "Cost", based on their type of policy instrument in the Climate Policy Database. A detailed list of taxonomy is shown in Table A.8 in the Appendix. "Revenue" refers to economic policies that provide revenue, including funding and subsidies. Examples are infrastructure investments, RD&D funding and FiT schemes. "Cost" refers to policies that incur costs on firms, such as CO2 taxes and greenhouse gas (GHG) emissions allowances.

[6] Hydropower and offshore wind are excluded due to significant gaps in LCOE data: hydropower is only available as two period averages, while offshore wind has observations limited to three years (2010, 2023, and 2024) [60].

Import-Weighted Average Tariff: To assess the impact of import tariffs imposed on essential manufactured components used in solar PV and wind power systems, we referred to a comprehensive list of Harmonised System (HS) 4-digit or 6-digit product codes compiled by WTO [49] and downloaded the corresponding import tariff schedules for each of these products from World Integrated Trade Solution (WITS). In total, our study covered 33 product codes under the HS2022 version. Table A.9 in the Appendix provides a full list of the products, their respective HS codes and descriptions.

Under the assumption that countries need to import manufactured products for the operation of renewable energy power plants, import tariff rates are used as a proxy for input costs. To avoid the distortion where a country's import portfolio concentrates in a few product categories, we computed the trade-weighted average tariff rate $Tariff^k_{it}$. Suppose that for each technology k, there are multiple products, each of which denoted as p. A country's trade-weighted average tariff for a given technology k is defined as the total tariff revenue divided by the total value of imports of all products p under that technology. M_{ipt} is the import value of product p subject to duty T_{ipt} imposed by country i in year t.

$$Tariff^k_{it} = \frac{\sum_{p \in k}(T_{ipt} \times M_{ipt})}{\sum_{p \in k} M_{ipt}} \tag{8}$$

Installed Power Capacity: A widely used proxy variable for the "learning-by-doing" effect is the cumulative amount of installed power capacity as of a given date. The idea is that cost reductions occur as greater experience is gained. The data for installed electricity capacity is sourced from the IRENASTAT Online Data Query Tool. This database provides the longitudinal data for installed power capacity by country and technology.

Geographic Factors: Geographic factors vary across technologies, and they are measured in different units in the *Renewables.ninja* database. To ensure consistency with the other annual indicators in the index, the hourly geographic data were aggregated into annual values. For solar PV, the total hourly ground-level solar irradiance (kWh/m^2) in a year is utilised. For onshore wind energy, we computed the average wind speed (at 2 metres above ground in m/s) across all hourly wind speeds in a year.

Macroeconomic indicators: Beyond technology-specific drivers, including general macroeconomic indicators in the regression model is essential to account for the broader enabling environment that indirectly shapes the costs of renewable energy projects. Factors such as GDP per capita and GDP per capita growth serve as proxies for institutional quality and market maturity. Similarly, the lending interest rate serves as a proxy for the difficulty of securing financial resources to construct and operate renewable projects.

Innovation and industrial capacity: Lastly, to account for the capacity for cost-reducing innovation and the renewable energy supply chain cost structure, spanning upstream R&D expenditure and input costs at the midstream component manufacturing stage, we incorporate total R&D expenditure as a percentage of GDP and average annual manufacturing-sector wages into the regression. We acknowledge, however, that these aggregate indicators function as coarse proxies for technology-specific inputs. Aggregate R&D figures do not isolate investments specifically earmarked for renewable energy. Similarly, average manufacturing wages may be disproportionately influenced by traditional, labour-intensive industries such as textiles or food processing, potentially masking the specialised, high-skill labour costs inherent to the clean-tech sector. Despite these granularities being unobserved, we maintain that these variables are essential controls for a country's general innovation and industrial capacity to absorb and localise renewable energy technologies, which are critical determinants of long-term cost-competitiveness.

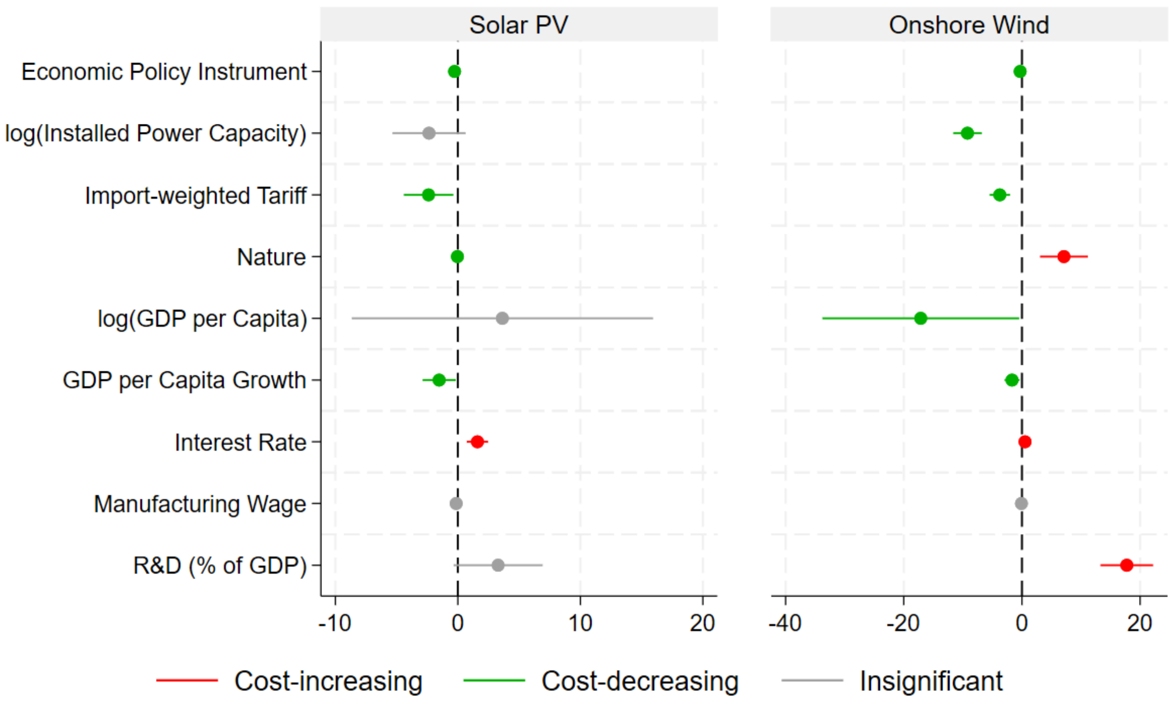
Table 5: Data Sources of the Clean Energy Cost Competitiveness Index

	Variable	Data Source
Dependent Variable		
Levelised Cost of Electricity (USD/MWh)	LCOE_{it}^{k}	IRENA [60]
Explanatory Variables		
Cumulative Number of Renewable Energy Economic Policy Instruments	Policy_{it}	Climate Policy Database
Installed Power Capacity (MW)	$\log(\text{Capacity}_{it}^{k})$	IRENA [60]
Import-weighted Average of Tariff Rate (%)	Tariff_{it}^{k}	HS codes from WTO [49] and Tariff Rates and Import Value from World Integrated Trade Solution (WITS) [142]
Geographic Factors: (Solar Irradiance, Wind Speed)	Nature_{it}^{k}	*Renewables.ninja*
Economic Development Level (PPP, current international USD)	$\log(\text{GDP per capita})_{it}$	World Bank
Economic Growth Rate (%)	GDP Growth_{it}	World Bank
Lending Interest Rate (%)	Interest_{it}	World Bank
Manufacturing Sector Average Annual Wages (Thousand USD)	Manuf Wage_{it}	BMI
R&D Expenditure (% of GDP)	$\text{R\&D}_{it}$	UNESCO

4.3 Global Regression Results

The empirical results from the global regression analysis, as illustrated in the coefficient plot in Figure 3, provide a comprehensive view of the relative impact of determining factors on the LCOE across solar PV and onshore wind. Furthermore, we unpack group heterogeneity by conducting a sub-sample analysis across Advanced Economies (AE) and Emerging Markets and Developing Economies (EMDE), whose results are shown in Figure A.1 in the Appendix.

Figure 3: Global Regression Result



Note: The regressions have controlled for year fixed effects. There are 90 and 193 observations for solar PV and onshore wind models, respectively. Regarding temporal coverage, the solar PV regression is based on data from 2018 to 2023, while the onshore wind regression covers 2000 to 2023. The spikes represent 90% confidence intervals.

Regarding economic policy instruments, the analysis reveals a relatively modest but statistically significant negative correlation with the LCOE of solar PV and onshore wind, suggesting that policy interventions effectively lower costs. However, it is worth noting that these policies not only encourage the deployment of the key technologies discussed in this study, namely, solar PV and onshore wind, but also other renewable energy technologies such as biomass and geothermal. Hence, the estimated impact of economic policy instruments is potentially an overestimation. Despite this, the result underscores the role of institutional support in de-risking investments into the broader renewables sector.

We also find strong evidence for the "learning-by-doing" effect for onshore wind, as evidenced by the negative coefficient of installed power capacity in the global sample in Figures 3 and A.1. Although solar PV also displays a negative coefficient for installed capacity, it fails to reach statistical significance at the global level.

Our global regression analysis yields a counterintuitive finding: higher import tariffs are associated with lower LCOE for solar PV and onshore wind. However, as illustrated by the sub-sample analysis in Figure A.1, this statistically significant cost-reducing effect is observed exclusively within the AE cohort and is notably absent in EMDE group.

To further investigate this heterogeneity, we examined the correlation between tariff rates and LCOE, which is shown in Figure A.2. While most EMDEs exhibit distinctly higher and more dispersed tariff rates than AEs, there is no discernible difference in LCOE between the two income groups, with the exception of a few "outlier" AEs with consistently high LCOE. For example, Canada's solar PV LCOE stood at 176 \$/MWh in 2018, the highest in our global sample for that year. Although this dropped to 93 \$/MWh by 2023, it remained the second-highest globally, trailing only Japan (103 \$/MWh). Similarly, Japan's onshore wind LCOE remained the highest in the sample between 2018 and 2023, ranging from 115 to 153 \$/mWh. Both Canada and Japan recorded near-zero import tariff rates. These high-cost, low-tariff outliers mathematically drive the negative correlation observed in both the global and AE samples.

Conversely, the insignificant results within the EMDE regression suggest that high tariff rates do not inherently act as a cost-addition burden. As shown in Figure A.2, tariff rates vary drastically across EMDEs, yet several nations have achieved remarkably low LCOE. China provides a primary example: despite maintaining tariffs around 3% (compared to the AE average of 0.9%), it accounted for over 60% of global manufacturing capacity [56] and achieved the lowest onshore wind LCOE globally in 2023. Brazil offers another case in point. Despite having some of the highest import tariffs in our sample (14% for onshore wind products and 15% for solar PV), the country's LCOE remained impressively low at 24 $/MWh and 55 $/MWh, respectively. More recently, Brazil increased import tariffs on selected products in 2024 to protect the roughly 5 GW of local manufacturing capacity (and jobs) from the influx of low-cost Chinese solar PV modules into the local market [46]. This suggests that when integrated with policy support for value chain localisation, high import tariffs can serve as a strategic tool to shield domestic industries from external market volatility rather than simply increasing project costs.

"Nature", which represents geographic endowments, shows a mixed impact across technologies. This is likely because our measure is a simplification of environmental conditions that affect the performance of the electricity generation infrastructure. Take onshore wind as an example, to optimise turbine configuration or the wind farm location, besides wind speed, it is also necessary to consider different meteorological conditions beyond wind speed, including wind direction, air pressure, air temperature, air density) [109, 99].

Macroeconomic stability and the broader industrial environment serve as critical foundations for renewable energy cost-competitiveness. Higher GDP per capita growth correlates with lower costs for onshore wind, but not solar PV. High-growth environments typically signal robust future electricity demand and reduced sovereign risk premiums, creating a favourable investment climate that facilitates the large-scale deployment of capital-intensive wind infrastructure. Given the high upfront capital intensity of renewable energy projects, high lending interest rates remain a cost-increasing factor for both solar PV and onshore wind.

Manufacturing wages consistently yield statistically insignificant coefficients across both technologies, suggesting that aggregate labour costs in the broader manufacturing sector do not directly determine the LCOE for a specific renewable energy technology, or the specialised technical efficiencies within the renewable energy supply chain can offset higher general wage levels. Lastly, R&D expenditure as a percentage of GDP exhibits a statistically significant cost-increasing effect for onshore wind in the global sample. There are two reasons behind this counterintuitive result. First, as with manufacturing wages, the aggregated R&D expenditures across all fields of technology mask the real impact of renewable energy innovation. Second, radical innovation typically takes time to reach commercial maturity. The high R&D expenditures observed today represent a necessary investment in the technical breakthroughs required for future, long-term cost reductions.

4.4 Index Results of ASEAN Countries

By applying the estimated coefficients in Figure 3 to ASEAN-specific socio-economic and geographic data, we construct a longitudinal CECCI for member states with available data for the explanatory variables listed in Table 5. A higher index value implies a more favourable environment for the deployment of solar PV (Figure 4), and onshore wind (Figure 5).

