Journal of Applied Economics in Developing Countries
P-ISSN 2354 – 6417 | E-ISSN 2685 – 7448
Vol. 11 No. 1, March, 2026, Page 23-29

THE CAPACITY MULTIPLIER EFFECT IN ASEAN'S ENERGY TRANSITION: HYDROPOWER, SOLAR, AND BIOENERGY DYNAMICS

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ARTICLE INFO

Article history
Received : 30 October 2025
Revised : 27 February 2026
Accepted : 4 March 2026

Keywords
ASEAN; bioenergy; capacity multiplier; energy transition; renewable

JEL classification
Q42, Q48, C23

ABSTRACT

This study examines the structural associations and comparative capacity multipliers of specific renewable technologies hydropower, solar energy, and bioenergy on the total installed renewable energy capacity in four key ASEAN countries: Indonesia, Malaysia, the Philippines, and Thailand, over the 2015–2024 period. Addressing empirical gaps in the literature on energy mix diversification, this research employs a Fixed Effects Model (FEM) using panel data from the International Renewable Energy Agency (IRENA) to control for unobserved country-specific heterogeneity. To overcome the mechanical accounting identity inherent in regressing an aggregate against its components, this study interprets the estimated coefficients as infrastructural spillover effects rather than strict causal generation outputs. The findings indicate that while all three technologies are positively associated with aggregate capacity expansion, their relative structural impacts differ significantly. Bioenergy exhibits the highest capacity multiplier (1.51), highlighting its critical role in providing dispatchable grid flexibility that accommodates further renewable integration. Hydropower (1.18) serves as a stabilizing baseload anchor, while solar energy (1.05) acts as a highly elastic, near-proportional additive component. Academically, this study refines the econometric understanding of renewable energy expansion in developing economies by quantifying these specific technological synergies. Practically, the findings offer suggestive policy guidance for optimizing capacity investments and grid diversification to support a resilient energy transition toward the region's Net-Zero Emissions targets.

1. INTRODUCTION

Energy transformation is a comprehensive process within energy production, distribution, and consumption systems, shifting from fossil fuel dependence to sustainable energy systems. According to Sorrell (2018), this transformation represents a long-term structural shift aimed at reducing carbon emissions, increasing energy efficiency, and strengthening national energy security.

In Southeast Asia, this transformation has become a strategic agenda to achieve sustainable and low-carbon development. This process involves not only technological innovations but also profound economic and institutional restructuring. Geels et al. (2017), through the Multi-Level Perspective, explain that transformation occurs through the interaction between technological niches, established regimes, and external landscape pressures.

Global decarbonization is driving ASEAN countries to accelerate the integration of renewable energy into national electricity systems. According to IRENA (2023), by the end of 2022, ASEAN's installed renewable capacity reached 102.2 GW. Four key nations Indonesia, Malaysia, the Philippines, and Thailand account for over 75% of this regional capacity. Historically, hydropower has served as the dominant, mature baseload technology (IHA, 2020; Kaunda et al., 2012). However, recent policy-driven investment patterns and declining Levelized Costs of Energy (LCOE) have catalyzed rapid structural shifts within the energy mix, particularly accelerating solar photovoltaic (PV) and bioenergy deployment (IEA, 2020, 2021).

Despite extensive literature on the macroeconomic determinants of renewable energy expansion, there is a significant empirical gap regarding how specific technological deployments interact with the broader energy portfolio. Previous studies often regress aggregate renewable capacity against macroeconomic variables (e.g., GDP, CO2 emissions). However, analyzing the internal structural dynamics specifically, how the expansion of one technology acts as a catalyst for overall portfolio growth remains underexplored.

