Does Renewable Energy Development Reduce Fossil Fuel Import Dependence? Evidence from Taiwan's Energy Generation

Jun-Jie Chang

Department of Agricultural Economics, National Taiwan University

Abstract

Reducing energy dependence is a stated objective of Taiwan's energy transition, yet whether the rapid build-out of renewable capacity has actually displaced imported fossil fuel remains untested for the Taiwanese case. This study estimates the long-run elasticity of power-sector fossil fuel imports with respect to renewable generation using monthly data from January 2000 to January 2026 (313 observations) and an Autoregressive Distributed Lag (ARDL) bounds testing framework. Fossil fuel imports are measured in energy-equivalent terms using the Energy Administration's official calorific values and are restricted to the fuels actually burned for electricity, namely steam coal, sub-bituminous coal and liquefied natural gas. The specification controls for electricity consumption, the nuclear share of generation, the exchange rate and a consumption-weighted Divisia index of international fuel prices. A stable long-run relationship is confirmed by the bounds test and by the three-test protocol that excludes degenerate cases. Over the transition period from 2016 onward the estimated elasticity is -0.039, with a bootstrap 95% confidence interval of $[-0.075, -0.001]$: a one percent increase in renewable generation is associated with a reduction in power-sector fossil fuel imports of less than one twenty-fifth of one percent. This magnitude confirms fractional displacement rather than substitution. Decomposing renewables reveals the mechanism: dispatchable sources carry an elasticity of -0.037 while variable solar and wind carry -0.003 and are statistically indistinguishable from zero. A rolling-window estimate shows the elasticity was significantly *positive* in windows ending around 2010–2011 and turned negative only after approximately 2022. The results imply that supply-side capacity targets alone are insufficient, and that demand-side management and grid flexibility are the binding constraints on translating renewable capacity into reduced import dependence.

1 Research Motivation and Questions

The energy security of Taiwan is a well-known concern, and the problem exposes the economy to high price sensitivity and geopolitical risk (Chuang & Ma, 2013). As the Energy Administration's 2024 report shows, imported energy contributed 95.8% of Taiwan's total annual energy supply (Energy Administration, Ministry of Economic Affairs, 2024a). To reduce energy security risks, the government has promoted energy transition measures since 2016, including a nuclear-free homeland by 2025 and the prioritization of renewable energy development. In 2021 the administration formally launched the Net Zero Transformation Action Plan targeting 2050 (Climate Change Administration, Ministry of Environment, 2022).

As of 2024, Taiwan's electricity production remained dominated by fossil fuels at 84.9%, while renewable energy had grown to 10.9% and nuclear power had declined to 4.2% (Ritchie et al., 2026). Figure 1 shows the trends of electricity production and the sectoral shares in 2024.

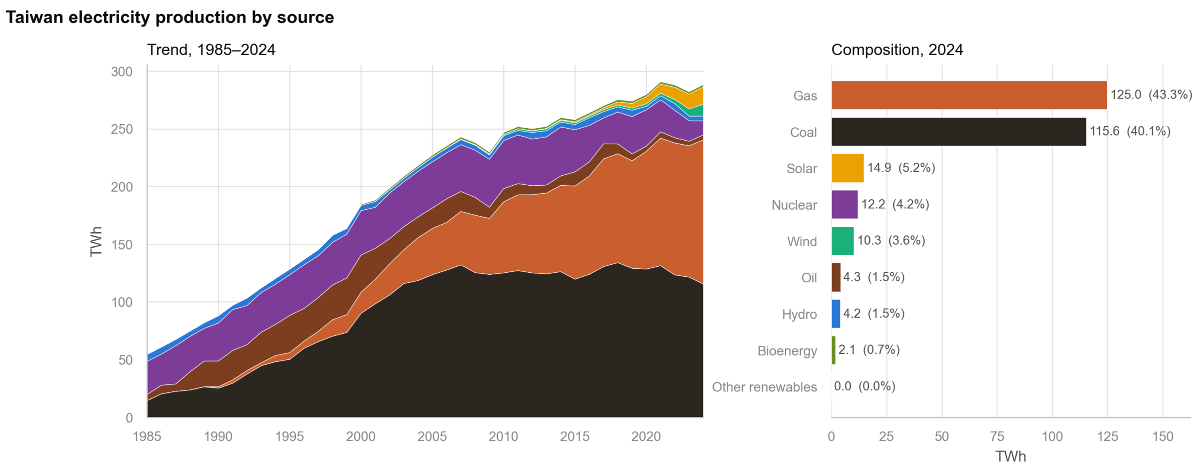


Figure 1: Electricity production by source (Ritchie et al., 2026)

This study addresses the core question: does renewable energy development effectively reduce fossil fuel import dependence in Taiwan? The question is not rhetorical. The official import-dependence indicator has indeed fallen, from an annual mean of 97.8% in 2000 to 95.7% in 2024 and 94.8% by January 2026, as Figure 2 shows. That decline is nevertheless a poor test of substitution, because the indicator is a ratio whose denominator includes domestic renewable supply; renewable expansion mechanically lowers it whether or not a single tonne of imported coal is displaced. Establishing displacement requires estimating the response of the *quantity* of fossil fuel imported to renewable generation, holding demand and the competing supply sources constant.

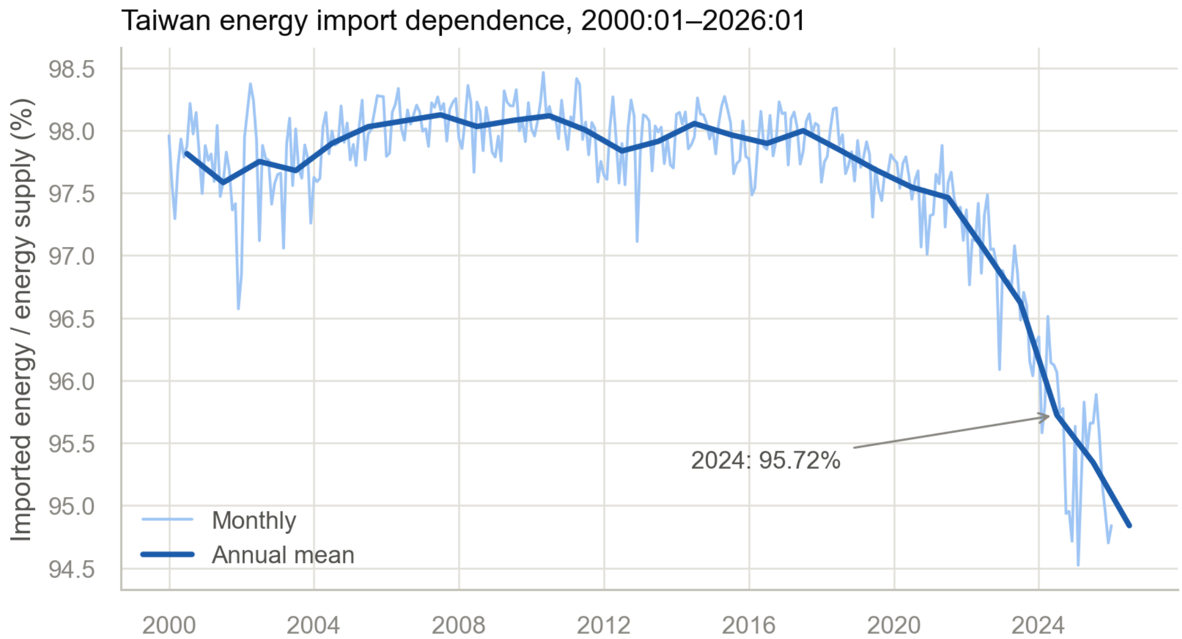


Figure 2: Taiwan energy import dependence, 2000:01–2026:01. Own calculation from Energy Administration, Ministry of Economic Affairs (2026). The 2024 annual mean of 95.72% corroborates the 95.8% figure reported by Energy Administration, Ministry of Economic Affairs (2024a).