Regarding the CECCI of Solar PV, all countries experienced a synchronised "V-shaped" dip around 2020, a trend that aligns with disrupted economic growth caused by the COVID-19 pandemic. This pattern reflects the high sensitivity of solar PV electricity production costs to macroeconomic conditions. In addition, according to World Bank data, Indonesia, Thailand, and Malaysia reduced their lending interest rates from 2020 to 2021, facilitating their recovery in cost competitiveness.

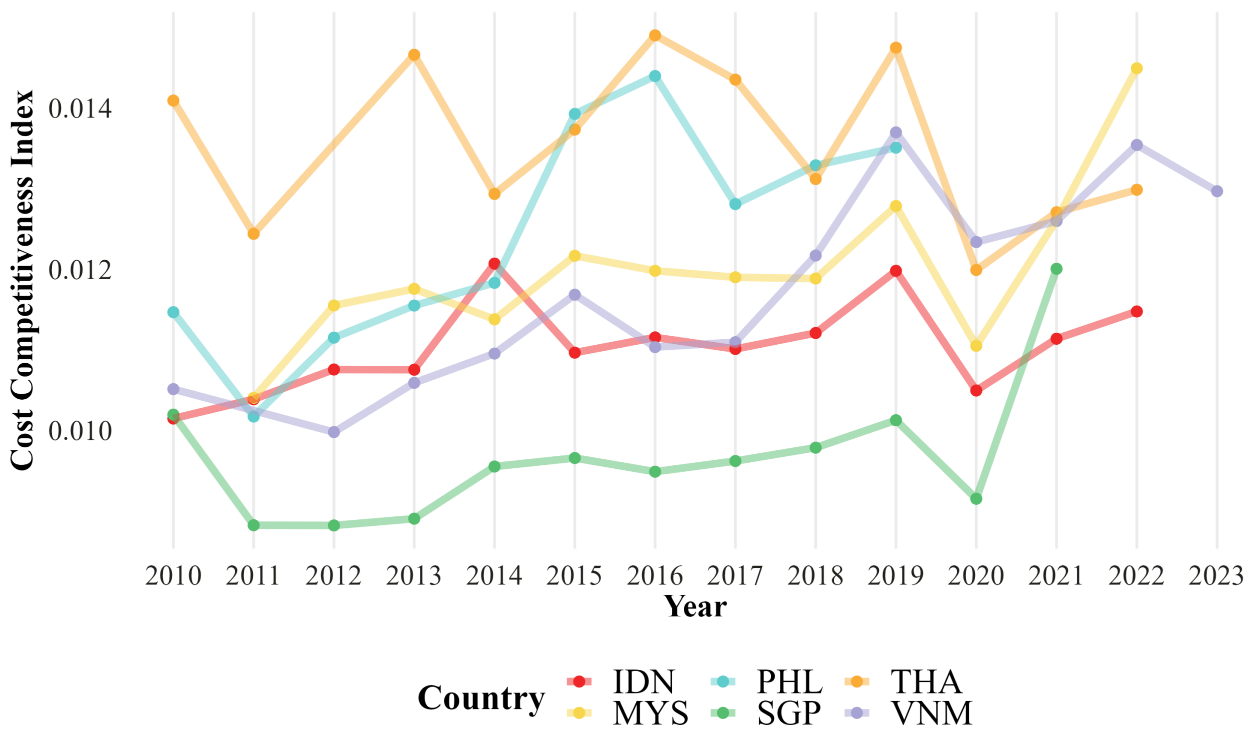
Thailand had maintained a leading position in solar PV competitiveness until it was surpassed by the Philippines in 2015. Both countries were among the pioneering adopters of solar PV technology in the region, hence benefiting from the early-mover advantage. [7] Since 2019, Vietnam's index had risen sharply, effectively

[7] According to our calculations using IRENA's data [60], between 2014 and 2018, Thailand's share in ASEAN's total solar PV installed power capacity averaged at 68.4%, while the Philippines's share averaged at 14.7%.

closing the gap with the aforementioned regional pioneers. Given the negative coefficient for cumulative installed capacity in our model, this trend can be largely explained by Vietnam's massive capacity expansion, thereby triggering a significant "learning-by-doing" effect that fundamentally shifts its structural cost base.

Interestingly, Malaysia's CECCI experienced an even sharper upward trajectory between 2020 and 2022 than Vietnam. Malaysia is uniquely positioned in the solar PV supply chain, with a well-integrated domestic production ecosystem that not only produces final products (i.e., solar PV cells and modules) but also critical intermediates, including silica sands and polysilicon [8, 43]. During the pandemic, both the prices of polysilicon in the commodity market and overseas shipping charges surged, exerting significant cost-increasing pressure on downstream manufacturing and project operation in countries that rely on imported equipment [54]. Luckily, for Malaysia-based component producers and project developers, the impact of such price volatility could have been softened by their ability to source high-quality components domestically. In this context, even though Malaysia's import-weighted tariff rate for selected solar PV products averaged around 4.3%, the highest among all ASEAN economies according to our calculations (see Figure A.3 in the Appendix), it effectively reflected the country's status as a mature industrial base with a high degree of supply chain resilience, which offered critical buffers in light of the inflationary shocks in the global market.

Figure 4: Solar PV Cost Competitiveness Index in ASEAN Countries



Note: Brunei, Cambodia, Laos and Myanmar are excluded due to significant data unavailability issues.

Source: Authors' calculation.

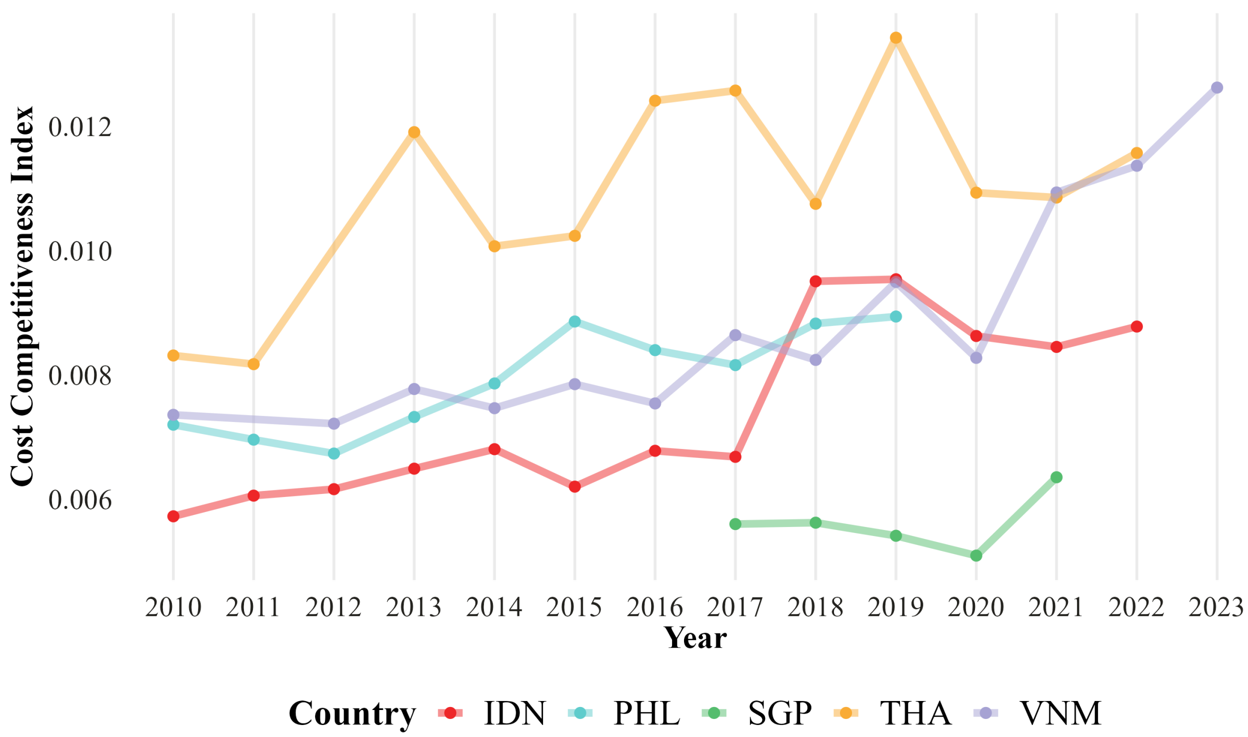
The onshore wind shows a less volatile upward trend in cost competitiveness than solar PV. Again, Thailand remained at the forefront during the period between 2010 and 2020. But its lead was being challenged by Vietnam's rapid ascent. Vietnam's CECCI steadily improved and accelerated significantly after 2020, reaching parity with Thailand in the following years. This surge was likely attributable to Vietnam's recent expansion of onshore wind power development. From 2020 to 2021, the country's installed power capacity surged by over seven times, from 419 MW to 3124 MW, enabling it to rapidly ascend the technological learning curve.

Another country that exhibited noticeable improvements in onshore wind cost competitiveness was Indonesia. Indonesia led the ASEAN region with the highest cumulative number (27) of economic policy instruments targeting renewable energy (see Figure A.4), demonstrating a strong institutional commitment to renewable energy adoption. And its primary instrument type was revenue-generating, which was similar to other economies in the region. Furthermore, unlike Malaysia, the Philippines, and Thailand, whose cumulative number of policies had plateaued since around 2017, Indonesia continued to issue supportive economic policy tools, as did Vietnam and Singapore.

But institutional support alone has proved to be insufficient. Indonesia's temporary progress in onshore wind cost competitiveness in 2018 was likely the result of installed capacity take-off after two utility-scale wind farms began operating in southern Sulawesi [68], sending the country's total installed power capacity from 1.46 MW in 2017 to 144 MW in 2018 [60]. Such expansion was unfortunately only transitory for Indonesia. Meanwhile, Vietnam, which had a similar onshore wind capacity (138 MW) as Indonesia in 2018, continued to deploy more onshore wind farm projects, reaching nearly 5,000 MW by 2023.

Lastly, we observed that Singapore consistently occupied the lower bound of the onshore wind CECCI. This outcome is driven by the nation's inherent geographic limitations. For most commercial wind turbines, the minimum average wind speed requirement is 4.5 m/s. But the average wind speed in Singapore is only about 2-3 m/s [29]. Hence, Singapore has negligible potential and capacity for wind energy, despite conducive macroeconomic conditions and continued institutional support.

Figure 5: Onshore Wind Cost Competitiveness Index in ASEAN Countries



Note: Malaysia, Brunei, and Laos have no onshore wind installed capacity. Cambodia and Myanmar are excluded due to significant data unavailability issues.

Source: Authors' calculation.

5 Further considerations

5.1 Supply Chain Costs of Renewable Power Equipment

Another critical determinant of clean energy costs lies in the structure and cost of the supply chain. As established, CAPEX, the main component of LCOE, is highly sensitive to material and equipment costs.

Using project-level data from the BMI database, we obtain partial visibility into the equipment supplier landscape for solar PV and wind projects across ASEAN. However, coverage remains limited: supplier data is available for only 14.7% of solar PV projects and 36.4% of wind projects [33]. As such, the analysis should be interpreted not as exhaustive, but as an indicative snapshot of supply chain dependencies. To complement this, product-level tariff data is used to identify which segments of the supply chain face the highest trade costs.

The supplier landscape is notably concentrated. Chinese firms dominate equipment provision across both solar PV and wind projects in ASEAN. Beyond China, supply chains depend on some firms originating from other advanced economies: German, Japanese, Swiss, and US firms appear in solar PV projects, while Danish, Spanish, German, French, and US firms are present in wind projects [33]. This suggests that while diversified country sources exist for both solar PV and wind, ASEAN depends more on a large number of Chinese equipment manufacturing firms. The likely reason behind this is the well-documented cost-competitiveness in Chinese clean technology manufacturing [57, 92, 44]. While this concentration offers immediate economic benefits, it essentially limits ASEAN's bargaining power, and any changes made by China's export firms or policy-makers could severely stall the region's renewable energy deployment targets. To reduce such supply chain vulnerabilities and ensure the long-term resilience of their energy transitions, ASEAN countries may therefore consider greater diversification of equipment suppliers whilst boosting domestic manufacturing capabilities in these clean technology industries. A full list of supplier countries and firms can be found in Table 6 below.

Table 6: Equipment Suppliers for Solar PV and Wind Projects

Supplier Country	**Supplier Company**	**No. of Projects**	**No. of Companies**
Solar PV			
China	JA Solar Holdings (5), Jiangsu Seraphim Solar System (3), JinkoSolar Holding (2), LONGi Solar Technology Co. Ltd (3), Arctech Solar (1), China Machinery Engineering Corporation (1), Jetion Solar (2), Risen Energy (1), Trina Solar Ltd (2)	20	9
Germany	SMA Solar Technology (10), Conergy Asia-Pacific (1), Siemens AG (1)	12	3
Japan	Kyocera Corporation (7), Sharp Corporation (2)	9	2
United States	General Electric (4), First Solar Group (2), Amber Kinetics (1)	7	3
Switzerland	Hitachi ABB Power Grids Ltd (6)	6	1
Wind			
Denmark	Vestas Wind Systems (21), MHI Vestas Offshore Wind (7)	28	2
Spain	Siemens Gamesa Renewable Energy (17), Gamesa (2)	19	2
United States	General Electric (10)	10	1
Germany	Enercon (3), Siemens AG (3)	6	2

Supplier Country	Supplier Company	No. of Projects	No. of Companies
China	Mingyang Smart Energy Group Co Ltd (2), Xinjiang Goldwind Science & Technology (2), Envision Energy (1), Goldwind (3)	8	4
France	GE Renewable Energy (2)	2	1

Note: "Wind" refers to wind projects without specification on onshore or offshore wind in the database. The numbers in the parentheses following the company names represent the number of projects that used the equipment by the respective supplier company.

