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Waewwan La-ongsri
Chiang Mai Rajabhat University
Nuttaphat Sukchitt
nuttaphat.s@cmu.ac.th
Chiang Mai University
Pasin Marupanthorn
Maejo University

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Asymmetric Energy-Price Shock Transmission and Electricity-Sector Carbon Transition in ASEAN: Panel NARDL and MIDAS Evidence

Waewwan La-ongsri[1†], Nuttaphat Sukchitt[2*†], Pasin Marupanthorn[3†]

[1]International College, Chiang Mai Rajabhat University, Chiang Mai, Thailand.
[2*]International College of Digital Innovation, Chiang Mai University, Chiang Mai, Thailand.
[3]Department of Mathematics, Faculty of Science, Maejo University, Chiang Mai, Thailand.

*Corresponding author(s). E-mail(s): nuttaphat.s@cmu.ac.th;
Contributing authors: waewwan_lao@g.cmru.ac.th;
quantfilab@gmail.com;
†These authors contributed equally to this work.

Abstract

This paper examines whether international energy-price shocks transmit asymmetrically to electricity-sector carbon-transition performance in ASEAN. Using an unbalanced country-year panel for ten ASEAN economies over 2000–2025, the analysis measures transition performance by the low-carbon share of electricity generation and constructs real local-currency fuel-cost pressure as the main shock variable. The empirical design combines positive and negative shock decomposition, fixed-effect panel nonlinear autoregressive distributed lag (NARDL) estimation, volatility-threshold conditioning, and country-specific rolling forecast comparisons, including mixed-data sampling (MIDAS) specifications. The results indicate statistically significant error correction and positive short-run transmission from fuel-cost increases. In the long run, however, the estimated response to fuel-cost increases and the absolute response to fuel-cost decreases are nearly identical, and the Wald test does not reject symmetry at the regional average. Threshold estimates suggest that high-volatility years may alter the negative-shock channel, although the interaction effects are imprecisely estimated. Forecast

comparisons reveal substantial heterogeneity across countries: asymmetric or mixed-frequency terms improve monitoring accuracy in several economies, but no single specification dominates the region. The findings support a cautious monitoring interpretation. Directional fuel-cost pressure, volatility states, and country-specific electricity-system structure are informative for ASEAN transition assessment, but the annual panel does not justify a causal claim that higher fossil-fuel prices directly accelerate decarbonization.

Keywords: energy transition, energy-price shocks, asymmetric transmission, panel NARDL, MIDAS, ASEAN

1 Introduction

ASEAN's electricity transition is shaped by the interaction between power-sector transformation and macro-financial exposure. Southeast Asia remains highly dependent on fossil fuels: fossil fuels have met nearly 80% of the region's growth in energy demand since 2010, and coal generated about half of regional electricity in 2023 [1]. At the same time, regional policy ambition has strengthened. The ASEAN Plan of Action for Energy Cooperation 2026–2030 sets aspirational targets of a 30% renewable-energy share in total primary energy supply, a 45% renewable-energy share in installed power capacity, and a 40% reduction in energy intensity by 2030 relative to 2005 [2]. Recent ASEAN power-sector assessments also show that clean-power progress is uneven across countries, with solar and hydropower becoming important transition drivers while fossil generation continues to absorb much of the increase in electricity demand [3]. These patterns imply that transition performance cannot be evaluated separately from the fuel-cost, exchange-rate, and policy conditions under which electricity systems adjust.

International energy-price shocks provide a natural channel through which those conditions enter transition dynamics. For import-dependent economies, an increase in Brent prices raises local-currency fuel costs through both the dollar price of oil and exchange-rate pass-through. Higher fuel costs may strengthen incentives for energy efficiency, fuel substitution, renewable procurement, and distributed generation. The same shock may also create inflationary pressure, intensify subsidy burdens, delay tariff adjustment, and reduce fiscal space for low-carbon investment. For fossil-fuel exporters, financial centers, and hydro-intensive electricity systems, the same global price movement can have different implications. A price decrease is therefore unlikely to be the exact mirror image of a price increase because administered tariffs, energy-security constraints, planning lags, subsidy rules, and investment irreversibility create asymmetric adjustment.

The energy-economics literature provides the econometric foundation for modelling such asymmetry. Oil and energy-price shocks have long been treated as macroeconomic disturbances whose effects depend on persistence, direction, and source [4]. Subsequent work shows that responses to energy-price increases and decreases should not be assumed to be symmetric [5]. The nonlinear ARDL framework of Shin et al.

[6] operationalizes this insight by decomposing price movements into positive and negative partial sums and estimating separate short-run and long-run effects. Recent transition-related applications extend this logic to renewable-energy consumption, clean-energy assets, and broader energy-transition outcomes. Murshed and Tanha [7] examine oil-price shocks and renewable-energy transition in net oil-importing South Asian economies; Mukhtarov et al. [8] show that the relationship between higher oil prices and renewable-energy consumption can be country-specific; Nchofoung [9] studies oil-price-shock effects on energy transition in Africa; and Mishra and Acharya [10] applies a panel NARDL design to renewable-energy firms' stock returns. The common message is that energy-price shocks may affect transition incentives, but the sign, horizon, and symmetry of the response are empirical questions.

ASEAN is a particularly useful setting because regional averages conceal substantial structural heterogeneity. Øverland et al. [11] describe the ASEAN climate-energy paradox: high climate vulnerability and stated transition ambition coexist with persistent fossil-fuel lock-in. Handayani et al. [12] show that moving beyond nationally determined contributions requires deep power-sector restructuring, while Vakulchuk et al. [13] identify investment climate, governance, and institutional quality as major barriers to renewable-energy deployment. More recent work emphasizes the roles of cross-border transmission, system flexibility, hydrogen, carbon capture, and regional coordination in ASEAN net-zero pathways [14–16]. These studies are central for long-run policy design, but they do not directly estimate how observed electricity-transition indicators respond to real local-currency energy-price shocks at the country-year frequency.

This paper addresses that gap by constructing an ASEAN panel analysis of asymmetric energy-price shock transmission. The dependent variable is the low-carbon share of electricity generation, measured from the OWID/Ember/Energy Institute annual energy data and cross-checked against public energy sources [17–19]. The main shock variable is real local-currency Brent exposure, combining Refinitiv Brent prices with country-level exchange-rate and consumer-price data. The ASEAN Energy Database System provides the regional energy-statistics platform, and Thailand's EPPO electricity statistics illustrate the type of higher-frequency national generation data needed for future extensions [20, 21]. The resulting design extends a Thailand-motivated setting into a regional panel with variation in energy structure, exchange-rate exposure, macroeconomic conditions, and transition performance.