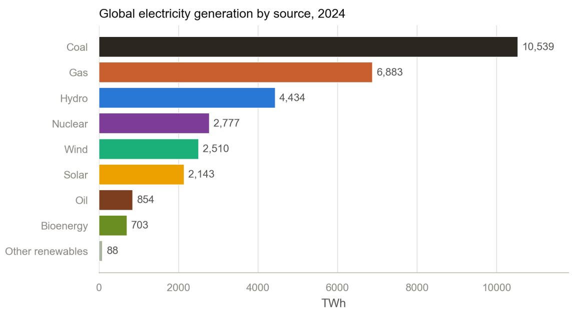
The remainder of the paper proceeds as follows. Section 2 reviews the international evidence on displacement and identifies the gap this study fills. Section 3 describes the data and the construction of each variable, including several measurement decisions that materially affect the answer. Section 4 sets out the empirical strategy. Section 5 reports the results and the robustness analysis. Section 6 discusses the interpretation, the policy implications and the limitations of the study. Section 7 concludes.

2 Literature Review

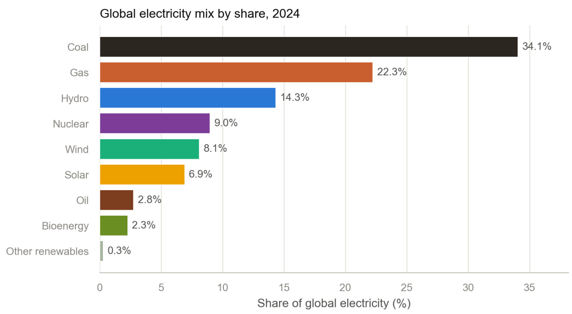
Because Taiwan-specific evidence on the energy transition is limited, this section assembles global cases with empirical evidence in order to identify the potential risks and problems along Taiwan's transition path.

2.1 The persistence of fossil fuel dominance in global power generation

Globally, the energy structure remains heavily reliant on fossil fuels. As of 2024, coal and natural gas together accounted for over 56% of total electricity generation, with coal alone contributing 10,544 TWh, more than double the combined output of wind and solar power (Ritchie & Rosado, 2026). Figure 3 shows the worldwide energy mix and its shares in 2024.



(a) Energy mix 2024



(b) Mix share 2024

Figure 3: Global electricity production by source (Ritchie & Rosado, 2026)

While renewable energy has seen exponential growth, with solar generation more than doubling from 857 TWh in 2020 to 2,128 TWh in 2024, this capacity expansion has largely functioned to meet rising global demand rather than displacing existing fossil fuel assets. Coal generation actually increased by over 1,100 TWh during the same period, illustrating that the global trend is currently one of energy *addition* rather than genuine energy *transition*. Figure 4 shows the worldwide electricity production trend by energy source from 1985 to 2024.

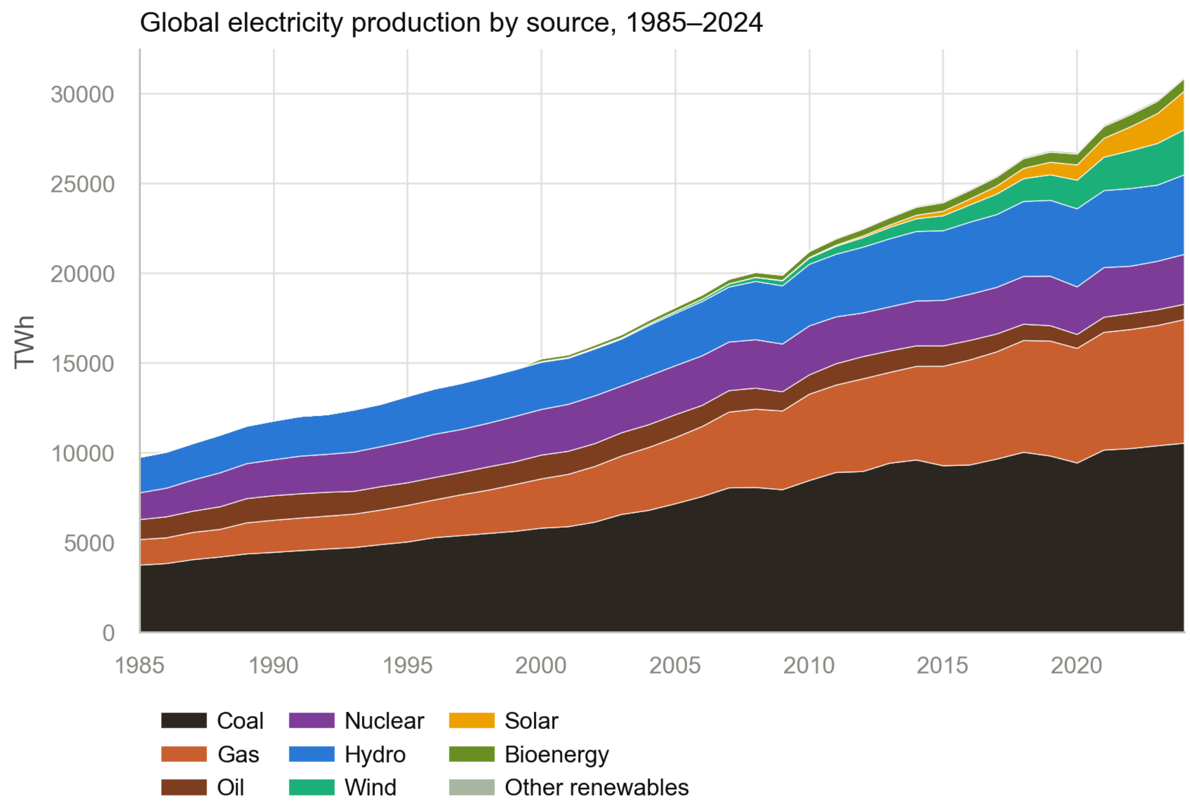


Figure 4: Global electricity production trend by source (Ritchie & Rosado, 2026)

This global persistence of fossil fuel dependence highlights a critical gap between policy ambition and empirical reality. If global markets with their diverse resource endowments struggle to achieve a substitution effect, the challenge is likely more acute for isolated, import-dependent economies. Indeed, Jacobson (2021) finds that in the absence of cross-border interconnection, maintaining grid stability under high renewable penetration requires disproportionate investment in storage and capacity overbuilding, leading to significantly higher aggregate costs. This motivates a careful examination of whether renewable energy expansion can effectively reduce energy supply from fossil fuel imports in national contexts such as Taiwan.

2.2 The empirical reality of substitution effects

Theoretically, the near-zero marginal cost of renewables prioritizes them in the dispatch order, potentially displacing fossil fuel generation. Seminal empirical work by York (2012) investigated this assumption and revealed a "fractional displacement" reality in which one unit of non-fossil electricity displaces significantly less than one unit of fossil-fuel-based electricity. York's findings indicate that the displacement coefficient is often far below unity, implying that the majority of renewable capacity is absorbed by consumption growth or system inefficiency rather than by retiring fossil fuel plants.

Karlilar Pata and Balcilar (2024) estimate an imperfect displacement of fossil-fuel generation capacity by renewables in 36 OECD countries over 2000–2020: on average, displacing one unit of fossil-fuel capacity requires about 1.15 units of renewable generation capacity, implying less than one-for-one substitution in aggregate.

The mechanism behind this limited substitution lies largely in the intermittency of variable renewable energy. Marques et al. (2018) provide empirical evidence from 10 European countries, showing that dispatchable renewables such as hydropower exhibit strong substitution effects against fossil fuels, while intermittent sources such as wind fail to displace them proportionally. Their European sample also finds a substitution effect for solar PV; the present study places solar in the variable-source category consistent with its dispatch profile in Taiwan's isolated grid, where the cross-border balancing that smooths solar output in the European mainland is absent. This necessitates flexible backup generation, primarily natural gas, to maintain grid stability, thereby perpetuating fossil fuel dependency.