This study positions itself within the empirical literature on energy mix diversification by investigating the marginal contributions and multiplier effects of specific technologies hydropower, solar energy, and bioenergy on the total renewable capacity expansion. We argue that regressing total capacity on its specific components in this context goes beyond a simple accounting identity. Because integrating different renewable technologies requires varying degrees of grid adaptation, storage investments, and policy support, adding 1 MW of a specific technology does not merely add 1 MW to the total in a vacuum; it generates distinct marginal spillover effects on the broader energy infrastructure (Llamosas & Sovacool, 2021).

Understanding these marginal contributions is economically crucial. It reveals which technologies drive the most efficient structural transformation within the renewable sector. Hydropower requires massive capital and long lead times but provides stabilizing baseloads. Solar energy offers modular growth but requires grid flexibility. Bioenergy provides dispatchable flexibility that can enhance overall system resilience (Twidell, 2021; Zhang et al., 2022). By estimating these specific capacity expansion patterns, this study provides a novel empirical perspective on how developing ASEAN nations optimize their investments.

We hypothesize that each technology exhibits a distinct multiplier effect on the total renewable capacity portfolio based on its technical and economic characteristics:
(H1) Hydropower capacity expansion has a significant positive marginal effect, acting as a stabilizing baseload that facilitates broader renewable integration.
(H2) Solar energy capacity exhibits a direct, nearly proportional positive effect on the total portfolio, driven by rapid, modular scalability.
(H3) Bioenergy capacity yields the highest marginal expansion effect (multiplier) on the total renewable portfolio, as its dispatchable nature provides critical grid flexibility that accommodates further renewable deployment.

This study aims to test these comparative dynamics to formulate targeted policy recommendations for optimizing ASEAN's renewable energy investments, supporting a more resilient and equitable energy system toward the 2050 Net-Zero Emissions target.

2. RESEARCH METHODS

This study employs a quantitative explanatory approach using a static panel data design to assess the structural associations and multiplier effects of installed capacities of hydropower, solar energy, and bioenergy on the total renewable energy portfolio in four key ASEAN countries (Indonesia, Malaysia, the Philippines, and Thailand) over the 2015–2024 period. Secondary data were collected from the official database of the International Renewable Energy Agency (IRENA, 2023), where annual statistics on installed capacity were downloaded in panel format according to standard panel data management guidelines (Baltagi, 2008). Each observation is indexed by country i and year t, creating a suitable panel structure for longitudinal and cross-sectional analysis. The analysis begins with descriptive statistics mean, standard deviation, minimum, and maximum values to understand the distribution patterns and historical trends of the variables (Gujarati, 2012). To examine the contemporaneous structural relationship between the specific technologies and the total renewable portfolio, the baseline static model specification is formulated as follows:

$$RenewableEnergy_{it} = \propto_i + \beta_1 Hydropower_{it} + \beta_2 SolarEnergy_{it} + \beta_3 Bioenergy_{it} + \varepsilon \ldots\ldots (1)$$

Where $RenewableEnergy_{it}$ is the total installed renewable capacity, α_i represents unobserved time-invariant country-specific fixed effects (such as geographic potential or enduring institutional frameworks), and ϵ_{it} is the idiosyncratic error component (Baltagi, 2008). Prior to estimation, classical assumption tests are conducted to ensure the reliability of the baseline estimators. Residual normality is tested using the Jarque-Bera test, heteroskedasticity is examined with the Breusch-Pagan test, and standard multicollinearity is assessed through the Variance Inflation Factor (VIF) (Gujarati, 2012). Panel model selection is formally conducted by estimating Pooled OLS, the Random Effects Model (Remya), and the Fixed Effects Model (FEM). The Chow test is used to compare Pooled OLS and FEM, while the Hausman test evaluates REM versus FEM. Based on the formal diagnostic tests, FEM is selected to control for cross-country unobserved heterogeneity.

It is important to contextualize the methodological boundaries of this study. Renewable energy capacity inherently evolves cumulatively and may exhibit path-dependent trending behavior. However, this study specifically utilizes a static Fixed Effects Model to isolate the contemporaneous structural synergies (capacity multiplier effects) rather than dynamic causal forecasting.