The econometric strategy combines three elements. First, a fixed-effect panel NARDL model separates positive and negative energy-price shocks and recovers dynamic long-run multipliers. Second, a volatility-threshold extension allows transmission slopes to vary in energy-stress years, following the threshold-econometric logic of Hansen [22]. Third, a country-specific MIDAS forecast comparison evaluates whether monthly Refinitiv price information improves annual transition monitoring, building on the mixed-frequency regression framework of Ghysels et al. [23]. This design is consistent with climate-finance evidence that transition risk is state dependent, priced unevenly across firms and sectors, and shaped by investor preferences, policy credibility, and macro-financial conditions [24–27]. It is also consistent with mitigation evidence showing that decarbonization depends on

technology, policy, demand growth, and system constraints rather than on a single fuel-price channel [28].

The paper makes three contributions. First, it provides a transparent ASEAN country-year dataset that links electricity-sector transition performance to real local-currency energy-price exposure. Second, it estimates asymmetric short-run and long-run transmission using a panel NARDL framework and explicitly tests whether positive and negative energy-price shocks have different long-run effects. Third, it evaluates whether volatility states and mixed-frequency price information improve practical transition monitoring at the country level. The results support a cautious interpretation: energy-price pressure is relevant for monitoring ASEAN transition performance, especially in the short-run positive-shock channel, but the annual regional panel does not support a strong causal claim that fuel-price increases mechanically accelerate decarbonization.

The remainder of the paper is organized as follows. Section 2 describes the data sources, variable construction, and panel coverage. Section 3 presents the panel NARDL, volatility-threshold, and MIDAS forecasting specifications. Section 4 reports the empirical results and policy interpretation. Section 5 concludes.

2 Data and Source Construction

The empirical unit is a country-year observation for an ASEAN member state. The sample covers Brunei Darussalam, Cambodia, Indonesia, Lao PDR, Malaysia, Myanmar, the Philippines, Singapore, Thailand, and Vietnam over 2000–2025, subject to country-specific data availability. The panel is intentionally unbalanced: the electricity-transition outcome is retained whenever it is observed, while regression equations use the common support required by the lagged outcome, positive and negative shock decompositions, and macroeconomic controls. This design avoids interpolating the transition outcome and keeps the calibration tied to observed annual data.

2.1 Source hierarchy and transition outcome

The data pipeline follows a fixed source hierarchy. Annual electricity variables are taken from the OWID energy dataset, which harmonizes electricity statistics from Ember and the Energy Institute [17, 18]. These series are cross-checked with ASEAN Energy Database System documentation and, for the motivating Thailand case, EPPO electricity statistics [20, 21]. Macroeconomic variables are obtained from World Bank WDI, complemented by available Refinitiv Workspace exports for Brent prices and country FX/CPI checks [19, 29]. When Refinitiv local FX or CPI files are not available for a country, the public WDI series are used so that the regional panel can be replicated without proprietary country-level macro files.

The transition-performance variable is the low-carbon share of electricity generation,

$$y_{i,t} = 100 \times \frac{LCG_{i,t}}{EG_{i,t}}, \tag{1}$$

where $LCG_{i,t}$ denotes low-carbon electricity generation and $EG_{i,t}$ denotes total electricity generation for country i in year t. The low-carbon block includes non-fossil electricity sources recorded in the harmonized energy file, including hydro, solar, wind, nuclear, geothermal, bioenergy, and other renewable generation where reported. The variable is expressed in percentage points, so estimated coefficients measure changes in the transition share rather than changes in physical generation volume. This is important for ASEAN because country size differs sharply, while the research question concerns transition performance within each national electricity system.

Operationally, let $G_{i,t}^{k}$ denote annual electricity generation, measured in terawatt-hours, from technology k. The low-carbon numerator is classified as

$$\begin{aligned} LCG_{i,t} = G_{i,t}^{\text{hydro}} + G_{i,t}^{\text{solar}} + G_{i,t}^{\text{wind}} + G_{i,t}^{\text{nuclear}} + G_{i,t}^{\text{geothermal}} \\ + G_{i,t}^{\text{bioenergy}} + G_{i,t}^{\text{other renew.}}. \end{aligned} \tag{2}$$

Thus, low-carbon electricity is defined by generation technology, following OWID's low-carbon electricity definition [30]. In the implemented annual panel, $y_{i,t}$ is taken from OWID's low-carbon electricity share, which incorporates Ember and Energy Institute electricity statistics; the renewable electricity share is used only when the low-carbon share is unavailable. Refinitiv enters the study through Brent prices, monthly price volatility, and available FX/CPI checks.

2.2 Energy-price exposure and asymmetric shocks

The main price-pressure variable is real local-currency Brent exposure. Let Brent_t^{USD} be the annual Brent price in US dollars, $FX_{i,t}$ be local currency per US dollar, and $CPI_{i,t}$ be the consumer-price index. The nominal fuel-cost exposure is first converted into local currency and then deflated by the country-specific CPI base:

$$P_{i,t}^{E} = \frac{\text{Brent}_t^{USD} \times FX_{i,t}}{CPI_{i,t}/CPI_{i,0}}, \tag{3}$$

where $CPI_{i,0}$ is the first available CPI observation for country i. This construction captures two channels that are especially relevant for ASEAN: movements in the world oil price and exchange-rate pass-through into domestic fuel costs. Because levels differ greatly across currencies, the econometric models use log changes and cumulative partial sums rather than raw price levels.

Equation (3) should therefore be interpreted as a real local-currency exposure to the common international oil-price shock, not as a direct observation of each country's administered or retail fuel price. A fully domestic fuel-price measure would require a harmonized country-year panel of power-sector fuel input prices or retail diesel, gasoline, gas, and coal prices with consistent tax, subsidy, and tariff treatment. Such a panel is not available with balanced ASEAN coverage over 2000–2025 in the current data environment, and national retail prices may partly reflect policy smoothing rather than the external shock itself. Brent is therefore used as the common external benchmark, while $FX_{i,t}$ and $CPI_{i,t}$ convert that benchmark into country-specific

real purchasing-power terms. This choice keeps the shock variable comparable across countries and preserves the interpretation of the NARDL estimates as responses to external fuel-cost pressure.