These findings suggest that the "additionality" of renewables is a global phenomenon driven by grid constraints and the technical necessity of backup power. However, most existing literature focuses on continental grids with cross-border balancing capability. The implications for isolated island economies, where grid stability relies entirely on domestic reserves, remain under-explored. This study fills that gap by investigating the substitution dynamics within Taiwan's isolated and import-dependent energy system, and by testing the dispatchable-versus-variable distinction of Marques et al. (2018) directly in that setting.

3 Data

3.1 Sources and coverage

The analysis uses a balanced monthly panel covering January 2000 to January 2026, 313 observations, with no missing months and no missing values in any series. Quantity and generation series are drawn from the Energy Administration's Energy Statistics Query

System (Energy Administration, Ministry of Economic Affairs, 2026): fossil fuel imports by country of origin and coal type, renewable and nuclear electricity generation, electricity consumption, and the aggregate energy indicators. The exchange rate is the Central Bank's monthly average of the New Taiwan Dollar against the US Dollar (Central Bank of the Republic of China (Taiwan), 2026). International fuel prices are taken from the World Bank Pink Sheet (World Bank, 2026). Table 1 reports descriptive statistics for the full sample and for the transition sub-sample.

Table 1: Descriptive statistics

		Full sample					Transition sample		
Variable	Unit	Mean	SD	Min	Max	N	Mean	SD	N
$\ln FFI^{power}$	ln TJ	11.985	0.224	11.185	12.371	313	12.151	0.113	121
$\ln FFI^{all}$	ln TJ	12.694	0.139	12.188	12.966	313	12.761	0.096	121
$\ln RE$	ln MWh	13.746	0.547	12.589	15.140	313	14.288	0.438	121
$\ln RE^{disp}$	ln MWh	13.362	0.247	12.589	14.124	313	13.449	0.255	121
$\ln RE^{var}$	ln MWh	11.400	2.411	5.130	14.948	302	13.543	0.847	121
$\ln EC$	ln MWh	16.804	0.167	16.278	17.111	313	16.934	0.094	121
NUC^{share}	ratio	0.145	0.059	0.000	0.283	313	0.085	0.040	121
$\ln ER$	ln NTD/USD	3.447	0.056	3.321	3.557	313	3.419	0.047	121
$\ln PF$	ln index	4.729	0.544	3.657	6.021	313	5.021	0.369	121
$\ln P^{coal}$	ln USD/mt	4.311	0.615	3.105	6.066	313	4.716	0.518	121
$\ln P^{LNG}$	ln USD/mmbtu	2.227	0.445	1.376	3.167	313	2.391	0.288	121

Full sample 2000:01–2026:01; transition sample 2016:01–2026:01. $\ln RE^{var}$ is undefined for eleven months of 2000 in which solar and wind output was zero, hence $N = 302$ in the full sample.

3.2 Measuring fossil fuel imports

Three measurement decisions materially affect the answer and are therefore stated explicitly.

Common energy units. The three import series are reported in incommensurable physical units: coal and liquefied natural gas in tonnes, crude oil in thousand barrels. They cannot be added directly. All quantities are therefore converted to terajoules using the net calorific values published by the Energy Administration (Energy Administration, Ministry of Economic Affairs, 2024b), with one kilocalorie taken as 4.1868×10^{-6} GJ, consistent with that table's own convention that one kilogram of oil equivalent equals 10,000 kcal. The values applied are 5,846 kcal/kg for imported steam coal for power generation, 4,710 kcal/kg for sub-bituminous coal for power generation, 7,010 kcal/kg for imported coking coal, 7,415 kcal/kg for anthracite, and 8,613 kcal per litre for crude oil.

Liquefied natural gas is the one exception. The official table quotes 8,710 kcal per *cubic metre* of regasified gas, a volume basis, whereas the import series records the *mass* of liquefied gas landed. Converting tonnes of liquid to cubic metres of gas requires a regasification factor the table does not supply, so LNG retains the international mass-basis convention of approximately 52 GJ per tonne, which lies within the standard 48–54 GJ/t range. This is recorded as a residual measurement limitation in Section 6.4.

Restricting to power-sector fuels. The research question concerns electricity generation, but total fossil fuel imports are dominated by fuels that are not burned for power. Crude oil accounts for 38–55% of imported fossil energy across the sample yet is refined largely for transport and petrochemical feedstock; coking coal is consumed by the steel industry. Including them injects variation unrelated to the power sector, biasing the estimated elasticity toward zero and inviting a spurious reading in favour of the additionality paradox. Fortunately the source data disaggregate coal by type, which permits a clean separation. The primary dependent variable is therefore

$$FFI_t^{power} = \text{steam coal}_t + \text{sub-bituminous coal}_t + \text{LNG}_t, \tag{1}$$

measured in terajoules, with the all-fuel aggregate FFI_t^{all} retained as a robustness check. Within FFI^{power}, the LNG share rose from 35.9% in 2016 to 52.5% in 2025 while the steam coal share fell from 52.6% to 40.2%, so the composition of the dependent variable is itself shifting over the transition period.

Shipment lumpiness. Monthly import data are driven partly by vessel scheduling rather than by economic conditions. The first difference of $\ln FFI^{power}$ exhibits a first-order autocorrelation of -0.35, and the corresponding figure for crude oil is -0.49; aggregating to quarterly frequency reduces it to -0.01. This mean-reverting noise is not an economic signal, and it is accommodated in two ways: the distributed-lag structure of the ARDL absorbs it within the monthly specification, and a quarterly specification is estimated as a robustness check.

3.3 Renewable generation and the choice of sample period

The composition of renewable generation changed fundamentally over the sample. Hydropower accounted for 71.8% of renewable output in 2000 but only 14.3% by 2025, while solar photovoltaics and wind rose from zero to 43.4% and 31.6% respectively (Figure 5). Early-sample renewable generation is therefore essentially a function of rainfall, which is climate-driven and dispatchable; late-sample renewable generation is policy-driven and intermittent. These are not the same economic mechanism, and a single elasticity estimated across the whole period would not have a stable interpretation.