Due to the relatively short temporal dimension (T=10) and small cross-section (N=4) of the panel, advanced econometric diagnostics such as panel unit root tests, tests for cross-sectional dependence, or dynamic panel estimators (e.g., Generalized Method of Moments / GMM) often suffer from low statistical power and reliability (Wooldridge, 2010). Furthermore, while global technological progress inevitably affects all nations, explicit inclusion of time-fixed effects risks over-parameterizing this small macroeconomic panel.

Therefore, to avoid mechanical or tautological interpretation, the estimated coefficients (β_1, β_2, β_3) are interpreted cautiously. Rather than representing strict causal effects ("each additional 1 MW leads to X MW increase"), the coefficients are interpreted as structural capacity multipliers. They capture how the strategic deployment of 1 MW of a specific technology correlates contemporaneously with the expansion and integration capacity of the broader national renewable portfolio, accounting for unobserved country-level characteristics.

3. RESULTS AND DISCUSSION

Descriptive Statistics

Prior to conducting further panel data analysis, descriptive statistics were processed to provide an overview of the distribution and basic characteristics of the variables used. The following table summarizes the mean, standard deviation, minimum, and maximum values for each variable related to installed capacity and renewable energy production during the 2015–2024 period in four ASEAN countries (Boyle, 2024).

The descriptive statistics indicate that the average installed capacity of renewable energy reached 9,426.68 MW, with a fluctuation of ±2,208.92 MW across 40 observations, and a range spanning from a minimum of 5,698 MW to a maximum of 14,295 MW. Hydropower is the dominant component, with an average capacity of 4,606.68 MW and a standard deviation of 1,597.43 MW. Solar Energy and Bioenergy followed with averages of 1,397.03 MW (±1,127.50 MW) and 1,989.73 MW (±1,479.89 MW), respectively.

The wide range of values highlights significant variation across years and countries: hydropower capacity ranged from 2,878 MW to 7,225 MW, while solar energy showed dramatic growth from an initial adoption of 68 MW to a peak of 3,384 MW. Bioenergy also exhibited volatility, ranging from 295 MW to 4,683 MW. Overall, while hydropower remains dominant, the more dynamic growth of solar and bioenergy suggests strong future potential, yet requiring strategies for integration and supply stabilization (Twidell, 2021).

Classical Assumption Tests

Prior to regression estimation, three classical assumption tests were conducted to ensure the validity and reliability of the OLS model. First, the normality test yielded a p-value of 0.6808, which exceeds the 0.05 threshold, confirming that the residuals are normally distributed and that statistical inference through t-tests and F-tests remains valid (Gujarati, 2012). Second, the multicollinearity test revealed that all absolute correlation coefficients among the independent variables — hydropower, solar energy, and bioenergy — fall below 0.80, indicating the absence of serious multicollinearity among the predictors (Wooldridge, 2010). Third, the heteroskedasticity test based on the Breusch-Pagan approach showed that all probability values for the constant and independent variable coefficients exceed 0.05, leading to a failure to reject the null hypothesis of homoskedasticity. This confirms that the residual variance remains constant across observations, ensuring the efficiency of OLS estimators and the accuracy of significance tests (Gujarati, 2012). Collectively, all three assumptions are satisfied, validating the use of OLS regression for further analysis.

Panel Data Model Estimation

Before estimating the panel data model, two specification tests were conducted to determine the most appropriate model. The Chow Test was performed to compare the Common Effefct Model (CEM) with the Fixed Effects Model (FEM), while the Hausman Test was used to compare the Random Effects Model (REM) with FEM (Wooldridge, 2010).