Positive and negative energy-price shocks are constructed from annual log changes in real local-currency exposure. Define $\Delta p^{E}_{i,t}$ as the annual log change in real local-currency Brent exposure:

$$\Delta p^{E}_{i,t} = \log P^{E}_{i,t} - \log P^{E}_{i,t-1}. \tag{4}$$

For each country, the partial sums begin at the first year $t_{i,0}$ for which consecutive observations are available. In the summation below, $\Delta p^{E}_{i,s}$ is the same log-change variable evaluated in year s:

$$P^{+}_{i,t} = \sum_{s=t_{i,0}+1}^{t} \max\bigl(\Delta p^{E}_{i,s}, 0\bigr), \qquad P^{-}_{i,t} = \sum_{s=t_{i,0}+1}^{t} \min\bigl(\Delta p^{E}_{i,s}, 0\bigr). \tag{5}$$

The positive partial sum $P^{+}_{i,t}$ accumulates only fuel-cost increases, while the negative partial sum $P^{-}_{i,t}$ is non-positive and accumulates only fuel-cost decreases. This sign convention is important: a one-unit fuel-cost decrease corresponds to a negative innovation in $P^{-}_{i,t}$. The separation is central to the NARDL design because renewable investment, tariff adjustment, subsidy pressure, and fuel switching may react differently to price increases and decreases. Observations with missing CPI or exchange-rate values are not filled by interpolation.

2.3 Controls, volatility state, and mixed-frequency block

The baseline control vector $X_{i,t}$ contains inflation, exchange-rate change, and real GDP growth. Inflation captures the domestic price environment, exchange-rate change isolates currency movement beyond the constructed energy-price exposure, and GDP growth controls for business-cycle conditions that may affect electricity demand and investment. Additional WDI indicators, including renewable final-energy share, energy intensity, CO_2 intensity, and net energy-import shares, are retained for diagnostic interpretation but are not all included in the compact baseline because doing so would reduce the ASEAN sample substantially.

The threshold state is annual energy-price volatility, denoted V_t. It is computed from within-year Refinitiv monthly Brent log returns and annualized as a realized volatility measure. This common regional stress indicator is appropriate because Brent is the external price driver shared across countries, while the country-specific exposure is introduced through $FX_{i,t}$ and $CPI_{i,t}$. The MIDAS shock, $\widetilde{\Delta p}^{E}_{i,t}$, summarizes monthly Refinitiv energy-price information within an annual transition equation. When local monthly FX/CPI files exist in the Refinitiv cache, the monthly input is local-currency real Brent exposure; otherwise, the common monthly Brent return is used as a transparent high-frequency proxy.

Table 1 reports the variables, symbols, sources, frequencies, and model roles. Table 2 shows that the outcome panel contains 256 country-year observations,

with strong cross-country heterogeneity: Brunei and Singapore have low average low-carbon electricity shares, Lao PDR is hydro-intensive, and Cambodia, Myanmar, the Philippines, and Vietnam display higher but more volatile transition shares. Table 3 reports the final variable-level support used across descriptive and regression blocks. The energy-price variables have fewer observations than the transition outcome because the real local-currency exposure requires matched Brent, CPI, and exchange-rate information.

Table 1 ASEAN data sources and empirical model symbols.

Symbol	Variable	Data source	Frequency	Model role
$LCG_{i,t}$	Low-carbon electricity generation	OWID energy data incorporating Ember and Energy Institute technology-level electricity data	Annual	Numerator of transition outcome
$EG_{i,t}$	Total electricity generation	OWID energy data incorporating Ember and Energy Institute electricity data	Annual	Denominator of transition outcome
$y_{i,t}$	Low-carbon electricity share	OWID energy data incorporating Ember and Energy Institute electricity data	Annual	Transition outcome
$P^{E}_{i,t}$	Real local-currency Brent exposure	Refinitiv Brent; Refinitiv or World Bank exchange-rate and CPI series	Daily or annual to annual	Energy-price pressure
$P^{+}_{i,t}$	Cumulative positive energy-price shock	Constructed from $P^{E}_{i,t}$	Annual	Positive NARDL shock
$P^{-}_{i,t}$	Cumulative negative energy-price shock	Constructed from $P^{E}_{i,t}$	Annual	Negative NARDL shock
V_t	Energy-price volatility	Refinitiv Brent monthly returns	Monthly to annual	Threshold state
$\widetilde{\Delta p}^{E}_{i,t}$	MIDAS energy shock	Refinitiv monthly Brent and available local FX/CPI exports	Monthly to annual	Mixed-frequency forecast term
$X_{i,t}$	Macroeconomic controls	World Bank WDI and available Refinitiv local macro exports	Annual	Control vector

Table 2 ASEAN transition-performance panel coverage.

Country	Sample years	Observations	Mean ($\bar{y}_i$)	Std. dev. ($y_{i,t}$)
Brunei Darussalam	2000–2024	25	0.007	0.036
Cambodia	2000–2025	26	29.246	23.895
Indonesia	2000–2024	25	17.084	1.792
Lao PDR	2000–2024	25	87.296	13.689
Malaysia	2000–2025	26	11.718	5.365
Myanmar	2000–2024	25	54.473	11.788
Philippines	2000–2025	26	28.228	6.112
Singapore	2000–2025	26	2.958	0.882
Thailand	2000–2025	26	9.757	3.845
Vietnam	2000–2025	26	41.378	7.366

Notes: Mean ($\bar{y}_i$) is the country-specific sample average of $y_{i,t}$, the low-carbon electricity share, measured in percentage points. Std. dev. reports the within-country sample standard deviation of $y_{i,t}$ over the available years.

Table 3 ASEAN panel data summary.

Variable	Observations	Mean	Std. dev.	Minimum	Maximum
Transition performance ($y_{i,t}$)	256.000	28.035	27.305	0.000	100.000
Real local-currency Brent exposure (level, $P^E_{i,t}$)	149.000	107370.875	289181.702	0.704	1468017.108
Positive energy-price shock ($P^+_{i,t}$)	139.000	0.967	1.210	0.191	5.792
Negative energy-price shock ($P^-_{i,t}$)	139.000	-0.876	0.612	-1.966	0.000
Inflation rate (component of $X_{i,t}$)	249.000	0.037	0.077	-0.550	0.452
Exchange-rate change (component of $X_{i,t}$)	250.000	0.031	0.307	-0.135	4.768
Real GDP growth (component of $X_{i,t}$)	250.000	5.014	3.810	-12.016	14.520
Energy-price volatility (V_t)	156.000	0.076	0.033	0.032	0.165

Notes: The large scale of the real local-currency Brent exposure reflects cross-country currency units after converting the common US-dollar Brent price into domestic currency and deflating by CPI. This raw level is reported only to document the construction of $P^E_{i,t}$. The fitted NARDL equations do not use the raw level directly; they use $\Delta \log P^E_{i,t}$ and the cumulative positive and negative partial sums. No z-score standardization is applied before fitting, because the log-change transformation removes the arbitrary currency-unit scale while preserving the economic interpretation of directional fuel-cost shocks.