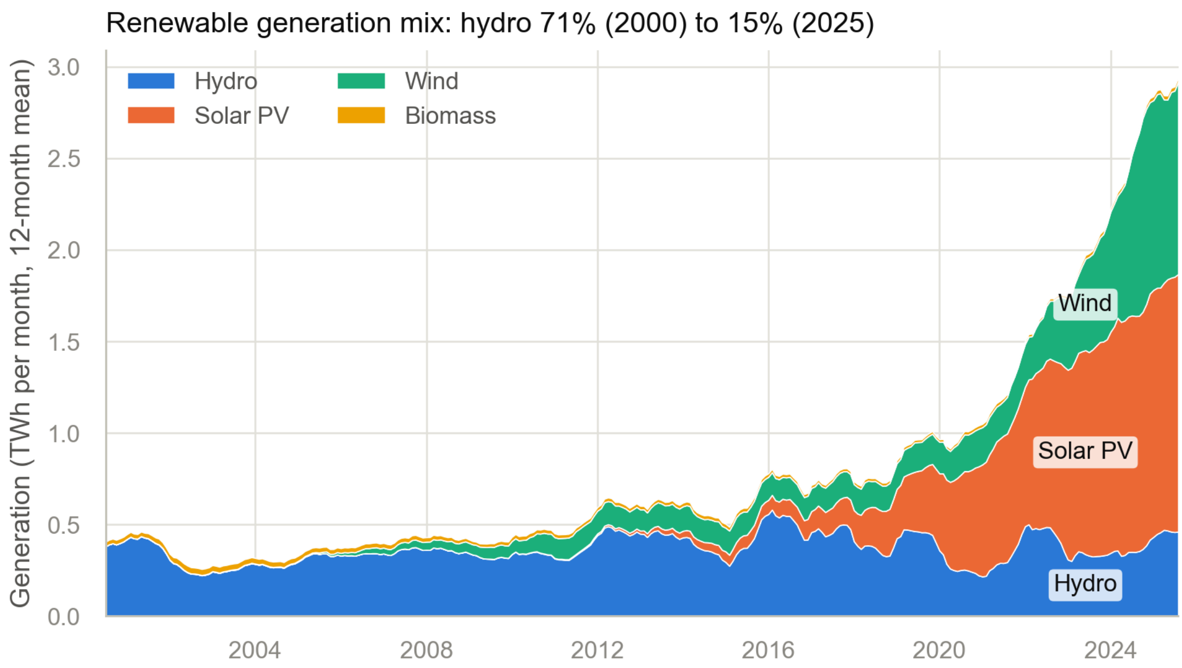


Figure 5: Renewable generation mix, 12-month moving mean. Own calculation from Energy Administration, Ministry of Economic Affairs (2026).

Three considerations lead to January 2016 as the start of the primary sample. It coincides with the launch of the transition policy package; solar and wind generation are strictly positive throughout, permitting logarithmic transformation that is unavailable for eleven months of 2000; and the partial correlation between the seasonally adjusted and detrended residuals of $\ln FFI^{power}$ and $\ln RE$ is -0.29 from 2016 onward against -0.01 before 2016, indicating that whatever displacement signal exists is concentrated in the later period. The full sample from 2000 is retained as a robustness check. Over the transition sample, renewable generation tripled, from a monthly mean of 1.06 TWh in 2016 to 3.22 TWh in 2025, while power-sector fossil fuel imports rose by 6.3%, from 179.2 PJ to 190.6 PJ per month. Figure 6 presents both series.

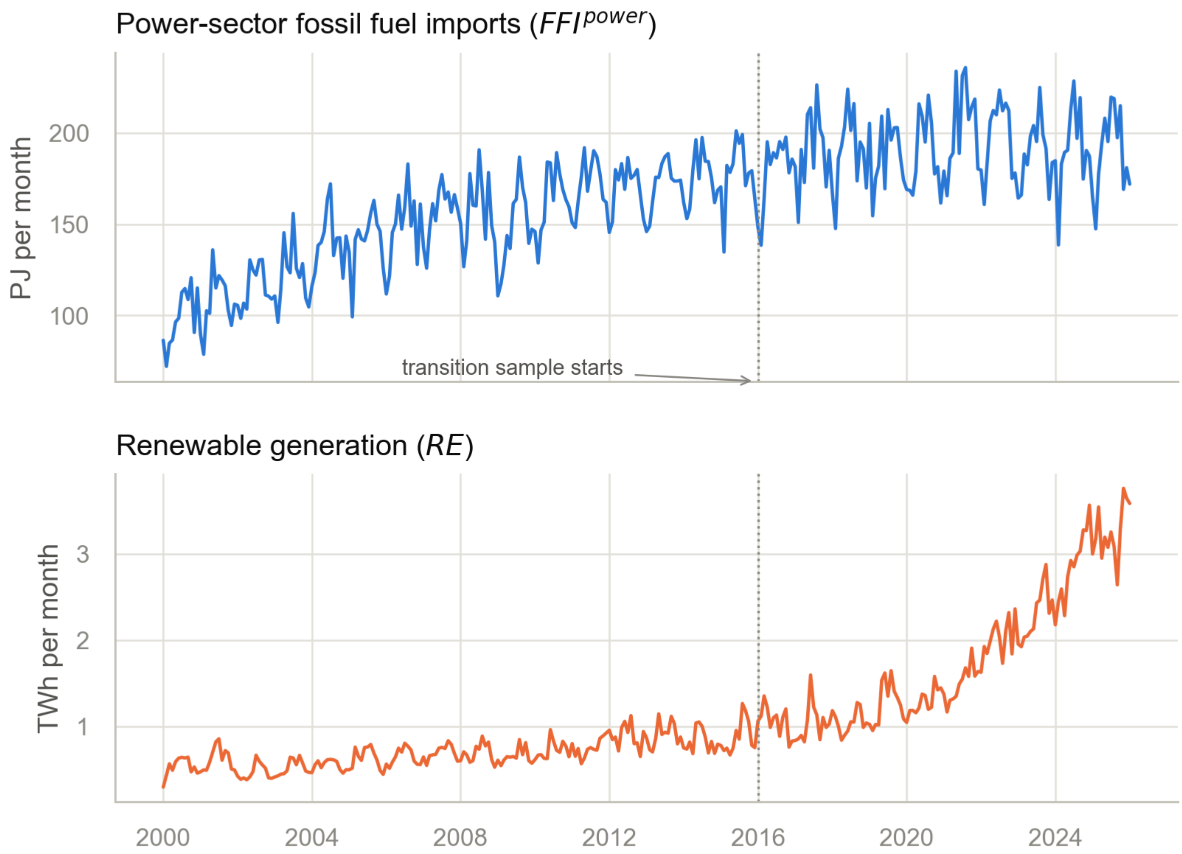


Figure 6: Power-sector fossil fuel imports and renewable generation. The two series are shown as separate panels on a shared time axis rather than on twin vertical axes, since the alignment of two independent scales on one plot is arbitrary and can suggest a correlation that is not present in the data. Own calculation from Energy Administration, Ministry of Economic Affairs (2026).

3.4 Control variables

Electricity consumption (EC_t) is aggregate consumption in MWh, spliced from two source files that partition at December 2017. The splice requires no level adjustment: year-on-year growth at the junction is +0.48% and +5.51%, well inside the sample distribution with mean +2.04% and standard deviation 4.95%. The two files use different industry disaggregations, so the sectoral breakdown is not comparable across the junction, but the aggregate and industrial-sector totals used here are defined consistently.

Nuclear generation enters as a share rather than in logarithms. Following the closure of the second Maanshan unit in May 2025, nuclear output is exactly zero in nine months of the sample, so $\ln(NUC_t)$ is undefined precisely during the most policy-relevant period. The specification therefore uses $NUC_t^{share} = NUC_t/EC_t$, which retains all 313 observations at the cost of interpreting the coefficient as a semi-elasticity. This is a deliberate departure from the original proposal and is discussed further in Section 6.4. The nuclear share fell from an annual mean of 0.126 in 2016 to 0.013 in 2025.

International fuel prices. The original design controlled import cost through the exchange rate alone. That is insufficient: the variation in import quantities over 2021–2023 was driven predominantly by price shocks, and omitting prices would load that variation onto the exchange rate coefficient. Taiwan's own import unit values were considered and rejected on two grounds. They are available only from 2014 in the customs query system, and more importantly they are endogenous, reflecting Taiwan's own contracting structure, purchase timing and freight arrangements, all of which co-move with domestic demand and dispatch decisions. International benchmark prices are exogenous to Taiwan, which is a price taker.

The three Pink Sheet series are selected to match Taiwan's actual sourcing structure, verified against the country-of-origin data over the transition sample. Australia is consistently the largest coal source, supplying 50.7% of coal imports, so the Newcastle f.o.b. quotation applies. Australia and Qatar together supply 56.4% of LNG over the period, a share rising from 43.6% in 2016 to 67.2% in 2025, and the Japan c.i.f. import price is the established Asian regional benchmark for such cargoes. Middle Eastern producers supply 70.7% of crude oil, led by Saudi Arabia at 31.5% and Kuwait at 18.9%, and these barrels are priced off Dubai. The Henry Hub and WTI series are deliberately *not* used: gas markets are regionally segmented, the correlation between Henry Hub and Japanese

LNG over the transition sample is only +0.60, and in September 2022 Henry Hub stood at 7.76 USD/mmbtu against 23.73 for Japanese LNG, so a US series would misrepresent the 2021–2023 shock entirely.