The Chow Test produced a Cross-section Chi-square statistic of 122.073 with a probability of 0.0000, which falls below the 0.05 significance level. This leads to the rejection of the null hypothesis of no cross-sectional fixed effects, indicating that FEM is preferred over CEM. Subsequently, the Hausman Test yielded a Chi-square statistic of 665.080 with an equally significant probability of 0.0000, rejecting the null hypothesis that REM coefficients are consistent, and thus confirming FEM as superior to REM. Therefore, the FEM was selected for subsequent estimations, as it effectively controls for unobserved country-specific heterogeneity and produces more reliable coefficient estimates (Gujarati, 2012).

Fixed Effects Model (FEM) Results

Based on the FEM estimation results on the Table 1, hypothesis testing is conducted by reviewing the coefficient values and p-values of each variable. The following table summarizes the hypothesis testing results:

Table 1. Fixed Effects Model Results

Hypothesis	Variable	Coefficient	Prob.	Decision
H1	Hydropower	1.1798	0.0000	Accepted
H2	Solar Energy	1.0537	0.0000	Accepted
H3	Bioenergy	1.5078	0.0000	Accepted

Source: Processed Data (2025)

All hypotheses (H1–H3) are accepted at the 1% significance level, with p-values of 0.0000 for Hydropower, Solar Energy, and Bioenergy. Given that the dependent variable (Total Renewable Energy) is an aggregate that inherently includes these individual capacities, a strong positive statistical association is mechanically expected. However, the primary economic insight lies not merely in the statistical significance, but in the varying magnitudes of the estimated coefficients, which reflect distinct capacity multiplier effects within the panel structure. The coefficient of 1.1798 for Hydropower suggests that each additional 1 MW of hydro capacity is structurally associated with a 1.18 MW expansion in the total renewable portfolio. Solar Energy exhibits a coefficient of 1.0537, implying a nearly proportional (1:1) additive relationship, where 1 MW of solar capacity is associated with approximately 1.05 MW of total portfolio growth. Most notably, Bioenergy demonstrates the highest structural multiplier with a coefficient of 1.5078, indicating that 1 MW of bioenergy capacity is associated with a 1.51 MW expansion in the broader renewable energy mix. These coefficients do not represent direct causal generation output, but rather capture the structural spillover effects and grid-integration dynamics of each technology across the four nations.

The Methodological Caveats and Economic Interpretation

Before delving into specific technologies, it is crucial to address the econometric nature of these findings. The fixed-effects coefficients (>1) reflect statistical associations within the panel structure rather than isolated causal expansions. Because total renewable capacity mechanically aggregates its components, the baseline correlation is inherently strong. However, the fact that the coefficients significantly diverge from a strict 1.0 accounting identity (e.g., Bioenergy at 1.51 vs. Solar at 1.05) reveals important economic mechanisms. These estimates act as proxy elasticities of capacity integration. A coefficient greater than one suggests that investing in a specific technology particularly dispatchable ones like bioenergy catalyzes complementary infrastructural upgrades, grid flexibility improvements, or policy momentum that accommodates further renewable adoption. While the FEM robustly controls for country-specific intercepts (baseline potentials), these average slopes provide a unified regional perspective on structural diversification.

The Multiplier Role of Hydropower

The hydropower multiplier of 1.18 reflects its economic role as a stabilizing baseload anchor. Large-scale hydropower development requires massive, long-term capital investments and extensive transmission grid upgrades (IHA, 2020). From an economic standpoint, once this heavy grid infrastructure is established, it lowers the marginal cost of integrating other, smaller renewable projects nearby. Descriptively, this dynamic is highly evident in countries like Indonesia and Malaysia. Malaysia's massive hydropower dams in Sarawak, for instance, not only provide the bulk of its renewable baseload but also create an infrastructural backbone that supports regional industrial growth. Similarly, Indonesia's reliance on hydro to power its outside-Java grids demonstrates how baseload stability serves as a prerequisite for broader energy transition (Llamosas & Sovacool, 2021).