3 Methodology

This section presents the econometric design used to connect annual ASEAN transition outcomes with directional energy-price pressure. The purpose is to estimate transmission patterns and develop monitoring evidence, not to claim experimental causal identification. The identifying variation comes from within-country changes in real local-currency Brent exposure, from the decomposition of price movements into positive and negative partial sums, and from differences in electricity-system adjustment across ASEAN countries. Country fixed effects remove time-invariant structural differences such as geography, long-run resource endowments, and persistent institutional features. Full year effects are not imposed in the baseline because they would absorb the common Brent component that is central to the research question;

instead, the model works with local-currency real exposure and macroeconomic controls.

3.1 Pre-estimation logic and variable transformation

Let $i = 1, \ldots, N$ index ASEAN economies and let t index calendar years. The dependent variable is $y_{i,t}$, the low-carbon electricity share. The empirical equations use the annual change $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$ because transition shares are persistent and country histories are short. The energy-price exposure $P^E_{i,t}$ is first converted to log differences and then split into positive and negative movements:

$$\Delta p^E_{i,t} = \Delta \log P^E_{i,t}, \qquad z^+_{i,t} = \max(\Delta p^E_{i,t}, 0), \qquad z^-_{i,t} = \min(\Delta p^E_{i,t}, 0). \tag{6}$$

The cumulative partial sums are

$$P^+_{i,t} = \sum_{s=t_{i,0}+1}^{t} z^+_{i,s}, \qquad P^-_{i,t} = \sum_{s=t_{i,0}+1}^{t} z^-_{i,s}. \tag{7}$$

This construction follows the nonlinear ARDL logic of Shin et al. [6]: price increases and price decreases are allowed to have different short-run and long-run effects. Since $P^-_{i,t} \leq 0$, coefficient signs for the negative component must be translated carefully when interpreting an actual fuel-price decrease. The approach is appropriate for variables with mixed stationary and persistent behavior, provided the system is not dominated by second-order integration; this is consistent with the ARDL error-correction tradition of Pesaran et al. [31]. In this application, unit-root tests are therefore used as diagnostics rather than as mechanical exclusion rules.

3.2 Fixed-effect panel NARDL specification

The baseline model is a fixed-effect panel nonlinear ARDL equation in error-correction form:

$$\begin{aligned} \Delta y_{i,t} = \alpha_i + \phi y_{i,t-1} + \beta^+ P^+_{i,t-1} + \beta^- P^-_{i,t-1} + \gamma' X_{i,t-1} + \psi \Delta y_{i,t-1} \\ + \pi^+ z^+_{i,t} + \pi^- z^-_{i,t} + u_{i,t}, \end{aligned} \tag{8}$$

where α_i denotes country fixed effects and $X_{i,t-1}$ contains lagged inflation, exchange-rate change, and real GDP growth. The coefficient ϕ is the error-correction parameter. A negative and statistically significant ϕ indicates that deviations from the country-specific transition path are partly corrected in the following year. The coefficients π^+ and π^- capture immediate transmission from current positive and negative energy-price movements, while β^+ and β^- identify the level-channel effects that determine the long-run multipliers.

When $\phi < 0$, the partial-sum long-run multipliers are

$$\theta^+ = -\frac{\beta^+}{\phi}, \qquad \theta^-_P = -\frac{\beta^-}{\phi}, \qquad \theta^-_{\text{fall}} = -\theta^-_P. \tag{9}$$

Here θ^{+} is the response to a one-unit positive fuel-cost shock, θ_{P}^{-} is the coefficient attached to a one-unit increase in the negative partial-sum state, and θ_{fall}^{-} is the economically relevant response to a one-unit fuel-cost decrease. Long-run asymmetry is evaluated by a Wald restriction on equality of the absolute multiplier magnitudes, which is equivalent to testing equality of β^{+} and β^{-} when the same ϕ governs both channels. Dynamic responses are computed from the full error-correction recursion. For $q \in \{+, -\}$, let m_h^q denote the cumulative multiplier at horizon h, let d_h^q denote the one-period change in that multiplier, and let $s_+ = 1$ and $s_- = -1$ denote a positive fuel-cost shock and an actual fuel-cost decrease. With $m_{-1}^q = d_{-1}^q = 0$,

$$\begin{aligned} d_0^q &= \pi^q s_q, & m_0^q &= d_0^q, \\ d_h^q &= \phi m_{h-1}^q + \psi d_{h-1}^q + \beta^q s_q, & m_h^q &= m_{h-1}^q + d_h^q, \quad h \geq 1. \end{aligned} \tag{10}$$

This recursion aligns the plotted dynamic multipliers with the sign convention in (7). Inference uses country-clustered standard errors; with ten countries, the p-values are interpreted cautiously and are complemented by economic magnitude and forecast performance.

3.3 Volatility-threshold extension

Energy-price transmission may be stronger or weaker during stress periods. To allow for this possibility, the baseline model is augmented with a volatility state based on annualized monthly Brent volatility. Define

$$D_t(c) = \mathbf{1}\{V_t > c\}, \tag{11}$$

where V_t is the annual energy-price volatility measure and c is a candidate threshold. The compact threshold specification is

$$\begin{aligned} \Delta y_{i,t} = \alpha_i + \phi y_{i,t-1} + \beta^{+} P_{i,t-1}^{+} + \beta^{-} P_{i,t-1}^{-} + \gamma' X_{i,t-1} + \psi \Delta y_{i,t-1} + \pi^{+} z_{i,t}^{+} + \pi^{-} z_{i,t}^{-} \\ + \eta^{+} P_{i,t-1}^{+} D_t(c) + \eta^{-} P_{i,t-1}^{-} D_t(c) + u_{i,t}. \end{aligned} \tag{12}$$

The interaction coefficients η^{+} and η^{-} measure how the positive and negative partial-sum slopes differ in high-volatility years. The threshold c is selected by a grid search over interior quantiles of V_t and the preferred cutoff minimizes the residual sum of squares, with AIC reported as a secondary fit criterion. Following the threshold-econometric logic of Hansen [22], the exercise is interpreted as a regime-conditioned calibration. It is not treated as a definitive structural-break test because the annual ASEAN panel is short and the volatility state is common across countries.