Because the dependent variable is an aggregate of two fuels, the price control is constructed as a Törnqvist (discrete Divisia) chained index over coal and LNG, with cost-share weights updated each period (Diewert, 1976):

$$\Delta \ln PF_t = \sum_i \frac{w_{it} + w_{i,t-1}}{2} \Delta \ln P_{it}, \qquad w_{it} = \frac{P_{it}Q_{it}}{\sum_j P_{jt}Q_{jt}}, \tag{2}$$

normalized to 100 in December 2015. A single index rather than separate fuel prices conserves degrees of freedom; fuel-specific prices are used in a robustness specification. Figure 7 plots the components and the index, which peaked at 411.8 in September 2022 against 92.9 in January 2016.

3.5 An indicator that cannot serve as the dependent variable

The Energy Administration publishes an import-dependence ratio, imported energy over total energy supply, which is verbally identical to the concept in this paper's title. It is not used as a dependent variable, for a reason worth stating because the temptation is real. Over the transition sample its correlation with $\ln RE$ is -0.930. That figure is an accounting identity, not an empirical finding: renewable output belongs to the denominator's domestic supply component, so renewable expansion reduces the ratio by construction. Regressing it on renewable generation would deliver a large, highly significant negative coefficient that measures nothing but the definition. The indicator is used here only descriptively, in Figure 2, and as a cross-check on the 95.8% figure cited in Section 1.

4 Methodology and Research Design

4.1 Empirical strategy

This study adopts the ARDL bounds testing approach. Unlike static cointegration techniques, the ARDL framework accommodates regressors with mixed orders of integration (Pesaran et al., 2001). Since the focus is the recent transition period, the approach

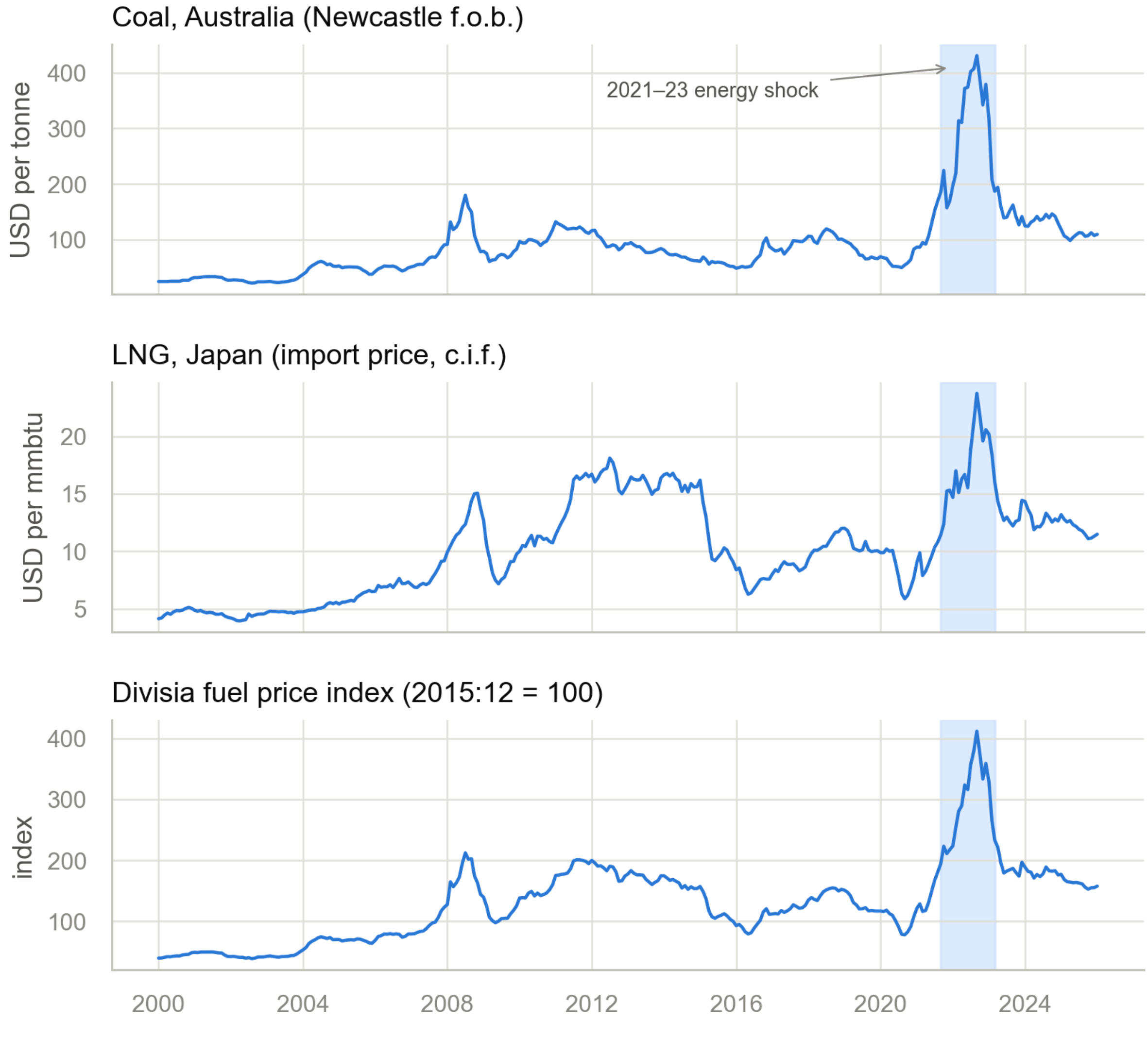


Figure 7: International benchmark fuel prices and the Divisia index (World Bank, 2026).

also has the advantage of performing acceptably in smaller samples (Wolde-Rufael, 2010). This flexibility is appropriate for Taiwan's energy transition, where policy interventions may introduce structural breaks and varying stationarity properties across series.

4.2 Long-run specification

A log-linear functional form is specified so that coefficients read as elasticities. The long-run relationship is

$$\begin{aligned}\ln(FFI_t^{power}) &= \alpha_0 + \alpha_1 \ln(RE_t) + \alpha_2 \ln(EC_t) + \alpha_3 NUC_t^{share} \\ &\quad + \alpha_4 \ln(ER_t) + \alpha_5 \ln(PF_t) + \psi D_t + \phi B_t + \epsilon_t, \end{aligned} \tag{3}$$

where D_t is a vector of eleven centered monthly dummies absorbing seasonality and B_t is a break dummy switching on in November 2022. Two elements depart from the original proposal: nuclear power enters as a share rather than in logarithms, for the reason given in Section 3, and the fuel price index is added. Both departures are motivated by the data rather than by convenience, and both are subjected to robustness checks.

Seasonality is not incidental. Wind generation runs 90% above its mean in December and 60% below in August, solar runs in the opposite direction, and both FFI^{power} and electricity consumption peak in the summer, reflecting the cooling-demand surge documented for Taiwan by Hung and Huang (2015) and Lan and Lee (2011) and the counter-cyclical wind profile reported by Taiwan Power Company (Taipower) (2025). Without seasonal controls these opposing cycles would generate spurious correlation.