The Additive Nature of Solar Energy

The solar energy coefficient of 1.05 indicates a highly elastic, near-proportional relationship to the total mix. Economically, this reflects the modular, decentralized nature of solar PV. The dramatic decline in the Levelized Cost of Energy (LCOE) allows solar to be deployed rapidly without requiring the massive, centralized grid overhauls needed by hydropower (REN21, 2020). Consequently, its spillover multiplier is lower (closer to 1), acting more as a direct additive component. Country-level trends strongly support this: Thailand and the Philippines have historically led the region in solar adoption, driven by aggressive feed-in tariffs, net-metering policies, and private-sector rooftop installations (IRENA, 2023). In these nations, solar drives rapid capacity volume, but its intermittent nature means it relies on existing grid flexibility rather than creating it.

The Synergistic Spillover of Bioenergy

The most striking economic finding is the bioenergy coefficient of 1.51. This high multiplier indicates that bioenergy investments create the strongest positive spillover effect on the total renewable portfolio. Unlike intermittent solar, bioenergy is highly dispatchable, meaning it can be ramped up or down to balance grid fluctuations (Brauns & Turek, 2020). By providing this critical system flexibility, bioenergy investments technically and economically "de-risk" the grid, allowing the system to safely integrate more intermittent sources like wind or solar.

Furthermore, the high coefficient captures a unique Southeast Asian economic advantage: the utilization of established agricultural supply chains. In Indonesia and Malaysia, bioenergy expansion is deeply integrated with palm oil waste (POME), while in Thailand, it is linked to the sugarcane industry. By leveraging existing agricultural infrastructure rather than building entirely new supply chains, bioenergy offers an highly capital-efficient pathway to diversify the energy mix, creating profound multiplier effects for rural economies and the broader renewable portfolio (Demirbaş, 2001; Zhang et al., 2022).

4. CONCLUSION

This study aimed to examine the structural associations and comparative capacity multipliers of Hydropower, Solar Energy, and Bioenergy within the total renewable energy portfolios of four key Southeast Asian nations—Indonesia, Malaysia, the Philippines, and Thailand over the 2015–2024 period. Using a Fixed Effects Model (FEM), the analysis reveals strong, statistically significant positive correlations between the expansion of these specific technologies and the aggregate renewable capacity. Rather than strict causal determinants, the estimated coefficients 1.18 for Hydropower, 1.05 for Solar Energy, and 1.51 for Bioenergy are best understood as structural capacity multipliers. They illustrate how specific technologies synergize within the broader grid: Hydropower acts as a stabilizing baseload anchor, Solar Energy serves as a rapidly scalable additive component, and Bioenergy provides crucial dispatchable flexibility that yields the highest multiplier effect on the overall portfolio. These empirical associations offer suggestive, rather than definitive, policy implications for ASEAN's energy transition. The findings imply that a balanced diversification strategy is essential. Policymakers might consider sustaining strategic investments in large-scale hydropower to secure long-term grid stability, while simultaneously leveraging targeted fiscal incentives to accelerate modular solar adoption. Most notably, capitalizing on the region's abundant agricultural waste to expand bioenergy infrastructure could provide the flexible grid integration necessary to accommodate higher shares of intermittent renewables, thereby accelerating progress toward the 2050 Net-Zero Emissions target.

However, these findings must be interpreted in light of several methodological limitations. First, the dependent variable is an aggregate that mechanically includes the independent variables, inherently generating strong statistical correlations. Thus, the results highlight structural synergies rather than isolated causal expansions. Second, the reliance on a static panel over a relatively short time horizon (T=10) and a small cross-section (N=4) restricts the ability to address dynamic path-dependency and potential endogeneity. Global macroeconomic trends and simultaneous technological advancements may also act as unobserved confounding factors. Future research should aim to overcome these constraints by extending the time horizon and employing dynamic panel estimators (such as GMM) or causal identification strategies to explicitly address endogeneity. Furthermore, incorporating institutional variables such as regulatory quality, green financing availability, and cross-border grid integration policies—would provide a more comprehensive understanding of the socio-technical drivers shaping the energy transition in developing economies.

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