3.4 MIDAS forecast component

The annual transition outcome may respond to within-year energy-market movements before those movements appear in annual averages. To retain monthly Refinitiv information, a parsimonious MIDAS term is constructed from monthly energy-price

changes. Let $m = 1, \ldots, M$ denote monthly observations within the forecast year, set $M = 12$, and let $r^{E}_{i,t,m}$ denote the corresponding monthly log return in real local-currency Brent exposure when available, or the common monthly Brent return otherwise. The beta-weighted MIDAS summary is

$$\widetilde{\Delta p}^{E}_{i,t} = \sum_{m=1}^{M} w_m(\theta_1, \theta_2) r^{E}_{i,t,m}, \qquad w_m = \frac{\tau_m^{\theta_1 - 1}(1 - \tau_m)^{\theta_2 - 1}}{\sum_{r=1}^{M} \tau_r^{\theta_1 - 1}(1 - \tau_r)^{\theta_2 - 1}}, \tag{13}$$

where $\tau_m = (m - 0.5)/M$ keeps the beta weights inside the unit interval, and θ_1 and θ_2 are beta-weight shape parameters. The restrictions $w_m \geq 0$ and $\sum_m w_m = 1$ make the MIDAS term interpretable as a smooth within-year energy-price signal, following Ghysels et al. [23].

The forecasting exercise is intentionally country specific. For each country, expanding-window one-step-ahead forecasts compare three parsimonious models: a symmetric ARDL benchmark, the NARDL model with positive and negative partial sums, and a MIDAS-augmented specification that replaces or supplements annual energy-price changes with $\widetilde{\Delta p}^{E}_{i,t}$. Forecast accuracy is summarized by

$$RMSE_{i,k} = \left(\frac{1}{|\mathcal{T}_i^F|} \sum_{t \in \mathcal{T}_i^F} \left(y_{i,t} - \widehat{y}^{(k)}_{i,t|t-1} \right)^2 \right)^{1/2}, \tag{14}$$

where $k \in \{ARDL, NARDL, MIDAS\}$ and $\mathcal{T}_i^F$ is the country-specific forecast evaluation set. This design avoids imposing a single pooled forecasting equation on economies with different fuel mixes, hydropower dependence, market institutions, and transition trajectories.

4 Empirical Results and Policy Interpretation

This section reports the empirical evidence in five steps and links each result to the paper's monitoring interpretation. First, the unit-root diagnostics verify that the data contain the mixed persistence normally expected in transition and energy-price variables. Second, the regional time-series figure motivates the error-correction and shock-decomposition design. Third, the panel NARDL estimates quantify average ASEAN transmission from positive and negative real energy-price shocks. Fourth, the volatility-threshold and country-level results show how the regional average masks state dependence and structural heterogeneity. Fifth, the rolling forecasts evaluate whether the additional asymmetric and mixed-frequency terms improve practical transition monitoring.

4.1 Persistence diagnostics and regional transition pattern

Table 4 summarizes country-wise ADF diagnostics by reporting the median statistic across country-level tests. The transition-performance variable is not stationary at the 5% level, with a median ADF statistic of -1.243 and a p-value of 0.655. The real

local-currency energy-price index is also persistent, with a p-value of 0.103, while the positive and negative partial sums are non-stationary by construction because they accumulate only price increases or decreases. In contrast, inflation and exchange-rate change are stationary at the 5% level, with p-values of 0.003 and 0.007, respectively. The diagnostics therefore support an error-correction design: estimating a simple levels equation would risk spurious persistence, whereas estimating only differences would discard the long-run transition relation implied by the NARDL framework. Because the panel contains only around two decades of annual observations for each economy, these tests are treated as supporting evidence rather than as formal pre-tests that mechanically determine the model.

Table 4 Country-wise unit-root screening summarized by median ADF statistic.

Series	ADF statistic	p-value	Observations	Stationary at 5%
Transition performance ($y_{i,t}$)	-1.243	0.655	256	False
Real local-currency Brent exposure ($P^{E}_{i,t}$)	-2.555	0.103	149	False
Positive energy-price shock ($P^{+}_{i,t}$)	-0.591	0.873	139	False
Negative energy-price shock ($P^{-}_{i,t}$)	-2.503	0.115	139	False
Inflation rate (component of $X_{i,t}$)	-3.881	0.003	249	True
Exchange-rate change (component of $X_{i,t}$)	-3.550	0.007	250	True

Figure 1 compares ASEAN's average low-carbon electricity share with the regional real local-currency energy-price index. The two series move at different speeds. The energy-price index changes sharply during global fuel-price episodes, falling strongly after the mid-2010s oil-price decline, weakening again around 2020, and rising sharply during the 2021–2022 energy shock and the most recent endpoint. By contrast, the average low-carbon share evolves slowly because generation assets, grid integration, hydropower conditions, procurement rules, and electricity-demand growth adjust with long lags. The transition series rises in the early 2010s, softens after 2014, recovers partly around 2021–2022, and weakens again at the end of the sample. This visual evidence motivates a model in which short-run energy-market pressure can enter contemporaneously, while long-run transition performance adjusts only gradually through an error-correction channel.

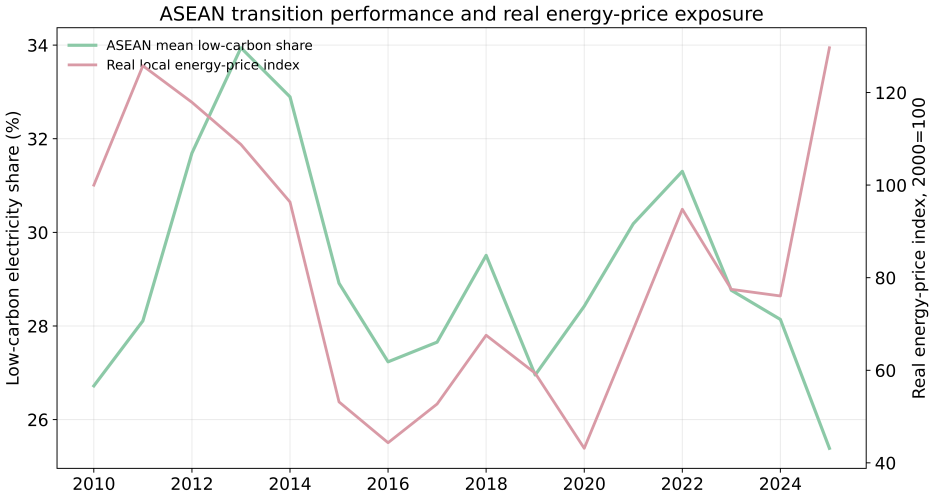


Fig. 1 ASEAN transition performance and real energy-price exposure.

4.2 Panel NARDL estimates and long-run asymmetry

Table 5 reports the fixed-effect panel NARDL estimates. The lagged transition-performance coefficient is -0.494 and statistically significant at the 1% level. This is the strongest evidence in the table: ASEAN transition performance displays error correction, and approximately one half of a deviation from the fitted transition path is corrected within the following year. The lagged dependent-variable change is also positive and significant, with a coefficient of 0.215, indicating short-run persistence in annual transition improvements. Together, these coefficients show that carbon-transition performance is neither a purely random annual movement nor an instant response to energy prices; it is a persistent adjustment process with partial mean reversion.