4.3 Unrestricted Error Correction Model

Equation (3) is re-parameterized into an Unrestricted Error Correction Model:

$$\begin{aligned}\Delta \ln(FFI_t) &= \beta_0 + \sum_{i=1}^{p-1} \beta_{1i} \Delta \ln(FFI_{t-i}) + \sum_{i=0}^{q_1-1} \beta_{2i} \Delta \ln(RE_{t-i}) \\ &\quad + \sum_{i=0}^{q_2-1} \beta_{3i} \Delta \ln(EC_{t-i}) + \sum_{i=0}^{q_3-1} \beta_{4i} \Delta NUC_{t-i}^{share} + \sum_{i=0}^{q_4-1} \beta_{5i} \Delta \ln(ER_{t-i}) \\ &\quad + \sum_{i=0}^{q_5-1} \beta_{6i} \Delta \ln(PF_{t-i}) + \lambda_1 \ln(FFI_{t-1}) + \lambda_2 \ln(RE_{t-1}) + \lambda_3 \ln(EC_{t-1}) \\ &\quad + \lambda_4 NUC_{t-1}^{share} + \lambda_5 \ln(ER_{t-1}) + \lambda_6 \ln(PF_{t-1}) + \psi D_t + \phi B_t + \mu_t. \end{aligned} \tag{4}$$

The β coefficients capture short-run dynamics and the λ coefficients on the lagged levels embody the long-run relationship. Lag orders are selected by the Akaike Information Criterion, subject to a maximum of two and to the selected model passing a Ljung–Box test for serial correlation at twelve lags. The maximum is deliberately restrictive: with 121 monthly observations in the transition sample and eleven seasonal dummies, higher orders would exhaust the degrees of freedom.

4.4 Cointegration testing

Testing proceeds in three stages rather than one. The bounds test examines the joint restriction $H_0 : \lambda_1 = \cdots = \lambda_6 = 0$; rejection against the upper critical bound indicates a stable long-run relationship (Pesaran et al., 2001). Because the asymptotic critical values over-reject in small samples, critical values are simulated at the actual sample size with 100,000 replications. This serves the same purpose as the small-sample tabulations of Narayan (2005) while being calibrated to the exact sample size and regressor count used here.

A significant overall F statistic is, however, not sufficient, because degenerate cases can produce it. The three-test protocol of McNown et al. (2018) is therefore applied: cointegration requires rejecting the overall F test, the t test on the lagged dependent variable, and the F test on the lagged independent levels jointly. All three must reject.

4.5 Elasticity and inference

Conditional on cointegration, the long-run elasticity of renewable energy is recovered by normalizing the lagged level coefficients:

$$\eta_{RE} = -\frac{\lambda_2}{\lambda_1}. \tag{5}$$

A statistically significant negative η_{RE} validates the substitution hypothesis; a value approaching zero supports the additionality paradox.

Because η_{RE} is a ratio of estimates, its finite-sample distribution is skewed and delta-method standard errors can understate the tails. Confidence intervals are therefore reported both from the delta method and from a residual bootstrap with 2,000 resamples (Efron, 1979), with the bootstrap interval preferred.

Stationarity is assessed with the Augmented Dickey–Fuller test, the KPSS test (Kwiatkowski et al., 1992), and the Zivot–Andrews test allowing one endogenous break (Zivot & Andrews, 1992). Parameter stability is assessed with recursive-residual CUSUM and CUSUMSQ statistics (Brown et al., 1975). All estimation is carried out in Python using `statsmodels` (Seabold & Perktold, 2010), with figures produced using `seaborn` (Waskom, 2021).

5 Results

5.1 Integration properties

Table 2 reports the unit root tests. The dependent variable $\ln FFI^{power}$ is $I(1)$ in both samples: the ADF test does not reject a unit root in levels ($p = 0.42$), rejects decisively in first differences, and Zivot–Andrews does not reject even when a break is permitted. This satisfies the prerequisite of the bounds test, which requires an $I(1)$ dependent variable and no $I(2)$ variables.

The renewable series present mixed evidence. Over the transition sample the ADF test rejects a unit root in the levels of $\ln RE$, $\ln RE^{disp}$ and $\ln RE^{var}$, while KPSS rejects stationarity for $\ln RE$. The ARDL framework explicitly permits regressors of mixed integration order, so this does not compromise the bounds test; the point is stated here rather than glossed over. It is also worth noting that the Zivot–Andrews break in $\ln ER$ falls in February 2022, coinciding with the invasion of Ukraine, which independently corroborates the break specification.

5.2 Cointegration

Table 3 reports the cointegration evidence. For the primary specification the overall F statistic is 17.62 against a simulated 99% upper bound of 5.01, so the null of no cointegration is rejected decisively. The simulated critical values are indeed more conservative than the asymptotic ones, 5.01 against 4.45 at the 99% level, which validates the decision to simulate. Critically, all nine specifications reject all three tests of the McNown et al. (2018) protocol, so the rejections are not attributable to degenerate cases.

Table 2: Unit root tests

	Level		First difference		Zivot–Andrews	
Variable	ADF	KPSS	ADF	KPSS	p	Break
Panel A: Transition sample (2016:01–2026:01)						
$\ln FFI^{power}$	0.422	0.100	0.000	0.100	0.527	2021:06
$\ln FFI^{all}$	0.429	0.100	0.000	0.100	0.962	2021:07
$\ln RE$	0.000	0.010	0.000	0.100	0.001	2021:05
$\ln RE^{disp}$	0.000	0.098	0.000	0.100	0.008	2021:05
$\ln RE^{var}$	0.000	0.100	0.000	0.100	0.001	2024:04
$\ln EC$	0.662	0.100	0.000	0.100	0.884	2021:02
NUC^{share}	0.896	0.010	0.000	0.100	0.235	2019:11
$\ln ER$	0.197	0.010	0.000	0.100	0.338	2022:02
$\ln PF$	0.262	0.071	0.000	0.100	0.273	2021:04
$\ln P^{coal}$	0.188	0.050	0.000	0.100	0.094	2021:11
$\ln P^{LNG}$	0.260	0.100	0.043	0.100	0.422	2021:09
Panel B: Full sample (2000:01–2026:01)						
$\ln FFI^{power}$	0.431	0.010	0.000	0.100	0.919	2003:12
$\ln FFI^{all}$	0.296	0.010	0.000	0.100	0.372	2003:11
$\ln RE$	0.981	0.010	0.000	0.100	0.460	2018:02
$\ln RE^{disp}$	0.049	0.032	0.000	0.100	0.268	2020:02
$\ln RE^{var}$	0.612	0.010	0.021	0.100	0.001	2005:03
$\ln EC$	0.098	0.010	0.000	0.100	0.001	2008:06
NUC^{share}	0.861	0.010	0.000	0.100	0.976	2020:03
$\ln ER$	0.021	0.029	0.000	0.100	0.149	2022:02
$\ln PF$	0.140	0.010	0.000	0.100	0.120	2013:12
$\ln P^{coal}$	0.049	0.022	0.000	0.100	0.292	2013:02
$\ln P^{LNG}$	0.369	0.010	0.000	0.100	0.008	2015:01

Entries are p-values. ADF includes a constant and trend in levels, a constant in differences; H_0: unit root. KPSS H_0: stationarity. Zivot–Andrews allows one endogenous break; H_0: unit root with break. KPSS p-values are bounded at 0.01 and 0.10 by the lookup table.