Source: Authors' synthesis based on the BMI database.

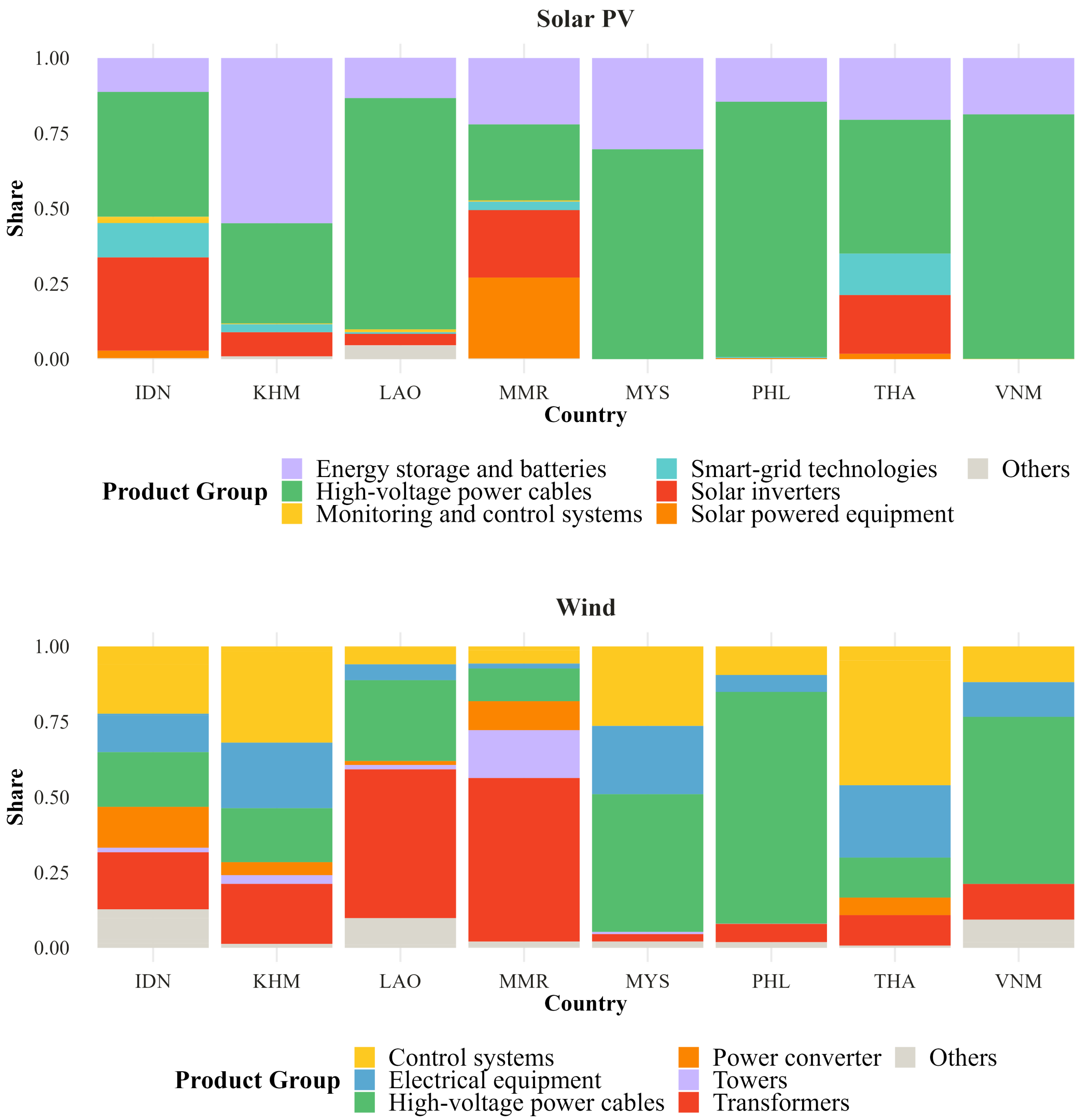
Given the important role that foreign equipment plays in local renewable power production, import tariffs are closely tied to the supply chain cost. Although our empirical evidence in Section 4.3 did not reveal a positive correlation between tariff rates and generation costs due to the nature of the dataset, recent literature generally believes that tariff liberalisation in environmental goods and lowering non-tariff barriers would rapidly boosts trade in clean technology products, increase the affordability of imported goods, and subsequently boost renewable energy deployment [134, 9, 16, 42].

Import-weighted tariff analysis reveals clear cross-country differences. As of 2023, Malaysia (4.7% for solar PV and 7.2% for wind) and Thailand (1.8% for solar PV and 3.9% for wind) exhibited higher tariff burdens, while Vietnam (0.36% for solar PV and 0.66% for wind) recorded low import-weighted tariffs across both solar PV and wind. The Philippines and Indonesia occupied an intermediate position, though generally trending towards lower tariff regimes. Over time, a downward trajectory in import-weighted tariffs is observed in Thailand, Vietnam, the Philippines, and Indonesia, indicating either active tariff liberalisation or a shift towards importing from lower-tariff products or suppliers. Malaysia, in contrast, shows little change over the years, while Singapore maintains a zero-tariff regime throughout (Figure A.3).

Disaggregating tariffs by product category reveals a consistent pattern where enabling infrastructure components form the main portion of import-weighted tariffs for all ASEAN countries, while core equipment for power generation (e.g., panels, turbines) have benefited from relatively lower trade barriers (Figure 6). In solar PV supply chains, high-voltage power cables, energy storage systems and batteries contribute disproportionately to overall tariff burdens. Similarly, in wind supply chains, high-voltage cables, transformers, electrical equipment, and control systems account for the largest tariff shares across key ASEAN wind energy producers: Indonesia, the Philippines, Thailand, and Vietnam.

Continued tariff liberalisation, particularly targeting supporting infrastructure, would directly reduce supply chain costs, which could translate to CAPEX reductions. Where feasible, localising production of these high-cost infrastructure components could further alleviate high-tariff frictions and strengthen domestic industrial capabilities.

Figure 6: Product-Level Contribution to ASEAN Countries' Import-Weighted Tariffs (2023)



Source: The share is calculated by dividing the tariff value of the product group by the total tariff value of all products under the respective technology. Tariff data is computed using HS codes from WTO [49] and Tariff Rates and Import Value from World Integrated Trade Solution (WITS) [142]. Regarding product group classification, solar PV modules/panels, solar PV cells, silicon wafers, polysilicon, gearbox, nacelles/generator rotor, blades, hubs are grouped into "Others".

5.2 Local Content Requirements (LCR) in Electricity Export Countries

Local content requirements are policies that mandate the use of domestically produced goods or services to bolster domestic industries and catalyse innovation. Yet, such policy instrument carries risks of escalating production costs and consumer prices and stifling market competition. Ultimately, these inefficiencies may erode the international competitiveness of the industry, yielding an outcome that contradicts the original policy objectives [95].

Strictly speaking, Indonesia remains the only ASEAN country to explicitly impose LCRs on renewable energy projects, as of 2026. This section will delve into the details of the LCR in Indonesia, including its evolving thresholds and their implications on clean power cost competitiveness.

Indonesia has imposed local content requirements on all renewable energy projects since 2009. The Electricity Law (2009) requires independent power producers (IPPs) to prioritise the use of products manufactured locally and services in developing electricity infrastructure and Regulation 54/2012 further specifies the LCR rates for different technologies. In August 2024, Indonesia relaxed the LCRs for developing power projects. Table 7 details the LCR for different types of power plants. The LCR rate of small-scale hydropower plants at 0-15 MW remained the highest, while the threshold for geothermal power plants was lower [65].

Table 7: Local Content Requirement Rates for Renewable Energy Projects

Power Plant Type	**LCR rates, After Aug 2024**	**LCR rates, 2009 – Aug 2024**
Solar	20%	40%–60%
Geothermal	20%–29%	28.95%–42%
Hydropower	23%–45%	47.60%–70.76%
Wind	15%	Unregulated
Biomass	21%	Unregulated
Biogas	25.19%	Unregulated
Waste	16.53%	Unregulated

Note: The LCR rate is a combination of local goods and services. Appendix A.10 provides a detailed list of the goods and services.
Source: Authors' compilation based on [65, 41, 105].

Administrative and financial sanctions could be imposed on IPPs for non-compliance with the LCRs. Administratively, IPPs which did not use local contents at all or had a local content deficiency of more than 5% of the requirements, could be blacklisted for two years. Financially, there was a tariff of 0.3 of the total contract value for every 0.01% deficiency in achieving the required local content threshold, and this was capped at 10% of the contract value if the deficiency exceeded 5% of the local content threshold [105].

A direct impact of LCRs on clean energy production costs is that it will raise the cost of renewable power equipment, as they prevent developers from sourcing equipment overseas, where the costs have been reduced significantly, compared to Indonesia. The high cost of components could be factored into the high power generation cost. Without government subsidies, the electricity tariff for renewable power will be higher, and making it an unattractive option for both users and investors. Research estimated that developers using Indonesian solar modules can achieve an internal rate of return (IRR) of 14% at the renewable energy ceiling price, compared to around 21% for those using cost-competitive modules sourced from overseas [69, 50].

LCRs also constrain capital acquisition for clean power projects, increasing the cost of capital and resulting in the higher discount rates shown in Table A.3. Especially, LCRs have limited Indonesia's access to financing from international lenders, such as the ADB, the World Bank, and the JICA, because local content cannot be accepted in their procurement processes [13]. The PLN mentioned that nine renewable projects, collectively amounting to Rp 51 trillion (about US$2.958 billion),[8] faced financial barriers as they failed to obtain funding from international lenders [13]. The Energy Ministry also admitted that the LCRs have hindered the progress of the solar power deployment and constrained the use of foreign investment [85]. There are also concerns that the LCR is slowing the disbursement of funds from the Just Energy Transition Partnership (JETP) , which includes US$ 10 billion of foreign capital, as the LCRs constrain project developers from sourcing relevant components overseas, whose prices are much lower [120].

LCRs further constrain the bankability of renewable energy projects due to impractical compliance thresholds and regulatory ambiguity. Even Indonesian state-owned enterprises and their affiliates struggle to meet these requirements, as locally manufactured components are usually in short supply or fail to satisfy project technical specifications [105]. While a waiver of LCRs could mitigate these constraints, its practical application remains

[8] 1 Indonesian Rp = 0.000058 USD

highly ambiguous. The Regulation 54/2012 allows project developers to request waivers for the LCRs, but its implementation is challenged by unclear procedures on how the Indonesian Ministry of Industry will issue an exemption. In practice, there is no standard practice for applying for a waiver. The inconsistent policy implementation has generated policy uncertainty for project developers and could erode their profit margins, which are already narrow. This could, in turn, further constrain the bankability of the projects.

Indonesia relaxed its LCRs in 2024 to foster a more favourable investment climate and unlock concessional loans from international development banks. Three dimensions of this relaxation are worth attention. Firstly, electricity infrastructures designated for cross-border electricity transactions are subject to a "special" minimum LCR rate, although as of 2026, no specific LCR rate has been determined by the energy minister for any technology [86]. This regulatory carve-out potentially allows developers of power export projects to utilise more cost-effective overseas products and services, thereby reducing supply chain costs compared to projects serving only the domestic market. Given the significant demand for solar power from Singapore (Table 1), this policy could stimulate market demand for solar PV cells and modules, which Indonesia has the manufacturing capacity. Consequently, Indonesian solar PV manufacturers may leverage this increased volume to achieve economies of scale, theoretically lowering the price of locally produced components [146].

However, granting the Minister discretionary power to set LCR rates introduces policy uncertainty, and these rates may not necessarily be lower than domestic thresholds. For instance, in 2023, a senior energy official stated that solar modules for export projects to Singapore must meet a 60% LCR threshold, the maximum requirement at that time. This aimed to attract investment into the domestic manufacturing sector [2]. Uncertainty also stems from the potential for the threshold to fluctuate between ministerial administrations or be applied on a case-by-case basis. Without concrete, consistent and clear standards or justifications for these rates, developers' incentive to invest in export-oriented power projects may be significantly diminished.

Secondly, an LCR waiver is introduced. For projects receiving at least 50 % of funding from foreign development banks or financial institutions, subject to ministerial approval, their LCR could be waived. This was not included in the previous LCR regulations. This addresses the issue that LCRs hamper access to funding from international lenders.

Thirdly, even for domestic electrical infrastructure, the LCR for solar, geothermal, and hydro power plants are significantly reduced, as shown in Table 7. There is also a temporary LCR relaxation for solar power plants whose PPAs were signed before 31 December 2024 and are planned to commence commercial operation by 30 June 2026 under the power supply business plan. Relaxation applies to the plants: 1) listed in a meeting organised by the Coordinating Minister for Maritime and Investment Affairs; 2) using solar modules assembled domestically or through importers who commit to investing in local manufacturing capabilities and meet the LCR for solar modules by the end of 2025 [65, 120].