The energy-price coefficients show stronger evidence for the positive-shock channel than for the negative-shock channel. The lagged positive partial-sum coefficient is 3.361, with a p-value of 0.073, indicating a marginally significant long-run level channel. The contemporaneous change in positive energy-price shocks is 4.919 and statistically significant at the 5% level. Thus, when real local-currency Brent exposure rises, ASEAN's low-carbon electricity share tends to increase in the short run, consistent with fuel-switching incentives, cost pressure on fossil generation, and stronger attention to energy-security alternatives. The negative-shock coefficients are positive in coefficient form but less precisely estimated: the lagged negative-shock coefficient has a p-value of 0.207 and the contemporaneous negative-shock coefficient has a p-value of 0.148. Because $P_{i,t}^{-}$ is non-positive, coefficient signs must be interpreted with the partial-sum convention; the main conclusion is that the annual panel does not estimate the negative-shock channel with enough precision to claim a distinct response.

The controls have mixed explanatory power. Lagged exchange-rate change is positive and significant, with a coefficient of 1.425 and a p-value of 0.005. This suggests

that currency movements contain additional information for transition outcomes even after real local-currency Brent exposure is included, possibly because exchange-rate pressure affects imported capital costs, fuel bills, tariff setting, and macroeconomic stress simultaneously. Inflation and real GDP growth are not statistically significant in the compact baseline. Their signs should not be overinterpreted because the annual panel is short and the energy-price and macroeconomic variables are correlated during global shocks. The intercept is also not significant, which is expected in a fixed-effect specification where country heterogeneity is absorbed by country dummies.

Table 5 Fixed-effect panel NARDL coefficient estimates.

Regressor	Coefficient	Std. error	p-value
Intercept (α_i)	0.399	0.938	0.671
Lagged transition performance ($y_{i,t-1}$)	-0.494	0.186	0.008
Lagged positive energy-price shock ($P^{+}_{i,t-1}$)	3.361	1.877	0.073
Lagged negative energy-price shock ($P^{-}_{i,t-1}$)	3.400	2.696	0.207
Lagged inflation rate (component of $X_{i,t-1}$)	-6.378	8.901	0.474
Lagged exchange-rate change (component of $X_{i,t-1}$)	1.425	0.508	0.005
Lagged real GDP growth (component of $X_{i,t-1}$)	-0.055	0.051	0.276
Lagged transition-performance change ($\Delta y_{i,t-1}$)	0.215	0.045	0.000
Positive shock increment ($z^{+}_{i,t}$)	4.919	2.091	0.019
Negative shock increment ($z^{-}_{i,t}$)	3.262	2.257	0.148

Table 6 converts the estimated level coefficients into long-run effects using the sign convention in (9). A one-unit positive fuel-cost shock raises the fitted low-carbon share by 6.803 percentage points in the long run. A one-unit fuel-cost decrease has the opposite signed response, -6.883 percentage points, because it enters through a negative innovation in $P^{-}_{i,t}$. The absolute magnitudes are almost identical, and the Wald p-value for long-run asymmetry is 0.967. This result is important for interpretation: the evidence supports energy-price transmission, especially through the short-run positive-shock channel, but it does not support a strong average ASEAN claim that increases and decreases have statistically different long-run absolute effects. In policy terms, real fuel-cost pressure is relevant for monitoring transition performance, but the annual panel does not prove that fuel-price increases mechanically accelerate decarbonization or that fuel-price declines mechanically reverse it.

Table 6 Panel long-run asymmetric effects and Wald test.

Quantity	Estimate
Long-run effect of a positive fuel-cost shock (θ^{+})	6.803
Long-run effect of a fuel-cost decrease (θ^{-}_{fall})	-6.883
Error-correction speed (ϕ)	-0.494
Absolute-magnitude asymmetry Wald p-value ($\lvert\theta^{+}\rvert = \lvert\theta^{-}_{\text{fall}}\rvert$)	0.967

Figure 2 confirms the table-based interpretation after applying the same sign convention to the dynamic recursion. The positive fuel-cost shock produces a positive

transition response that converges to about 6.8 percentage points. The actual fuel-cost decrease produces a negative response with a similar absolute long-run magnitude. The paths adjust rapidly and settle within roughly three to five annual steps, consistent with the estimated error-correction speed. The figure therefore shows economically meaningful transmission but little evidence that the absolute response to increases and decreases differs at the regional level.

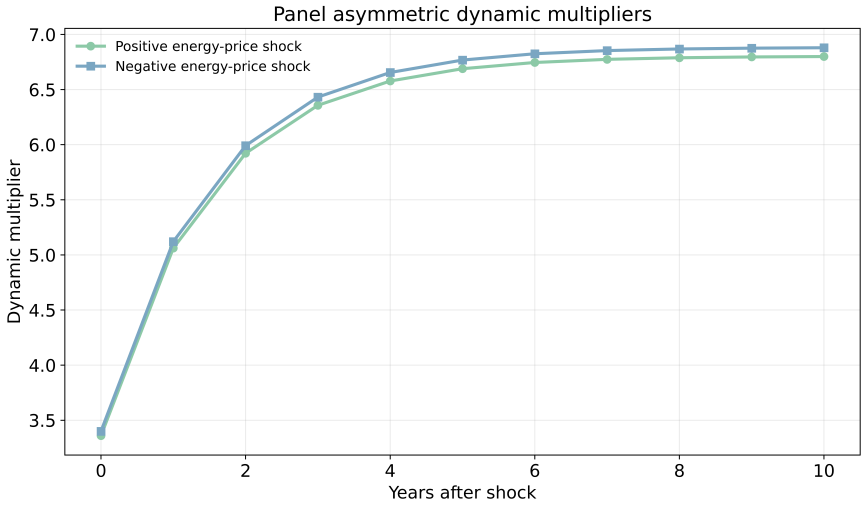


Fig. 2 Panel NARDL dynamic responses with the positive/negative partial-sum sign convention.

4.3 Volatility-threshold results

Table 7 reports the grid search over annualized Refinitiv Brent-volatility thresholds. The preferred cutoff is 0.083, which gives the lowest residual sum of squares, 1925.360, and the lowest AIC, 756.780, among the candidate values shown. The second-best threshold, 0.087, is very close in both SSE and AIC, while lower cutoffs such as 0.058, 0.055, and 0.067 fit less well. The threshold search therefore suggests a high-volatility state around an annualized monthly Brent-volatility level of roughly 8%, but the closeness of the first two candidates also indicates that the exact cutoff should not be treated as a structural boundary. It is best interpreted as a data-driven stress-state marker for monitoring.