Table 3: Cointegration: bounds test and the McNown et al. (2018) protocol

Spec.	$F_{overall}$	t_{DV}	F_{ind}	Simulated CV (99%)		Cointegrated
				Lower	Upper	
M1	17.623***	-10.228***	8.798***	3.603	5.006	Yes
M2	21.355***	-11.275***	3.010**	3.610	4.954	Yes
M3	53.684***	-17.917***	55.053***	3.478	4.779	Yes
M4	31.330***	-14.698***	7.685***	3.335	4.748	Yes
M5	41.510***	-14.351***	9.574***	3.936	5.304	Yes
M6	6.681***	-6.105***	4.664***	4.144	5.864	Yes
M7	20.623***	-11.059***	10.106***	3.603	5.006	Yes
M8	18.386***	-10.444***	6.021***	4.214	5.539	Yes
M9	14.037***	-9.833***	6.754***	3.315	4.732	Yes

$F_{overall}$ tests $H_0 : \lambda_1 = \cdots = \lambda_{k+1} = 0$ on the lagged levels. Cointegration additionally requires rejecting $H_0 : \lambda_y = 0$ (t_{DV}) and H_0: lagged independent levels jointly zero (F_{ind}), which rules out the degenerate cases. Critical values are simulated at the actual sample size (100,000 replications) rather than taken from the asymptotic table. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.3 Long-run coefficients

Table 4 reports the long-run coefficients for the primary specification and four variants. The estimated long-run relationship in the primary specification is

$$\begin{aligned}\ln(FFI^{power}) = {} & -0.039\ln(RE) + 0.555\ln(EC) - 0.480\,NUC^{share} \\ & - 0.145\ln(ER) + 0.047\ln(PF). \end{aligned} \tag{6}$$

The central estimate is $\eta_{RE} = -0.039$. A one percent increase in renewable generation is associated with a reduction in power-sector fossil fuel imports of 0.039 percent. The delta-method interval is $[-0.080, 0.002]$ with $p = 0.061$, marginally outside conventional significance; the bootstrap interval is $[-0.075, -0.001]$ and excludes zero. Given that η_{RE} is a ratio, the bootstrap interval is the more reliable of the two, and the honest summary is that the elasticity is negative and very small, with significance at the margin of the conventional threshold. The substantive conclusion does not turn on which side of 0.05 the p value falls: an elasticity of -0.039 is economically negligible whether or not it is statistically distinguishable from zero.

The control variables behave sensibly and are estimated far more precisely than the variable of interest. Electricity consumption carries an elasticity of $+0.555$ ($p = 0.003$): demand growth raises fossil fuel imports, inelastically but robustly. The nuclear share

Table 4: Long-run coefficients

Variable	M1	M2	M3	M4	M5
$\ln RE$	-0.0391*	-0.0375	-0.0422*		-0.0228
	(0.0209)	(0.0307)	(0.0237)		(0.0257)
$\ln RE^{disp}$				-0.0373	
				(0.0235)	
$\ln RE^{var}$				-0.0032	
				(0.0145)	
$\ln EC$	0.5551***	-0.0540	1.3616***	0.3804	0.5440**
	(0.1888)	(0.2889)	(0.0845)	(0.2670)	(0.2370)
NUC^{share}	-0.4795***	-0.4690*	-0.2778	-0.5318***	
	(0.1655)	(0.2415)	(0.2115)	(0.2039)	
$\ln ER$	-0.1452	0.1923	0.2625**	-0.1446	-0.2099
	(0.1232)	(0.1887)	(0.1114)	(0.1485)	(0.1550)
$\ln PF$	0.0466***	0.0781***	0.0640***	0.0462***	0.0420***
	(0.0116)	(0.0207)	(0.0145)	(0.0147)	(0.0147)
λ_y (ECM speed)	-1.653	-1.131	-1.044	-1.377	-1.335
η_{RE} bootstrap CI	[-0.075,-0.001]	[-0.090,0.016]	[-0.086,0.003]	[-0.029,0.022]	[-0.070,0.023]
Observations	119	120	311	120	120
Parameters	25	24	26	26	22
Adj. R^2	0.776	0.729	0.668	0.767	0.760

Long-run coefficients $\beta_i = -\lambda_i/\lambda_y$ from the unrestricted ECM, delta-method standard errors in parentheses. η_{RE} is the coefficient on the renewable term. M1 main; M2 FFI^{all}; M3 full sample; M4 renewables split into dispatchable and variable; M5 drops NUC^{share}. All specifications include centred seasonal dummies and a 2022:11 break dummy. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

carries −0.480 ($p = 0.004$), correctly signed, indicating that nuclear output does displace imported fossil fuel. The exchange rate is correctly signed but insignificant.

The error correction coefficient is $\lambda_1 = -1.653$. Its absolute value exceeds unity, which merits comment and is addressed in Section 6.3.

Table 5 reports the short-run dynamics. The break dummy for November 2022 is negative and significant (−0.069, $p = 0.027$), and the seasonal pattern is as expected, with significantly positive coefficients in the summer months.

Table 5: Short-run dynamics and error correction (specification M1)

Term	Coefficient	Std. error	p
Panel A: Lagged levels (error-correction block)			
$\ln FFI_{t-1}$	-1.6530***	(0.1616)	0.000
$\ln RE_{t-1}$	-0.0646*	(0.0356)	0.073
$\ln EC_{t-1}$	0.9175***	(0.3297)	0.007
NUC_{t-1}^{share}	-0.7927***	(0.2826)	0.006
$\ln ER_{t-1}$	-0.2401	(0.2046)	0.244
$\ln PF_{t-1}$	0.0771***	(0.0209)	0.000
Panel B: Short-run differences			
$\Delta \ln FFI_{t-1}$	0.2040**	(0.0967)	0.038
$\Delta \ln RE_t$	-0.0378	(0.0507)	0.458
$\Delta \ln EC_t$	0.8423***	(0.3091)	0.008
ΔNUC_t^{share}	-0.3495	(0.4643)	0.453
$\Delta \ln ER_t$	-0.3311	(0.4783)	0.491
$\Delta \ln PF_t$	-0.1660*	(0.0997)	0.099
Panel C: Deterministic terms			
Constant	5.9970	(5.5262)	0.281
B_t (2022:11 break)	-0.0694**	(0.0309)	0.027

Dependent variable $\Delta \ln FFI_t^{power}$. Seasonal dummies estimated but not reported. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 8 traces the cumulative dynamic multiplier of a permanent one percent increase in renewable generation. The response settles within roughly three months and converges to −0.0391, identical to the estimated long-run coefficient, which provides an independent numerical check on the elasticity calculation.

5.4 Diagnostics

Table 6 reports the diagnostic battery. The primary specification passes every test: no serial correlation at twelve lags ($p = 0.139$), no ARCH effects ($p = 0.271$), normally

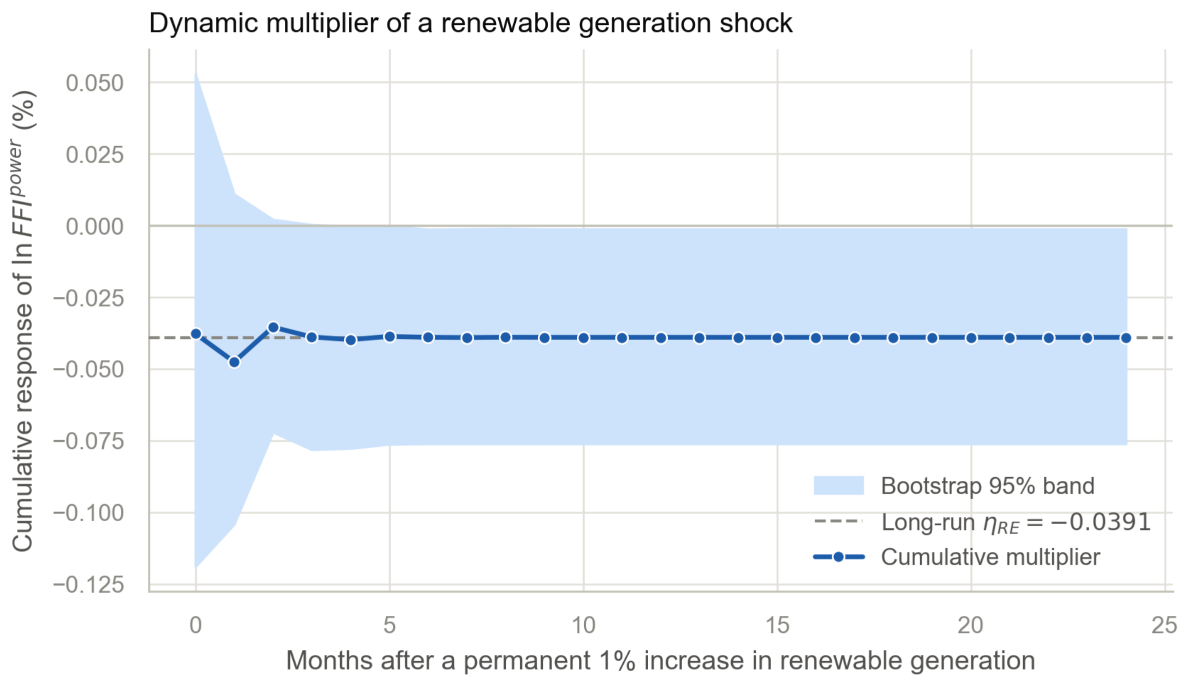


Figure 8: Cumulative dynamic multiplier of a permanent one percent increase in renewable generation, with bootstrap 95% band.