As of May 2026, it remains too early to draw firm conclusions about the effect of Indonesia's policy update on clean power generation costs. The main constraint is not the absence of a visible cost response, but the limited availability of post-update project-level CAPEX data. In the BMI Database, cost data are available for only three geothermal power plants constructed in 2025, one onshore wind plant in 2026, and one solar PV plant in 2026.[9] This small sample makes it difficult to distinguish any genuine cost effect from project-specific variation or data gaps. Consistent with this limitation, Figure A.5 shows no clear change in average CAPEX per MW before and after the policy update. However, this should not be interpreted as evidence that the policy update has had no effect. GEM data indicate that Indonesia's post-2024 clean power project base and pipeline are larger than what is captured in the available BMI cost data, including at least 14 operating solar PV projects, four operating geothermal projects, and one operating hydropower project, as well as 32 geothermal, 18 hydropower, three solar PV, and four wind projects that have been announced or are under construction or pre-construction [36]. Therefore, the current evidence primarily points to limited observable cost coverage, rather than a definitive post-policy CAPEX trend.

Although Indonesia is the only country with local content requirements in the ASEAN region, there are

[9] According to the BMI database, two of the geothermal power plants are located in West Java and one in West Sumatra; the solar PV plant is located in Riau; and the onshore wind plant is located in South Kalimantan.

restrictions on foreign ownership for renewable energy projects in other countries. Malaysia's Large Scale Solar (LSS) programme (since 2016) has imposed strict limitations on foreign ownership—foreign ownership should be less than or equal to 49% for project applicants of the programme [25]. Similarly, in Vietnam, the majority of offshore wind projects for export must be owned by domestic investors. Foreign investment in them for domestic consumption is also capped at 95%. National security approvals from multiple ministries are also required for projects involving foreign capital. Furthermore, wholly state-owned enterprises or their affiliates hold the right of first refusal to purchase part or all of the interests proposed for transfer [139]. There are also apprehensions that Thailand's 1,500 MW Community-based Solar Power Generation Project may impose limits on international investment, echoing a 2022 programme that restricted foreign equity to 49% and mandated that foreign nationals comprise no more than 50% of the total shareholder count [17].

6 Conclusion

Combining LCOE calculations using project-level CAPEX with a broader Clean Energy Cost Competitiveness Index (CECCI), this study examined clean power production cost competitiveness among ASEAN countries, identifying the underlying drivers shaping cost variations and implications for Singapore's low-carbon electricity import strategy.

Over time, LCOE has declined across technologies, suggesting improved clean power cost competitiveness across ASEAN are improving. Yet, the competitiveness remains uneven across technologies and countries. Using project-level CAPEX data and assumptions on capacity availability, discount rates, project lifetimes, and fixed O&M costs, the analysis finds that hydropower is the region's most cost-competitive clean energy source, led by Malaysia, Indonesia, and Vietnam. Solar PV power follows closely, with Indonesia, Cambodia, and Vietnam performing strongly. Wind power remains comparatively more expensive, with onshore wind, notably in Indonesia, Vietnam, and Thailand, more cost-competitive than offshore wind, which is currently only deployed in Vietnam. Most cost variation across countries and technologies is driven by project-specific CAPEX differences.

The CECCI further shows that ASEAN's clean energy cost competitiveness is also shaped by structural conditions. These include policy support, installed power capacity, tariffs of power generation equipment, geographic factors, financing costs, macroeconomic stability, and innovation and industrial capacity. By drawing on the global pattern, the study finds that economic policy instruments are associated with lower LCOE, while installed power capacity provides strong evidence of learning-by-doing effects, especially for onshore wind. Applied to ASEAN, the index shows that Thailand and the Philippines were early leaders in solar PV competitiveness, Vietnam has rapidly caught up through large-scale capacity expansion, and Malaysia has benefited from its stronger solar PV manufacturing base. For onshore wind, Thailand has historically led, but Vietnam has reached comparable levels through rapid deployment, while Indonesia's progress remains constrained by limited sustained capacity growth.

Some considerations of supply chain costs and local content requirements warrant special attention. In terms of trade dependence, Chinese firms dominate equipment supply for both solar PV and wind projects, creating concentration risk. In terms of import tariffs, enabling infrastructure components account for the largest share of import-weighted tariff burdens. Targeted tariff liberalisation on these components, alongside localisation of their production where feasible, could directly reduce CAPEX. Local content requirements have only been instituted in Indonesia so far, and have constrained project bankability and raised costs. However, the 2024 relaxation, particularly the special rate (so far undisclosed) for cross-border electricity export projects, could improve cost competitiveness for Singapore-bound power export, subject to regulatory clarity and consistency.

Singaporean policymakers should therefore design a clean energy import strategy that balances ASEAN countries' LCOE profiles with structural conditions that act as a tailwind for future cost competitiveness: most notably well-designed economic policy instruments, rising installed power capacity, favourable macroeconomic conditions, and access to low-cost financing. PPAs designed in cognisance of these variables will contribute to

Singapore's long-term energy security and decarbonisation targets.

References

[1] Alagappan, L., R. Orans, and C. K. Woo (2011, September). What drives renewable energy development? *Energy Policy 39*(9), 5099–5104.

[2] ANTARA. Infra for S'pore electricity exports must comply with TKDN rule: Govt.

[3] ASEAN Centre for Energy. 8th ASEAN Energy Outlook.

[4] ASEAN Centre for Energy. ASEAN Plan of Action for Energy Cooperation (APAEC) 2026-2030.

[5] ASEAN Centre for Energy (2016). Levelised cost of electricity of selected renewable technologies in the asean member states. Accessed May 11, 2026.

[6] ASEAN Centre for Energy (2019, February). Levelised Costs of Electricity for Renewable Energy Technologies in ASEAN Member States II.

[7] Asian Development Bank (2015). Renewable energy developments and potential in the greater mekong subregion. Accessed May 11, 2026.

[8] Asian Development Bank, Bloomberg Philanthropies, ClimateWorks Foundation, and Sustainable Energy for All (2023, August). *Renewable Energy Manufacturing: Opportunities for Southeast Asia.*

[9] Asian Infrastructure Investment Bank (2020, February). Protectionism and trade in renewable energy infrastructure. Working paper, Asian Infrastructure Investment Bank.

[10] Azhgaliyeva, D. (2023, July). Renewable Energy Investments and Feed-in Tariffs: Firm-Level Evidence from Southeast Asia.

[11] Azhgaliyeva, D., J. Beirne, and R. Mishra (2023, January). What matters for private investment in renewable energy? *Climate Policy 23*(1), 71–87.

[12] Bain & Company, GenZero, Standard Chartered, and Temasek. Southeast Asia's Green Economy 2024: Moving the needle.

[13] Belinda, Y. Local content rules holding back 9 renewable energy projects, PLN says.

[14] Berry, D. (2009, November). Innovation and the price of wind energy in the US. *Energy Policy 37*(11), 4493–4499.

[15] Blanco, M. I. (2009). The economics of wind energy. *Renewable and Sustainable Energy Reviews 13*(6–7), 1372–1382.

[16] BloombergNEF (2025, October). Clean energy trade and emerging markets. Technical report, BloombergNEF. Commissioned by Bloomberg Philanthropies.

[17] Boonsanong, S. and K. Nitungkorn. Thailand Approves 1,500 MW Community Solar Program with Time-Sensitive "First-Served" Selection (Thailand).

[18] Borenstein, S. (2008). The market value and cost of solar photovoltaic electricity production. Technical report, Center for the Study of Energy Markets, University of California Energy Institute.

[19] BusinessWorld (2025). Erc sets final prices for 4th green energy auction. Published June 16, 2025. Accessed April 29, 2026.

[20] Do, T. N. and P. J. Burke. Vietnam's Solar Power Boom: Policy Implications for Other ASEAN Member States.

[21] Economic Development Board, Singapore. Deal to explore exporting renewable energy from Vietnam to Singapore, Malaysia inked at ASEAN Summit.

[22] Ek, K. and P. Söderholm (2010, October). Technology Learning in the Presence of Public R&D: The Case of European Wind Power. *Ecological Economics 69*(12), 2356–2362.

[23] Elizondo Azuela, G., L. A. Barroso, and World Bank (2012). *Design and Performance of Policy Instruments to Promote the Development of Renewable Energy: Emerging Experience in Selected Developing Countries*, Volume 1 of 1. Washington, D.C: World Bank.

[24] Emblemsvåg, J. (2025, January). Rethinking the "Levelized Cost of Energy": A critical review and evaluation of the concept. *Energy Research & Social Science 119*, 103897.

[25] Energy Commission, Malaysia. Guidelines on Large Scale Solar Photovoltaic Plant for Connection to Electricity Networks.

[26] Energy Market Authority (EMA), Singapore. EMA Grants Conditional Approval for 1.2 Gigawatt (GW) of Electricity Imports from Vietnam.

[27] Energy Market Authority (EMA), Singapore. EMA Grants Conditional Approval of 1.75 GW of Electricity Imports from Australia.

[28] Energy Market Authority (EMA), Singapore. EMA Grants Conditional Approvals for 2 Gigawatt of Electricity Imports from Indonesia.

[29] Energy Market Authority (EMA), Singapore. Is Singapore considering the use of wind energy? https://ema.gov.sg/resources/faqs/energy-supply/low-carbon-alternatives/is-singapore-considering-the-use-of-wind-energy.

[30] Energy Market Authority (EMA), Singapore (2025, September). Regional Power Grids.

[31] Energy Market Authority (EMA), Singapore, Singapore. Natural Gas.

[32] Feldman, D., R. Jones-Albertus, and R. Margolis (2020, July). Quantifying the impact of r&d on pv project financing costs. *Energy Policy 142*, 111525.

[33] Fitch Solutions (2026). Bmi industry research.

[34] Fripp, M. and R. Wiser (2006). Effects of temporal wind patterns on the value of wind-generated electricity at different sites in california and the northwest. Technical report, Lawrence Berkeley National Laboratory, Berkeley, CA.

[35] Gernaat, D. E. H. J., H. S. de Boer, V. Daioglou, S. G. Yalew, C. Müller, and D. P. van Vuuren (2021, February). Climate change impacts on renewable energy supply. *Nature Climate Change 11*(2), 119–125.

[36] Global Energy Monitor (2026). Global integrated power tracker. https://globalenergymonitor.org/projects/global-integrated-power-tracker. March 2026 release, accessed May 8, 2026.

[37] Hansen, K. (2019, April). Decision-making based on energy costs: Comparing levelized cost of energy and energy system costs. *Energy Strategy Reviews 24*, 68–82.

[38] Hao, X., Q. Sun, P. Ma, K. Li, H. Wu, and Y. Xue (2024, September). Unlocking wind power potential: The pivotal role of r&d investment in boosting wind power enterprise performance. *Energy Strategy Reviews 55*, 101507.

[39] Hill Balliet, W., P. Balducci, V. Durvasulu, and T. Mosier (2025, February). Determining the profitability of energy storage over its life cycle using levelized cost of storage. *Energy Economics 142*, 108174.

[40] Hirth, L. (2013). The market value of variable renewables: The effect of solar wind power variability on their relative price. *Energy Economics 38*, 218–236.

[41] HKTDC Research. INDONESIA: Local Content Requirements for Energy Sector Reduced.

[42] Hu, X., H. Pollitt, J. Pirie, J.-F. Mercure, J. Liu, J. Meng, and S. Tao (2020). The impacts of the trade liberalization of environmental goods on power system and co2 emissions. *Energy Policy 140*, 111173.

[43] Huang, Y., B. Yan, K. G. Tan, and K. Y. Wong (2025). Mapping ASEAN's Position in the Global Solar PV Supply Chain.

[44] Huenteler, J., T. S. Schmidt, J. Ossenbrink, and V. H. Hoffmann (2016). Technology life-cycles in the energy sector — technological characteristics and the role of deployment for innovation. *Energy Policy 102*, 271–282.

[45] IEA. Global Energy and Climate Model Documentation 2024.

[46] IEA Photovoltaic Power Systems Programme (IEA PVPS) (2025). Snapshot of Global PV Markets - 2025.

[47] IMF (2023, April). World Economic Outlook Database - Groups and Aggregates. https://www.imf.org/en/publications/weo/weo-database/2023/april/groups-and-aggregates.

[48] Infocomm Media Development Authority (IMDA), Singapore. The Green Data Centre (DC) Roadmap.

[49] Informal Working Group on Environmental Goods and Services, World Trade Organization (2024, February). Trade and Environmental Sustainability Structured Discussions (TESSD) Statement by The TESSD Co-Convenors.

[50] Institute for Essential Services Reform (IESR). Indonesia Energy Transition Outlook 2023 Tracking Progress of Energy Transition in Indonesia: Pursuing Energy Security in the Time of Transition.

[51] International Energy Agency (2019, February). Have the prices from competitive auctions become the "new normal" prices for renewables? https://www.iea.org/articles/have-the-prices-from-competitive-auctions-become-the-new-normal-prices-for-renewables. Analysis from *Renewables 2018*.

[52] International Energy Agency (IEA) (2020, December). Projected Costs of Generating Electricity 2020. Technical report.

[53] International Energy Agency (IEA) (2022a, July). Securing Clean Energy Technology Supply Chains – Analysis. Technical report.

[54] International Energy Agency (IEA) (2022b, July). Solar PV Global Supply Chains: An IEA Special Report. Technical report.