Table 7 Threshold selection over Refinitiv energy-volatility candidates.

Threshold	SSE	AIC
0.083	1925.360	756.780
0.087	1930.079	757.096
0.058	1976.976	760.193
0.055	1977.122	760.203
0.067	1991.056	761.109

Observations: 129.

Table 8 shows that the main conclusions are robust after adding high-volatility interactions. The lagged transition-performance coefficient remains negative and significant, -0.487 with a p-value of 0.008, almost identical to the baseline estimate. The contemporaneous positive-shock effect remains positive and significant, 4.642 with a p-value of 0.026. Lagged exchange-rate change also remains significant. These stable coefficients imply that the main energy-price transmission result is not driven only by low-volatility or high-volatility years.

The interaction terms are economically informative but statistically imprecise. The positive-shock high-volatility interaction is 0.171, implying only a small additional positive-shock slope in stress years, and its p-value is 0.185. The negative partial-sum high-volatility interaction is -1.657 with a p-value of 0.260. Because $P^{-}_{i,t}$ is non-positive, the coefficient on this interaction must be sign-adjusted before interpreting an actual price decrease. Given its imprecision, the safest conclusion is that volatility conditioning improves the monitoring narrative but does not deliver conclusive evidence of a statistically distinct high-volatility transmission regime.

Table 8 Best fixed-effect threshold interaction model.

Regressor	Coefficient	p-value
Intercept (α_i)	0.250	0.780
Lagged transition performance ($y_{i,t-1}$)	-0.487	0.008
Lagged positive energy-price shock ($P^{+}_{i,t-1}$)	3.280	0.089
Lagged negative energy-price shock ($P^{-}_{i,t-1}$)	3.789	0.211
Lagged inflation rate (component of $X_{i,t-1}$)	1.063	0.905
Lagged exchange-rate change (component of $X_{i,t-1}$)	1.469	0.004
Lagged real GDP growth (component of $X_{i,t-1}$)	0.081	0.421
Lagged transition-performance change ($\Delta y_{i,t-1}$)	0.210	0.000
Positive shock increment ($z^{+}_{i,t}$)	4.642	0.026
Negative shock increment ($z^{-}_{i,t}$)	4.303	0.152
Positive-shock high-volatility interaction ($P^{+}_{i,t-1} I(V_t > c)$)	0.171	0.185
Negative partial-sum high-volatility interaction ($P^{-}_{i,t-1} I(V_t > c)$)	-1.657	0.260

4.4 Country heterogeneity

Figure 3 shows why the regional average must be interpreted cautiously. The country-specific calibrations are based on only 13 or 14 usable observations for most countries, so they are not presented as standalone causal estimates. Their role is diagnostic: they reveal whether the regional average is hiding economically meaningful cross-country differences.

The heterogeneity is substantial and economically important. Lao PDR has the largest country-specific effect, but this estimate requires a specific interpretation. Its low-carbon electricity share is hydro-dominant and remains close to 100% for much of the early sample before falling sharply after 2014 and partially recovering after 2020. The fitted NARDL therefore links large movements in a high-base transition share to a short annual history of energy-price shocks. The resulting multiplier is best interpreted as evidence that hydro-intensive systems can display high measured transition

sensitivity, not as evidence that Brent-price movements alone caused the Lao transition path. Hydrological conditions, electricity exports, thermal backup, grid constraints, and investment timing are plausible confounding channels in this case. Singapore and Vietnam show positive responses to fuel-cost increases, suggesting that higher fuel-cost pressure may align with transition improvements in these systems. Indonesia and the Philippines show near-zero or mixed responses, indicating weaker direct energy-price transmission in the annual data. Cambodia, Malaysia, and Thailand show negative positive-shock effects, while their responses to fuel-cost decreases differ in sign after applying the $P_{i,t}^{-}$ sign convention. These country estimates should not be interpreted as structural causal effects; they more likely reflect country-specific timing of fuel-price cycles, hydropower variation, investment lags, tariff smoothing, demand growth, and policy interventions. Brunei is reported as not available because the transition share is almost flat and offers insufficient variation for a meaningful asymmetric calibration.

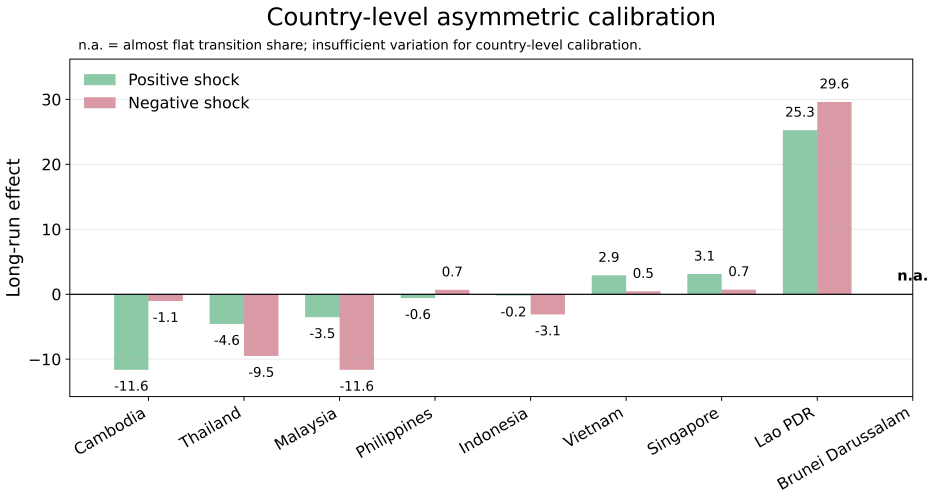


Fig. 3 Country-level asymmetric calibration summaries with actual shock signs. The bar labels report long-run effects; n.a. indicates that Brunei Darussalam has an almost flat transition share, so a stable country-level asymmetric multiplier cannot be estimated from the annual data.

4.5 Rolling forecast comparison

Figure 4 evaluates the practical forecasting value of the ARDL, NARDL, and MIDAS specifications. The lowest country-average RMSE is obtained by the parsimonious ARDL benchmark, 3.245 percentage points, followed by MIDAS at 4.494 and NARDL at 5.116. This average ranking indicates that additional nonlinear and mixed-frequency terms can overfit when annual country histories are short. It does not imply, however, that the richer models are uninformative. NARDL is the best model for Indonesia, Malaysia, Myanmar, and Singapore, while MIDAS is best for Thailand. ARDL is best for Cambodia, Lao PDR, the Philippines, Vietnam, and the almost flat Brunei series.