[55] International Energy Agency (IEA) (2023a, January). Energy Technology Perspectives 2023. Technical report.

[56] International Energy Agency (IEA) (2023b, May). The State of Clean Technology Manufacturing. Technical report.

[57] International Energy Agency (IEA) (2024). Renewables 2024: Electricity. IEA, Paris. Accessed May 4, 2026.

[58] International Renewable Energy Agency (IRENA) (2012, June). Renewable energy technologies: Cost analysis series – wind power. Technical report, International Renewable Energy Agency, Abu Dhabi.

[59] International Renewable Energy Agency (IRENA) (2023). The cost of financing for renewable power. Technical report, International Renewable Energy Agency, Abu Dhabi. May 2023. Accessed April 29, 2026.

[60] International Renewable Energy Agency (IRENA) (2025, July). Renewable Power Generation Costs in 2024. Technical report.

[61] Jamasb, T. and J. Kohler (2007, October). Learning Curves For Energy Technology: A Critical Assessment.

[62] Jenner, S., F. Groba, and J. Indvik (2013, January). Assessing the strength and effectiveness of renewable electricity feed-in tariffs in European Union countries. *Energy Policy 52*, 385–401.

[63] Jiang, H., L. Yao, and C. Zhou. Assessment of offshore wind-solar energy potentials and spatial layout optimization in mainland China. *287*, 115914.

[64] Joskow, P. L. (2008). Comparing the costs of intermittent and dispatchable electricity generating technologies. *Energy Journal 29*(1), 1–14.

[65] Kasmali, M., M. Bubb, and K. S. Antonio. Indonesia relaxes local content rules to energise green energy investment.

[66] Kavlak, G., J. McNerney, and J. E. Trancik (2018, December). Evaluating the causes of cost reduction in photovoltaic modules. *Energy Policy 123*, 700–710.

[67] Klaassen, G., A. Miketa, K. Larsen, and T. Sundqvist (2005, August). The impact of r&d on innovation for wind energy in denmark, germany and the united kingdom. *Ecological Economics 54*(2), 227–240.

[68] Koons, E. (2024, February). Wind Energy In Indonesia: Slow Growth, Promising Future.

[69] Kuneman, E., G. D. Vivero, P. Kokchang, C. Juta, S. Vanaphongsai, and Chetna Hareesh Kumar. Electricity market designs in Southeast Asia: Harnessing opportunities for renewable energy growth – Indonesia, Thailand, Viet Nam and the Philippines.

[70] Lamont, A. D. (2008). Assessing the long-term system value of intermittent electric generation technologies. *Energy Economics 30*(3), 1208–1231.

[71] Lee, N., F. Flores-Espino, R. Cardoso De Oliveira, B. Roberts, T. Brown, and J. Katz (2020, June). Exploring Renewable Energy Opportunities in Select Southeast Asian Countries: A Geospatial Analysis of the Levelized Cost of Energy of Utility-Scale Wind and Solar Photovoltaics. Technical Report NREL/TP–7A40-71814, 1527336, MainId:20963.

[72] Lewis, J. I. (2014). The Rise of Renewable Energy Protectionism: Emerging Trade Conflicts and Implications for Low Carbon Development. *Global Environmental Politics 14*(4), 10–35.

[73] Lewis, J. I. (2021). Green Industrial Policy After Paris: Renewable Energy Policy Measures and Climate Goals. *Global Environmental Politics 21*(4), 42–63.

[74] Lin, B. and Y. Chen (2023, March). Impact of the Feed-in Tariff Policy on Renewable Innovation: Evidence from Wind Power Industry and Photovoltaic Power Industry in China. *The Energy Journal 44*(2), 29–46.

[75] Liu, J. Not All Policies Are Created Equal: Impact of Different Climate Policy Instruments on Sustainable Venture Investments.

[76] Loan, T. D. et al. (2025). Economic analysis of solar power plant and battery energy storage: Case study of binh phuoc province, vietnam. *Cleaner Engineering and Technology*. Accessed May 11, 2026.

[77] Ma, R., H. Cai, Q. Ji, and P. Zhai (2021, April). The impact of feed-in tariff degression on R&D investment in renewable energy: The case of the solar PV industry. *Energy Policy 151*, 112209.

[78] Maandal, A. S. et al. (2021). Techno-economic analysis of offshore wind energy potential in the philippines. *Journal of Marine Science and Engineering 9*(7), 758. Accessed May 11, 2026.

[79] Manila Bulletin (2023). Re auction only corners 3,580 mw capacity for delivery. Published July 3, 2023. Accessed April 29, 2026.

[80] Martín, H., S. Coronas, Alonso, J. de la Hoz, and J. Matas (2020). Renewable energy auction prices: Near subsidy-free? *Energies 13*(13), 3383.

[81] Matsuo, Y. (2022, January). Re-Defining System LCOE: Costs and Values of Power Sources. *Energies 15*(18), 6845.

[82] Matthäus, D., S. Schwenen, and D. Wozabal (2021). Renewable auctions: Bidding for real options. *European Journal of Operational Research 291*(3), 1091–1105.

[83] Miller, L., R. Carriveau, S. Harper, and S. Singh (2017, June). Evaluating the link between LCOE and PPA elements and structure for wind energy. *Energy Strategy Reviews 16*, 33–42.

[84] Ministry of Energy and Mineral Resources, Indonesia. Keputusan menteri energi dan sumber daya mineral nomor 191.k/ek.01/mem.e/2024.

[85] Ministry of Energy and Mineral Resources, Indonesia. Pemerintah Terbitkan Aturan Baru TKDN Infrastruktur Ketenagalistrikan.

[86] Ministry of Energy and Mineral Resources, Indonesia. Peraturan Menteri Energi dan Sumber Daya Mineral Nomor 11 Tahun 2024 Penggunaan Produk Dalam Negeri Untuk Pembangunan Infrastruktur Ketenagalistrikan (Use of Domestic Products for Electricity Infrastructure Development).

[87] Ministry of Finance (MOF), Singapore. Budget 2026 Speech Securing Our Future Together in a Changed World.

[88] Ministry of Finance (MOF), Singapore. Budget Statement - Onward Together for a Better Tomorrow.

[89] Ministry of Trade and Industry (MTI) and Energy Market Authority (EMA), Singapore. Establishment of Future Energy Fund to Support Singapore's Infrastructure Investments.

[90] Ministry of Trade and Industry (MTI), Singapore. Speech by 2M Tan See Leng at MTI's Committee of Supply Debate 2025.

[91] National Renewable Energy Laboratory (NREL) (2010). Western wind and solar integration study (WWSIS): Executive summary. Technical Report NREL/SR-550-47781, National Renewable Energy Laboratory.

[92] Nemet, G. F. (2019). *How Solar Energy Became Cheap: A Model for Low-Carbon Innovation.* Routledge.

[93] NewClimate Institute, Wageningen University and Research & PBL Netherlands Environmental Assessment Agency. Climate Policy Database Codebook (2023 version).

[94] Nian, V., Y. Liu, and S. Zhong (2019, January). Life cycle cost-benefit analysis of offshore wind energy under the climatic conditions in Southeast Asia – Setting the bottom-line for deployment. *Applied Energy 233–234*, 1003–1014.

[95] OECD. Local content requirements.

[96] OneMonroe Titan (2025, May). How Will Tariffs Effect the Solar Industry: Expert Strategies for Business Continuity.

[97] Osman, A. I., L. Chen, M. Yang, G. Msigwa, M. Farghali, S. Fawzy, D. W. Rooney, and P.-S. Yap (2023, April). Cost, environmental impact, and resilience of renewable energy under a changing climate: A review. *Environmental Chemistry Letters 21*(2), 741–764.

[98] Ouyang, X. and B. Lin (2014, July). Levelized cost of electricity (LCOE) of renewable energies and required subsidies in China. *Energy Policy 70*, 64–73.

[99] Paraschiv, S., L. S. Paraschiv, A. Serban, and A. G. Cristea (2022, August). Assessment of onshore wind energy potential under temperate continental climate conditions. *Energy Reports 8*, 251–258.

[100] Picard, V. Trade Barriers Are Slowing Clean Energy Deployment – Here's How to Fix It.

[101] Popp, D. (2019, March). Environmental Policy and Innovation: A Decade of Research.

[102] Poudineh, R. (2025). From Scarcity to Scale: The New Economics of Energy. *Oxford Institute for Energy Studies*.

[103] Pratama, Y. W., M. J. Gidden, J. Greene, A. Zaiser, G. Nemet, and K. Riahi (2025, January). Learning, economies of scale, and knowledge gap effects on power generation technology cost improvements. *iScience 28*(1), 111644.

[104] Qiu, Y. and L. D. Anadon (2012, May). The price of wind power in China during its expansion: Technology adoption, learning-by-doing, economies of scale, and manufacturing localization. *Energy Economics 34*(3), 772–785.

[105] Rajah, T. A.-A. F. Assegaf, and M. I. Pratama. Time to Reflect on Indonesia's Local Content Requirement for Renewable Energy.

[106] Rubin, E. S., I. M. L. Azevedo, P. Jaramillo, and S. Yeh (2015, November). A review of learning rates for electricity supply technologies. *Energy Policy 86*, 198–218.

[107] Saieed, Z. Sarawak in talks to supply 1GW renewable energy to S'pore by 2032: Sarawak Energy.

[108] Samadi, S. (2016, November). A Review of Factors Influencing the Cost Development of Electricity Generation Technologies. *Energies 9*(11), 970.

[109] Satymov, R., D. Bogdanov, and C. Breyer (2022, October). Global-local analysis of cost-optimal onshore wind turbine configurations considering wind classes and hub heights. *Energy 256*, 124629.

[110] See, E., K. Wee, and B. Tan. Middle East oil shocks send S-E Asia scrambling for alternatives, but cleaner mix is no easy choice.

[111] Sembcorp. Sembcorp Awarded Conditional Approval by EMA to Import Renewable Energy from Sarawak to Singapore.

[112] Shah, S. (2020, January). LCOE and its Limitations. https://energyforgrowth.org/wp-content/uploads/2020/01/LCOE-and-its-Limitations.pdf.

[113] Shahsavari, A. and M. Akbari (2018, July). Potential of solar energy in developing countries for reducing energy-related emissions. *Renewable and Sustainable Energy Reviews 90*, 275–291.

[114] Shen, W., X. Chen, J. Qiu, J. A. Hayward, S. Sayeef, P. Osman, K. Meng, and Z. Y. Dong (2020, November). A comprehensive review of variable renewable energy levelized cost of electricity. *Renewable and Sustainable Energy Reviews 133*, 110301.

[115] Singapore Energy Interconnections. Singapore Energy Interconnections (SGEI).

[116] Singapore Green Plan 2030. Our Targets.

[117] Smits, M. and S. R. Bush (2010). A light left in the dark: The practice and politics of pico-hydropower in the lao pdr. *Energy Policy 38*(1), 116–127.

[118] Söderholm, P. and G. Klaassen (2007, February). Wind Power in Europe: A SimultaneousInnovation–Diffusion Model. *Environmental and Resource Economics 36*(2), 163–190.

[119] Stetter, C., J.-H. Piel, J. F. H. Hamann, and M. H. Breitner (2020, August). Competitive and risk-adequate auction bids for onshore wind projects in Germany. *Energy Economics 90*, 104849.

[120] Strangio, S. Indonesia Relaxes Local Content Rules to Spur Green Energy Investments.

[121] Supriyanto, E., J. Sentanuhady, W. H. Hasan, A. D. Nugraha, and M. A. Muflikhun (2022, January). Policy and Strategies of Tariff Incentives Related to Renewable Energy: Comparison between Indonesia and Other Developing and Developed Countries. *Sustainability 14*(20), 13442.

[122] Suruhanjaya Tenaga (Energy Commission Malaysia) (2017). Large scale solar 2017–2018: Bid opening price. Technical report, Suruhanjaya Tenaga, Putrajaya, Malaysia. Accessed April 29, 2026.

[123] Suruhanjaya Tenaga (Energy Commission Malaysia) (2020). Bid price opening: Large scale solar @ mentari (lss@mentari). Technical report, Suruhanjaya Tenaga, Putrajaya, Malaysia. Accessed April 29, 2026.

[124] Taghizadeh-Hesary, F., N. Yoshino, and Y. Inagaki (2018, April). Empirical Analysis of Factors Influencing Price of Solar Modules. (836).

[125] TaiyangNews (2019). Se asia's lowest solar bid of $0.0387/kwh in cambodia. Published September 5, 2019. Accessed April 29, 2026.

[126] Tan, C. Construction of S'pore's largest floating solar farm at Kranji Reservoir to begin in 2025.

[127] The ASEAN Secretariat and United Nations Trade and Development. ASEAN Investment Report 2025.

[128] The National Climate Change Secretariat, Singapore. Carbon Tax.

[129] The National Climate Change Secretariat, Singapore. Singapore Submits 2035 Nationally Determined Contribution.

[130] Timilsina, G. R. (2020, June). Demystifying the Costs of Electricity Generation Technologies. Technical Report 9303.

[131] Timilsina, G. R. (2021, December). Are renewable energy technologies cost competitive for electricity generation? *Renewable Energy 180*, 658–672.

[132] Tran, T. T. D. and A. D. Smith (2018, April). Incorporating performance-based global sensitivity and uncertainty analysis into LCOE calculations for emerging renewable energy technologies. *Applied Energy 216*, 157–171.

[133] Ueckerdt, F., L. Hirth, G. Luderer, and O. Edenhofer (2013). System lcoe: What are the costs of variable renewables? *Energy 63*, 61–75.

[134] UN Trade and Development (UNCTAD) (2024, October). Powering Trade: Fine-tuning Trade Policy for Solar and Wind Energy Value Chains. United Nations Global Crisis Response Group Briefs.

[135] U.S. Energy Information Administration (2025). Levelized Costs of New Generation Resources in the Annual Energy Outlook 2025.

[136] Verdolini, E., L. D. Anadón, E. Baker, V. Bosetti, and L. Aleluia Reis (2018, January). Future Prospects for Energy Technologies: Insights from Expert Elicitations. *Review of Environmental Economics and Policy 12*(1), 133–153.

[137] Verdolini, E., L. D. Anadon, J. Lu, and G. F. Nemet (2015, May). The Effects of Expert Selection, Elicitation Design, and R&D Assumptions on Experts' Estimates of the Future Costs of Photovoltaics. *Energy Policy 80*, 233–243.

[138] Veronese, E., G. Manzolini, and D. Moser (2021). Improving the traditional levelized cost of electricity approach by including the integration costs in the techno-economic evaluation of future photovoltaic plants. *International Journal of Energy Research 45*(6), 9252–9269.

[139] Vietnam Investment Review. Legal reforms powering Vietnam's energy transformation.

[140] Vorarat, S. and W. Tantawat (2023). Comprehensive analysis and comparison of the life cycle costand the levelized cost of energy ofcommercialonshore wind energy farmsin thailand. *Journal of Renewable Energy and Smart Grid Technology 18*(1). Accessed May 11, 2026.

[141] World Bank (n.d.a). Solar photovoltaic power systems: A historical overview and cost evolution. Technical report, World Bank.

[142] World Bank (n.d.b). World integrated trade solution (wits). Accessed May 4, 2026.

[143] Xiao, M., T. Junne, J. Haas, and M. Klein (2021). Plummeting costs of renewables: Are energy scenarios lagging? *Energy Strategy Reviews 35*, 100636.

[144] Yang, D.-x., Y.-q. Jing, C. Wang, P.-y. Nie, and P. Sun (2021, March). Analysis of renewable energy subsidy in China under uncertainty: Feed-in tariff vs. renewable portfolio standard. *Energy Strategy Reviews 34*, 100628.

[145] Yao, Y., J.-H. Xu, and D.-Q. Sun (2021). Untangling global levelised cost of electricity based on multi-factor learning curve for renewable energy: Wind, solar, geothermal, hydropower and bioenergy. *285*, 124827.

[146] Yustika, M. Maximizing reciprocal benefits from Indonesia's green electricity export to Singapore.

[147] Zhou, Y., B. Zhang, J. Zou, J. Bi, and K. Wang (2012, July). Joint r&d in low-carbon technology development in china: A case study of the wind-turbine manufacturing industry. *Energy Policy 46*, 100–108.

Appendix

Table A.1: CAPEX Distribution by Country and Technology (USD million per MW): Summary Statistics

Country	Technology	SD	Mean	Median	P25	P75	Min	Max
KHM	Hydropower	0.415	2.407	2.394	2.134	2.667	1.953	2.888
IDN	Hydropower	2.528	2.899	2.105	1.759	2.789	0.865	10.340
LAO	Hydropower	0.661	2.266	2.333	1.896	2.678	0.775	3.482
MYS	Hydropower	1.202	3.264	3.367	2.500	4.131	1.847	4.475
MMR	Hydropower	1.115	1.788	1.788	1.394	2.182	1.000	2.577
PHL	Hydropower	1.178	2.679	2.659	1.868	3.380	0.786	5.278
VNM	Hydropower	0.327	1.325	1.430	1.069	1.558	0.769	1.775
KHM	Solar PV	0.143	0.998	0.967	0.941	0.992	0.850	1.270
IDN	Solar PV	0.243	0.844	0.844	0.758	0.930	0.672	1.016
LAO	Solar PV	–	1.078	1.078	1.078	1.078	1.078	1.078
MYS	Solar PV	0.725	1.818	1.780	1.680	1.870	0.690	3.158
MMR	Solar PV	0.115	1.353	1.275	1.267	1.455	1.267	1.500
PHL	Solar PV	1.084	1.368	1.330	0.945	1.410	0.043	8.000
VNM	Solar PV	0.177	1.015	1.040	0.936	1.107	0.640	1.327
VNM	Offshore Wind	1.119	2.349	2.200	1.958	2.455	1.088	5.875
IDN	Onshore Wind	0.131	2.118	2.160	2.066	2.191	1.971	2.222
LAO	Onshore Wind	–	2.500	2.500	2.500	2.500	2.500	2.500
PHL	Onshore Wind	0.665	2.396	2.532	1.910	2.990	1.419	3.111
THA	Onshore Wind	0.000	2.029	2.029	2.029	2.029	2.029	2.029
VNM	Onshore Wind	0.540	1.703	1.640	1.358	1.975	0.770	2.708

Note: CAPEX dispersion varies by country and technology. Hydropower shows relatively stable costs in Vietnam, Myanmar, and Cambodia, but wider variation in Indonesia, Malaysia, and the Philippines, partly due to high-cost projects. Solar PV costs are generally less dispersed, except in the Philippines and Malaysia, where outliers widen the range. Onshore wind shows comparatively contained variability, though the Philippines records higher within-sample dispersion. Offshore wind data are available only for Vietnam and should be interpreted cautiously given limited observations and possible high-cost outliers.

Table A.2: Capacity Availability Factors (CAF) by Country and Technology

Country	Technology	Source	CAF
MYS	Hydropower	ACE (2017) Country Data	0.76
IDN	Hydropower	ACE (2017) Country Data	0.68
VNM	Hydropower	ACE (2017) Country Data	0.39
MMR	Hydropower	ACE (2017) Country Data	0.72
KHM	Hydropower	ACE (2017) ASEAN Aggregate	0.52
LAO	Hydropower	ACE (2017) Country Data	0.41
PHL	Hydropower	ACE (2017) Country Data	0.39
VNM	Offshore Wind	ACE (2017) Country Data	0.20
IDN	Onshore Wind	IRENA (2024)	0.3805
VNM	Onshore Wind	ACE (2017) Country Data	0.20
THA	Onshore Wind	ACE (2017) Country Data	0.1949
PHL	Onshore Wind	ACE (2017) Country Data	0.2711
LAO	Onshore Wind	ACE (2017) ASEAN Aggregate	0.2214
IDN	Solar PV	ACE (2017) Country Data	0.18
LAO	Solar PV	ACE (2017) ASEAN Aggregate	0.16
KHM	Solar PV	ACE (2017) ASEAN Aggregate	0.16
VNM	Solar PV	ACE (2017) ASEAN Aggregate	0.16
PHL	Solar PV	ACE (2017) Country Data	0.17
MYS	Solar PV	ACE (2017) ASEAN Aggregate	0.16
MMR	Solar PV	ACE (2017) ASEAN Aggregate	0.16

Notes: CAF values are sourced from the ASEAN Centre for Energy (ACE, 2017) and IRENA (2024). Where country-level data is unavailable, ASEAN-level aggregates are applied.

Capacity factors vary across technologies and countries, reflecting underlying resource endowments. Hydropower exhibits significant variation across ASEAN, with Malaysia (76%), Myanmar (72%), and Indonesia (68%) achieving higher capacity factors due to favourable geographic and hydrological conditions. Onshore wind capacity factors are relatively higher in Indonesia (38%) and the Philippines (27.1%), indicating stronger wind resource potential compared to regional peers. In contrast, solar PV capacity factors appear broadly similar across countries (16-18%); however, this likely reflects data limitations, as most estimates are based on ASEAN-level aggregates rather than country-specific measurements [3, 60].

Table A.3: Discount Rate, Economic Life, and Capital Recovery Factor (CRF) by Country and Technology

Country	**Technology**	**Discount Rate**	**Economic Life (Years)**	**CRF**
MYS	Hydropower	0.0676	30	0.0786
IDN	Hydropower	0.0761	30	0.0856
VNM	Hydropower	0.0891	30	0.0966
MMR	Hydropower	0.1627	30	0.1645
KHM	Hydropower	0.0845	30	0.0926
LAO	Hydropower	0.0750	30	0.0847
PHL	Hydropower	0.0745	30	0.0842
VNM	Offshore Wind	0.0891	25	0.1011
IDN	Onshore Wind	0.0761	25	0.0906
VNM	Onshore Wind	0.0643	25	0.0814
THA	Onshore Wind	0.0739	25	0.0888
PHL	Onshore Wind	0.0745	25	0.0893
LAO	Onshore Wind	0.0750	25	0.0897
IDN	Solar PV	0.0761	25	0.0906
LAO	Solar PV	0.0750	25	0.0897
KHM	Solar PV	0.0845	25	0.0973
VNM	Solar PV	0.0741	25	0.0890
PHL	Solar PV	0.0745	25	0.0893
MYS	Solar PV	0.0676	25	0.0839
MMR	Solar PV	0.1627	25	0.1665

Notes: Discount rates and economic life assumptions are sourced from *IRENA* (2025). CRF is computed accordingly. Hydropower economic life is conservatively assumed at 30 years.
Across ASEAN, discount rates largely cluster within the 6–9% range, consistent with moderate-risk emerging market conditions, but Myanmar stands out as a high-risk outlier with rates exceeding 16%. Technology-specific risk premiums are also evident: in Vietnam, offshore wind carries a higher discount rate than onshore wind, reflecting the relative novelty and uncertainty of the technology. Conversely, Vietnamese onshore wind (6.4%), Malaysian solar PV (6.8%), and Malaysian hydropower (6.8%) benefit from some of the lowest discount rates in the region, indicating more favourable financing conditions [60].

Table A.4: Fixed Operating and Maintenance (O&M) Costs by Country and Technology (USD/MW-year)

Country	Technology	Source	Fixed O&M Cost
MYS	Hydropower	8th ASEAN Energy Outlook (2024)	5.66
IDN	Hydropower	8th ASEAN Energy Outlook (2024)	6.33
VNM	Hydropower	8th ASEAN Energy Outlook (2024)	11.04
MMR	Hydropower	8th ASEAN Energy Outlook (2024)	5.98
KHM	Hydropower	8th ASEAN Energy Outlook (2024)	8.28
LAO	Hydropower	8th ASEAN Energy Outlook (2024)	10.50
PHL	Hydropower	8th ASEAN Energy Outlook (2024)	11.04
VNM	Offshore Wind	8th ASEAN Energy Outlook (2024)	44.92
IDN	Onshore Wind	USAID (2020)	25.00
VNM	Onshore Wind	USAID (2020)	35.00
THA	Onshore Wind	USAID (2020)	25.00
PHL	Onshore Wind	USAID (2020)	52.50
LAO	Onshore Wind	USAID (2020)	39.00
IDN	Solar PV	USAID (2020)	18.50
LAO	Solar PV	USAID (2020)	11.00
KHM	Solar PV	USAID (2020)	16.00
VNM	Solar PV	USAID (2020)	24.60
PHL	Solar PV	USAID (2020)	13.50
MYS	Solar PV	USAID (2020)	5.90
MMR	Solar PV	USAID (2020)	5.00

Notes: Fixed O&M costs for Hydropower and Offshore Wind are sourced from the *8th ASEAN Energy Outlook* (2024). Solar PV and Onshore Wind costs are sourced from *USAID* (2020) and are already annualised.

For FOMC, a clear cost hierarchy emerges: hydropower has the lowest annualised fixed O&M costs, followed by solar PV, while wind technologies (both onshore and offshore) are the most expensive. Wind also exhibits the greatest cross-country variation, with Thailand (25 USD/MWh) and Indonesia (25 USD/MWh) recording the lowest costs and the Philippines (onshore wind) standing out as a high-cost outlier (52.5 USD/MWh), exceeding even Vietnam's offshore wind (44.9 USD/MWh). Hydropower costs remain consistently low across the region, particularly in Malaysia (5.66 USD/MWh) and Myanmar (5.98 USD/MWh), followed closely by Indonesia (6.33 USD/MWh). Solar PV remains relatively cost-efficient overall, though variation persists, with Myanmar (5 USD/MWh) and Malaysia (5.9 USD/MWh) at the lower end and Vietnam (24.6 USD/MWh) recording the highest costs despite its leadership in deployment [3, 71].