The country-level RMSEs clarify the economic interpretation. Malaysia and Singapore have low RMSEs under all specifications, but NARDL gives the best accuracy, suggesting that directional energy-price movements add useful information

in relatively smooth transition paths. Indonesia also benefits from NARDL, though by a smaller margin. Thailand is the only country for which MIDAS is the best model, with an RMSE of 1.339 compared with 1.433 for ARDL and 2.144 for NARDL; this indicates that within-year Refinitiv energy-price information is useful for Thailand's annual transition monitoring. Cambodia and Lao PDR have much larger forecast errors, especially under NARDL, reflecting volatile transition shares and the difficulty of estimating asymmetric dynamics from short annual histories. Figure 4 reinforces this conclusion by showing that forecast performance is country contingent rather than regionally uniform.

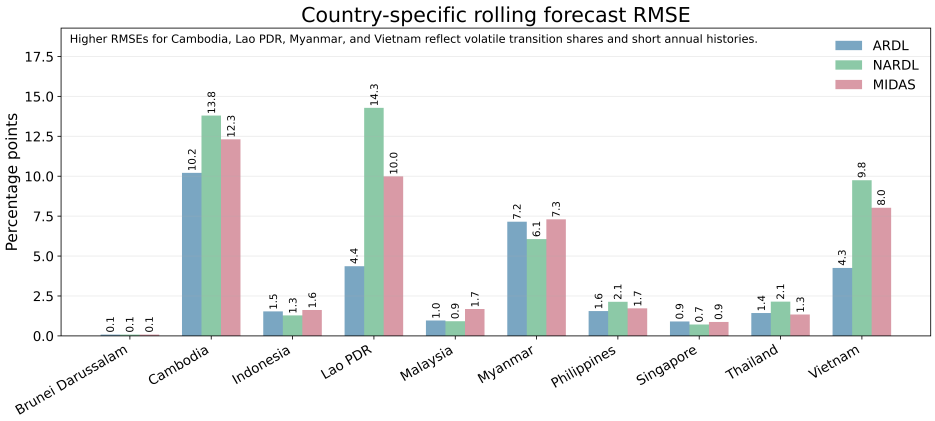


Fig. 4 Country-specific rolling forecast RMSE comparison. Bar labels report RMSE values in percentage points. Higher errors for Cambodia, Lao PDR, Myanmar, and Vietnam reflect volatile transition shares and short annual histories, which make one-step forecasting more difficult.

4.6 Policy interpretation

The policy message is deliberately measured. ASEAN transition monitoring should track three energy-price indicators: real local-currency Brent exposure, positive and negative partial-sum shocks, and volatility states. The baseline panel shows significant error correction and a positive short-run response to positive energy-price shocks. The long-run multiplier estimates, however, are almost symmetric in absolute magnitude, and the threshold interactions are imprecise. Therefore, the correct interpretation is not that higher fossil-fuel prices automatically cause decarbonization. Rather, energy-price pressure is a useful transition-monitoring signal whose relevance depends on the country, the volatility state, and the time horizon.

For policy design, the results imply that regional ASEAN dashboards should not rely only on annual renewable shares or fossil-fuel prices in US dollars. They should convert energy-price pressure into local real terms, separate increases from decreases, flag high-volatility periods, and benchmark countries separately. The most important empirical extension is clear: a harmonized monthly generation-by-fuel panel from EPPO, ASEAN Energy Database System records, and national energy agencies would allow a fully mixed-frequency NARDL-MIDAS model. Such data would make it possible to distinguish imported-fuel cost shocks from demand cycles, hydropower

conditions, power-sector planning, and explicit policy interventions, thereby moving from monitoring calibration toward stronger causal identification.

5 Conclusion

This paper examines asymmetric energy-price shock transmission to electricity-sector carbon-transition performance in ASEAN. By combining low-carbon electricity shares with real local-currency Brent exposure, the analysis converts global fuel-price movements into country-specific transition-pressure measures. The panel NARDL estimates show statistically significant error correction and positive short-run transmission from positive energy-price shocks. In the long run, however, the positive-shock effect and the absolute response to fuel-cost decreases are almost identical, and the Wald test does not support a strong ASEAN-wide asymmetry claim. The central conclusion is therefore not that fossil-fuel price increases automatically accelerate decarbonization, but that transition monitoring should incorporate direction-specific energy-price pressure.

The threshold and forecasting evidence reinforces this cautious conclusion. High-volatility years appear to alter the negative partial-sum channel, but the interaction estimates are too imprecise to establish a distinct volatility regime. Country-level estimates show that the ASEAN average masks sharply different transition structures across hydro-intensive economies, fossil-fuel exporters, import-dependent systems, and financial centers. The rolling forecasts also show that no single model dominates: NARDL improves monitoring accuracy for several economies, MIDAS is most useful for Thailand, and ARDL remains competitive for smoother or more idiosyncratic transition paths. These findings support a practical regional monitoring framework that combines asymmetric shocks, volatility states, and country heterogeneity.

The main limitation is data frequency. The dependent variable is annual, while many policy, price, and generation adjustments occur monthly or quarterly. Future work should therefore build a harmonized ASEAN monthly generation-by-fuel panel from national energy agencies, EPPO, and ASEAN energy records, and then estimate a fully mixed-frequency NARDL–MIDAS model with explicit policy-event timing. Such an extension would allow sharper identification of how imported-fuel costs, domestic policy responses, hydropower conditions, and power-sector planning jointly shape ASEAN decarbonization.

Declarations

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Competing interests. The authors declare no competing interests.
Ethics approval and consent to participate. Not applicable.
Consent for publication. Not applicable.
Clinical trial number: not applicable.
Data availability. The public energy and macroeconomic data used in this study are available from the cited OWID, Ember, Energy Institute, World Bank, ASEAN Energy Database System, and EPPO sources. Refinitiv Workspace price and country

macro exports are proprietary and can be reconstructed by licensed users. Processed replication files can be made available subject to the relevant data-license restrictions.
Materials availability. Not applicable.
Code availability. The code used to process the data and generate the tables and figures is available from the corresponding author on reasonable request, subject to the licensing restrictions that apply to proprietary Refinitiv Workspace inputs.
Author contributions. Waewwan La-ongsri, Nuttaphat Sukchitt, and Pasin Marupanthorn contributed equally to this work. All authors contributed to conceptualization, methodology, empirical design, interpretation, manuscript drafting, and manuscript revision. Nuttaphat Sukchitt handled correspondence. All authors read and approved the final manuscript.

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