Table A.5: LCOE distribution by country and technology based on varying CAPEX values (USD/kWh)

Country	**Technology**	**Mean**	**Median**	**P25**	**P75**	**Min**	**Max**
IDN	Hydropower	0.0480	0.0366	0.0316	0.0464	0.0188	0.1549
KHM	Hydropower	0.0572	0.0569	0.0517	0.0625	0.0480	0.0670
LAO	Hydropower	0.0639	0.0655	0.0552	0.0736	0.0288	0.0926
MMR	Hydropower	0.0526	0.0526	0.0423	0.0629	0.0321	0.0732
MYS	Hydropower	0.0442	0.0454	0.0352	0.0544	0.0275	0.0585
PHL	Hydropower	0.0771	0.0766	0.0571	0.0944	0.0304	0.1411
VNM	Hydropower	0.0485	0.0515	0.0413	0.0551	0.0328	0.0612
VNM	Offshore wind	0.1804	0.1719	0.1579	0.1866	0.1077	0.3839
IDN	Onshore wind	0.0825	0.0837	0.0811	0.0845	0.0786	0.0854
LAO	Onshore wind	0.1546	0.1546	0.1546	0.1546	0.1546	0.1546
PHL	Onshore wind	0.1426	0.1477	0.1243	0.1649	0.1059	0.1695
THA	Onshore wind	0.1306	0.1306	0.1306	0.1306	0.1306	0.1306
VNM	Onshore wind	0.1141	0.1112	0.0981	0.1268	0.0708	0.1609
IDN	Solar PV	0.0670	0.0670	0.0620	0.0719	0.0571	0.0769
KHM	Solar PV	0.0852	0.0831	0.0813	0.0848	0.0750	0.1041
LAO	Solar PV	0.0800	0.0800	0.0800	0.0800	0.0800	0.0800
MMR	Solar PV	0.1657	0.1565	0.1555	0.1778	0.1555	0.1832
MYS	Solar PV	0.1148	0.1125	0.1065	0.1179	0.0472	0.1950
PHL	Solar PV	0.0955	0.0932	0.0702	0.0980	0.0161	0.4931
VNM	Solar PV	0.0891	0.0907	0.0841	0.0949	0.0653	0.1089

Note: LCOE was calculated separately for each CAPEX summary statistic figure.

Table A.6: Average LCOE by Time Period

Period	Country	Technology	LCOE (USD/kWh)
2009–2015	IDN	Hydropower	0.064707
2009–2015	KHM	Hydropower	0.050432
2009–2015	LAO	Hydropower	0.065092
2009–2015	MYS	Hydropower	0.032616

Continued on next page

Table A.6 – continued

Period	Country	Technology	LCOE (USD/kWh)
2009–2015	PHL	Hydropower	0.114864
2009–2015	VNM	Hydropower	0.050295
2009–2015	VNM	Offshore wind	0.285667
2009–2015	PHL	Onshore wind	0.160395
2009–2015	THA	Onshore wind	0.130558
2009–2015	VNM	Onshore wind	0.138670
2009–2015	MYS	Solar PV	0.194898
2009–2015	PHL	Solar PV	0.204704
2016–2020	IDN	Hydropower	0.040425
2016–2020	LAO	Hydropower	0.059126
2016–2020	PHL	Hydropower	0.074696
2016–2020	VNM	Hydropower	0.050463
2016–2020	VNM	Offshore wind	0.174312
2016–2020	IDN	Onshore wind	0.084536
2016–2020	VNM	Onshore wind	0.108660
2016–2020	KHM	Solar PV	0.086332
2016–2020	MMR	Solar PV	0.180518
2016–2020	MYS	Solar PV	0.112073
2016–2020	PHL	Solar PV	0.089864
2016–2020	VNM	Solar PV	0.091140
2021–2025	IDN	Hydropower	0.038678
2021–2025	KHM	Hydropower	0.063984
2021–2025	LAO	Hydropower	0.079639
2021–2025	MMR	Hydropower	0.052609
2021–2025	MYS	Hydropower	0.055795
2021–2025	PHL	Hydropower	0.067291
2021–2025	VNM	Hydropower	0.033868
2021–2025	VNM	Offshore wind	0.152345

Continued on next page

Table A.6 – continued

Period	Country	Technology	LCOE (USD/kWh)
2021–2025	IDN	Onshore wind	0.078568
2021–2025	LAO	Onshore wind	0.154635
2021–2025	PHL	Onshore wind	0.115872
2021–2025	VNM	Onshore wind	0.116012
2021–2025	IDN	Solar PV	0.066972
2021–2025	KHM	Solar PV	0.083047
2021–2025	LAO	Solar PV	0.080006
2021–2025	MMR	Solar PV	0.155825
2021–2025	MYS	Solar PV	0.090709
2021–2025	PHL	Solar PV	0.084361
2021–2025	VNM	Solar PV	0.078606

Table A.7: Economy Groupings by Clean Energy Technology

Group	**Economies**
Solar PV	
EMDE	BRA, CHL, CHN, IND, MEX, POL, SAU, TUR, ZAF
AE	AUS, CAN, DEU, ESP, FRA, GBR, GRC, ITA, JPN, KOR, NLD, PRT, USA
Onshore Wind	
EMDE	ARG, BRA, CHL, CHN, DOM, EGY, IND, MAR, MEX, PER, POL, RUS, TUR
AE	AUS, AUT, CAN, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, JPN, KOR, NLD, NZL, SWE, USA

Note: EMDE stands for Emerging Market and Developing Economies; AE stands for Advanced Economies. Regional classifications follow the IMF standards.

Source: Authors' compilation based on IMF.

Table A.8: Economic Policy Instrument Classification

Revenue	
Funds to sub-national governments	Feed-in tariffs or premiums
Infrastructure investments	Grants and subsidies
Procurement rules	Loans
RD&D funding	Net metering
Tax relief	Tendering schemes
Retirement premium	
Cost	
CO2 taxes	White certificates
Energy and other taxes	Green certificates
User charges	GHG emissions allowances
GHG emission reduction crediting and offsetting mechanism	

Note: Policies categorised generally as "Fiscal or financial incentives" without a specific instrument designation in the database—such as CO2 taxes, energy taxes, or user charges—are reclassified under "Economic Policy Instrument - Others".

Source: Authors' compilation based on [75, 93]

Table A.9: Classification of Renewable Energy Technologies and HS Codes

HS2022	**HS1996**	**Product Group**	**Description**
Solar PV			
854143	854140	Solar PV modules / panels	Photovoltaic cells assembled in modules or made up into panels
854142	854140	Solar PV cells	Photovoltaic cells not assembled in modules or made up into panels
381800		Silicon wafers	Chemical elements and compounds doped for use in electronics... (discs, wafers, cylinders)
280461		Polysilicon	Silicon containing $\geq$ 99,99% by weight of silicon
280469		Polysilicon	Silicon containing 99,99% by weight of silicon
8507		Energy storage batteries	Electric accumulators, incl. separators therefor, whether or not square or rectangular
850440		Solar inverters	Electrical static converters
8544		High-voltage power cables	Insulated "incl. enamelled or anodised" wire, cable "incl. coaxial cable"
902830		Control systems	Electricity supply or production meters, incl. calibrating meters therefor
903031		Control systems	Multimeters for voltage, current, resistance or electrical power, without recording device
903032	903083	Control systems	Multimeters with recording device
903082		Control systems	Instruments and apparatus for measuring or checking semiconductor wafers or devices

Continued on next page

HS2022	HS1996	Product Group	Description
903289		Smart-grid technologies	Regulating or controlling instruments and apparatus (excl. hydraulic or pneumatic)
841912	841919	Solar powered equipment	Solar water heaters
850239		Solar powered equipment	Solar powered appliances and equipment: solar power electric generating sets
Wind			
850231		Nacelles; Generator	Generating sets, wind-powered
848340		Gearbox	Gears and gearing for machinery; ball or roller screws; gear boxes
850440		Power converter	Static converters
8537		Control systems	Boards, panels, consoles, desks, cabinets and other bases, equipped with two or more apparatus
9032		Control systems	Regulating or controlling instruments and apparatus (excl. taps, cocks and valves)
841280		Rotor	Engines and motors (excl. steam turbines, internal combustion piston engines)
841290		Rotor; Hubs; Blades	Parts of non-electrical engines and motors, n.e.s.
732599		Hubs	Cast articles of iron or steel, n.e.s. (excl. articles of non-malleable cast iron)
730820		Towers	Towers and lattice masts, of iron or steel
8504		Transformers	Electrical transformers, static converters, e.g. rectifiers, and inductors; parts thereof
8544		High-voltage power cables	Insulated "incl. enamelled or anodised" wire, cable "incl. coaxial cable"
853710		Electrical equipment	Boards, cabinets and similar combinations of apparatus for electric control
902830		Electrical equipment	Electricity supply or production meters, incl. calibrating meters therefor

Note: HS1996 column is left blank where it matches the HS2022 code. However, there are some HS codes only available in the 2022 version, meaning that these products lack historical trade flows and tariff schedules prior to the nomenclature update. To maintain temporal consistency, we performed a concordance mapping between the 2022 and 1996 HS versions. For example, for HS codes of solar PV cells and panels, the WTO's product list only captures "854142" and "854143" under HS2022. To source data before 2022, we use "854140", the code for solar PV cells and modules in the 1996 version of the HS codes.

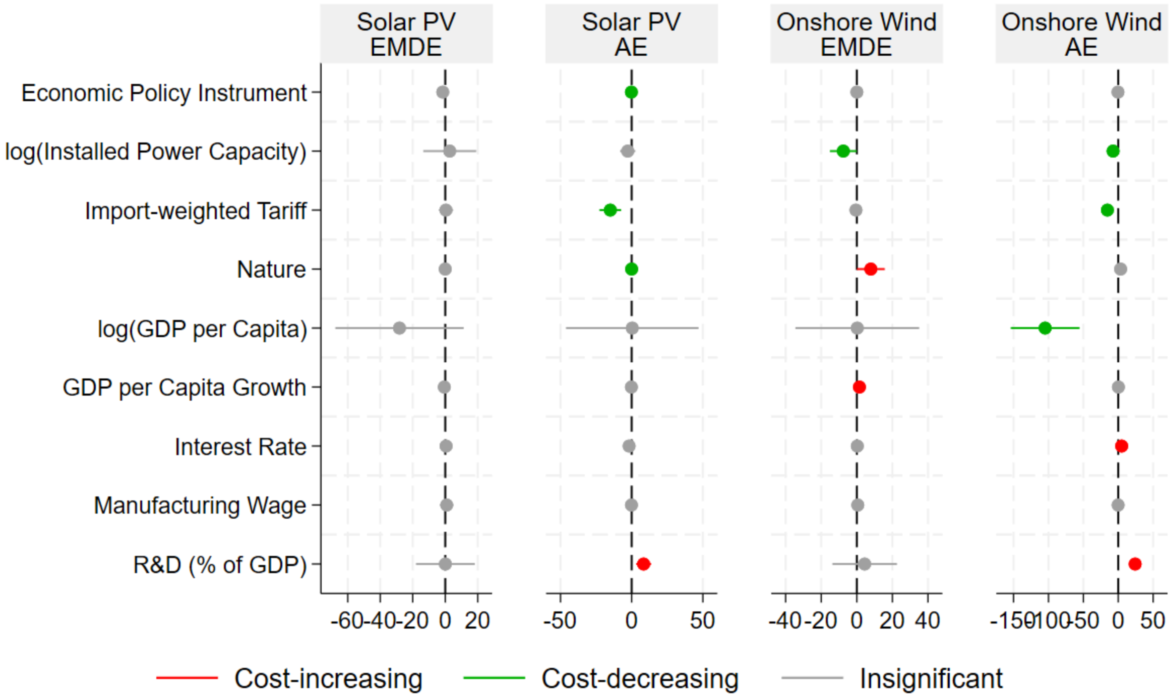
Source: Author's compilation based on World Trade Organization (WTO) [49]

Table A.10: Details of Indonesia's Local Content Requirements (August 2024 Onwards)

Technology	**Capacity/Type**	**Rate of Local Content Requirements**	**Coverage of Products and Services**
Solar	All Capacities	20%	Solar modules, inverters, mounting structure, cables, balance of system (batteries, distribution panels, etc.), protection systems, interconnection, consultancy (FS, DED, survey), EPC services, and supporting services.
Geothermal	≤ 60 MW >60 MW Partial Project	24% 29% 20%	Civil work, well drilling, fluid collection and reinjection systems, power plant, interconnection, survey services, consultancy (FS, FEED), EPC services, testing, and certification.
Hydropower	≤ 10 MW 10–50 MW >50 MW	45% 35% 23%	Civil works, metalwork, electro-mechanical, electrical, instrumentation and control, interconnection, consultancy (FS, DED, survey), EPC services, and supporting services (permits, testing, inspection).
Wind	All Capacities	15%	Civil works, metalwork, electro-mechanical, electrical, instrumentation and control, balance of system (batteries, transformers, etc.), interconnection, consultancy (FS, DED, survey), EPC services, and supporting services.
Biomass Biogas Waste	All Capacities All Capacities All Capacities	21% 25.19% 16.53%	Direct materials and equipment (boilers, gensets, pumps, etc.), project management and engineering, tools and work facilities, construction and fabrication costs, and general services (insurance, licenses, O&M spares).

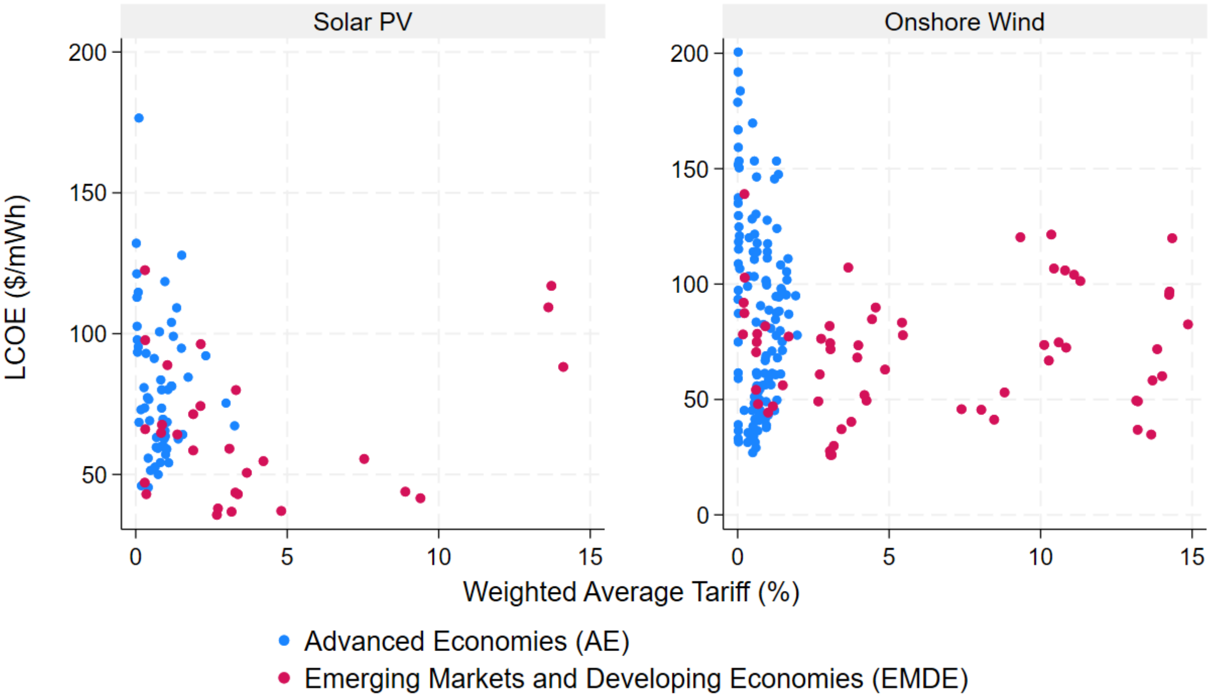
Source: Authors' compilations based on [84].

Figure A.1: Subsample Result



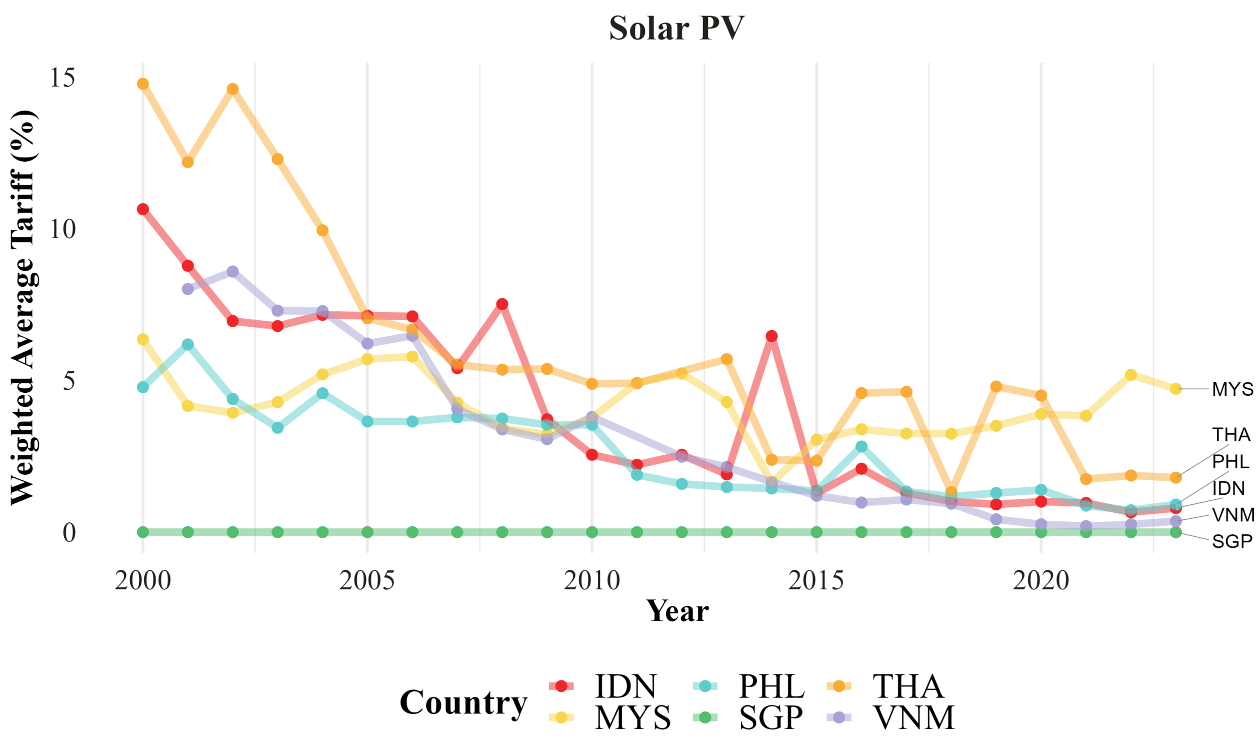
Note: EMDE - Emerging Market and Developing Economies; AE - Advanced Economies. The regressions have controlled for year fixed effects. The group classification is sourced from the International Monetary Fund (IMF) [47]. For EMDE, there are 29 and 62 observations for solar PV and onshore wind models, respectively. For AE, there are 61 and 131 observations for solar PV and onshore wind models, respectively. The spikes represent 90% confidence intervals.

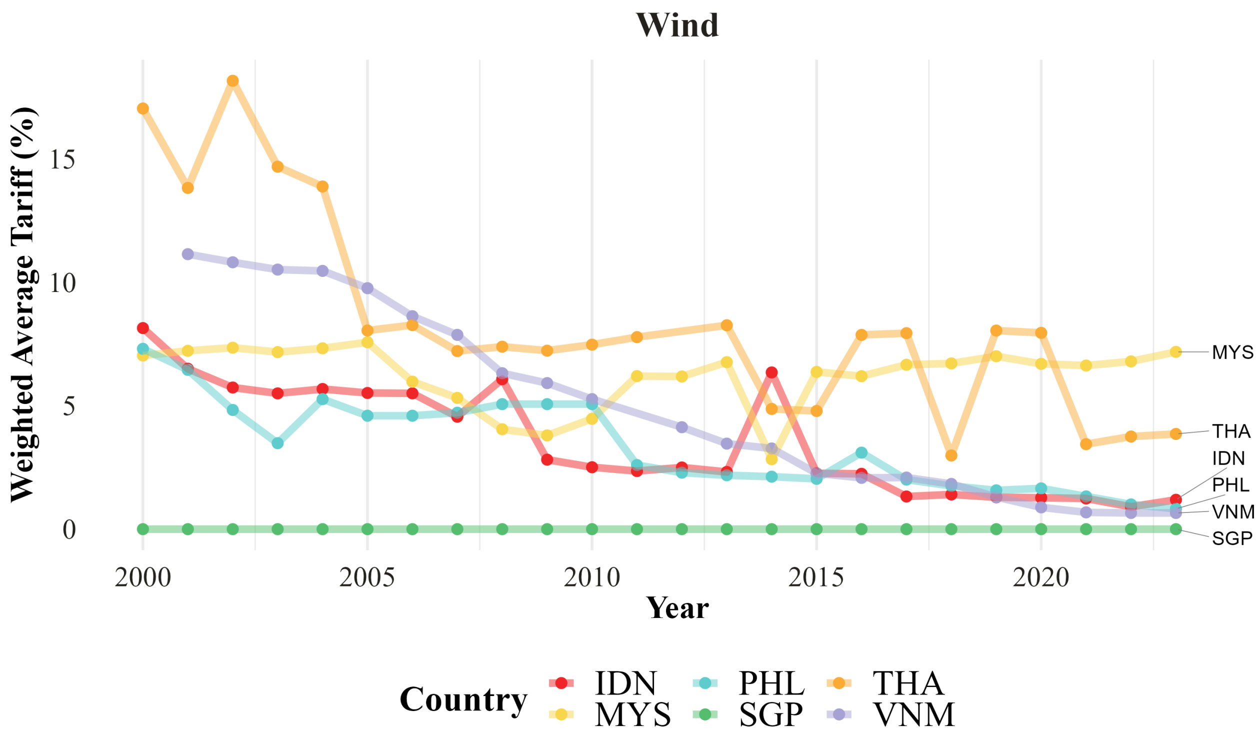
Figure A.2: Correlation Between Tariff and LCOE, by Country Group



Source: LCOE data is sourced from IRENA [60]. Tariff data is computed using HS codes from WTO [49] and Tariff Rates and Import Value from World Integrated Trade Solution (WITS) [142].

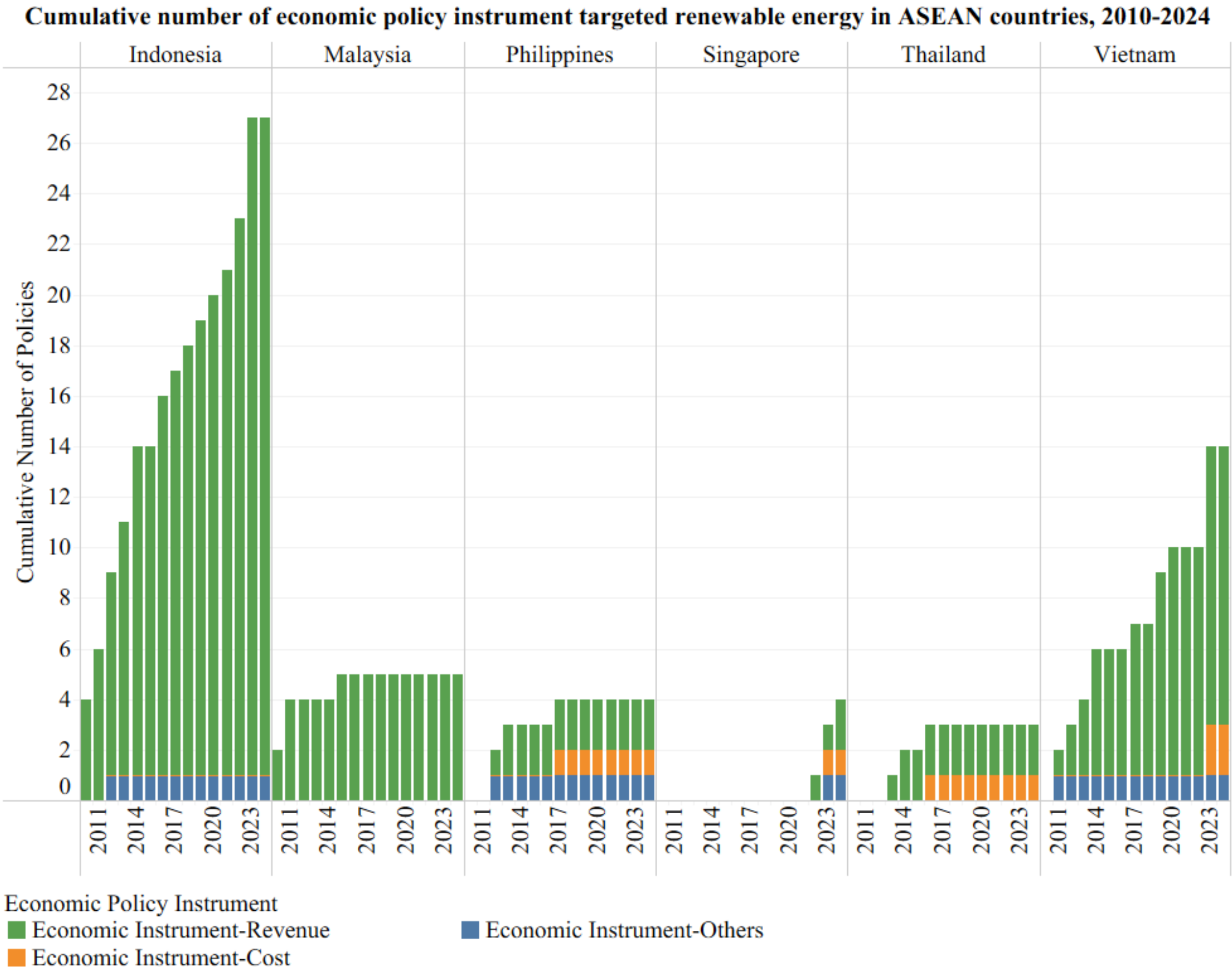
Figure A.3: Import-Weighted Tariff Rate of Six ASEAN Countries by Renewable Energy Technology





Source: Tariff data is computed using HS codes from WTO [49] and Tariff Rates and Import Value from World Integrated Trade Solution (WITS) [142]. For visualisation clarity, only countries with available CECCI results (see Section 4.4) are shown here.

Figure A.4: Cumulative Number of Economic Policy Instruments Targeting Renewable Energy in ASEAN Countries, 2010–2024



Source: Authors' calculation based on Climate Policy Database.

Figure A.5: Average CAPEX Per MW by Technology and Year in Indonesia

Note: Average CAPEX per MW was calculated using a two-step process: first, by deriving the CAPEX/MW ratio at the project level, and second, by calculating the mean of those ratios for each technology-year grouping. This chart only includes the technology subject to local content requirements in the respective countries. Only the projects with data available for total value, size and construction start year are included in the calculation.

Source: Authors' creation based on BMI Database.