distributed residuals ($p = 0.898$), correct functional form by the RESET test ($p = 0.652$), and parameter stability by both CUSUM and CUSUMSQ. Adjusted R^2 is 0.776. One exception should be recorded: the full-sample specification M3 fails the ARCH test at the 5% level ($p = 0.041$), which is unsurprising over a 26-year window spanning two energy price shocks and is a further reason to treat the transition sample as primary.

Table 6: Diagnostic tests and stability

Test	M1	M2	M3	M4	M5	M6	M7	M8	M9
Ljung–Box(12)	0.139	0.136	0.069	0.064	0.099	0.116	0.155	0.258	0.104
ARCH(12)	0.271	0.695	0.041	0.211	0.212	0.084	0.151	0.328	0.323
Jarque–Bera	0.898	0.617	0.867	0.945	0.997	0.369	0.753	0.964	0.888
RESET	0.652	0.433	0.627	0.607	0.472	0.315	0.726	0.810	0.653
Adj. R^2	0.776	0.729	0.668	0.767	0.760	0.982	0.782	0.780	0.770
Resid. SD	0.052	0.054	0.066	0.052	0.054	0.023	0.052	0.051	0.052
Max VIF	3.36	3.38	7.00	3.26	2.79	4.90	3.36	3.36	5.50
CUSUM stable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No
CUSUMSQ stable	Yes	Yes	No	Yes	Yes	No	Yes	Yes	Yes

Entries for the four tests are p-values; values above 0.05 mean the null of no serial correlation, no ARCH, normality and correct functional form is not rejected. VIF is computed on the lagged level terms. Stability from recursive-residual CUSUM and CUSUMSQ at the 5% level.

The concern that renewable generation and the nuclear share would prove too collinear to separate does not materialize. Although their correlation in levels is -0.767, the maximum variance inflation factor in the estimated model is only 3.36, because the UECM enters the variables as differences and lagged levels rather than as raw levels. Figure 9 presents the stability plots.

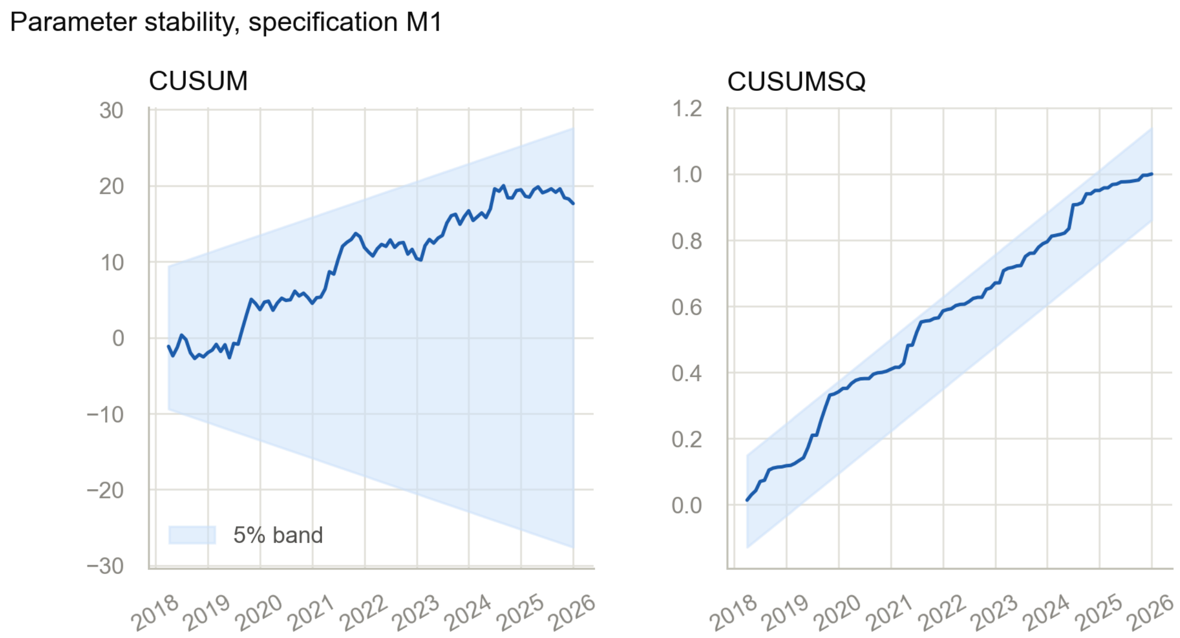


Figure 9: Recursive-residual CUSUM and CUSUMSQ for the primary specification, with 5% bands (Brown et al., 1975).

5.5 Robustness

Table 7 collects the elasticity across all specifications. **Every specification returns a negative estimate**, ranging from −0.003 to −0.075. The bootstrap interval excludes zero in M1, M6, M7 and M8, and includes it in M2, M3, M4, M5 and M9. The estimate is not sensitive to the seasonal specification: replacing eleven monthly dummies with three Fourier pairs, which conserves five degrees of freedom, moves the elasticity only from −0.0391 to −0.0403. Aggregating to quarterly frequency, which removes the shipment-lumpiness noise, roughly doubles the estimate to −0.0739 and sharpens its significance.

Two variants deserve individual attention.

Dropping the nuclear control (M5) attenuates the elasticity from −0.039 to −0.023 and renders it insignificant. The direction is exactly what omitted-variable bias predicts: with the simultaneous nuclear phase-out unaccounted for, part of the fossil fuel expansion required to replace nuclear output is wrongly attributed to renewables, pulling the estimate toward zero. This supports retaining the control.

Table 7: Robustness of the long-run renewable elasticity η_{RE}

Spec.	Variation	η_{RE}	Std. err.	p	Bootstrap 95% CI
M1	Main: FFI_power, lnRE, 2016+, Case III	-0.0391*	0.0209	0.061	[-0.075, -0.001]
M2	FFI_all (incl. crude oil and coking coal)	-0.0375	0.0307	0.221	[-0.090, 0.016]
M3	Full sample 2000-01 onward	-0.0422*	0.0237	0.075	[-0.086, 0.003]
M4	RE split: dispatchable vs variable	-0.0032	0.0145	0.827	[-0.029, 0.022]
M5	Drop nuc_share (collinearity check)	-0.0228	0.0257	0.374	[-0.070, 0.023]
M6	Quarterly frequency (shipment-lumpiness check)	-0.0739**	0.0306	0.016	[-0.123, -0.027]
M7	Fourier seasonality (order 3) instead of 11 dummies	-0.0403**	0.0200	0.044	[-0.075, -0.003]
M8	Case V (unrestricted intercept and trend)	-0.0754**	0.0294	0.010	[-0.127, -0.025]
M9	Fuel-specific prices instead of the Divisia index	-0.0377*	0.0218	0.084	[-0.076, 0.001]
M10: rolling η_{RE}, 96-month window					
218 windows; η_{RE} ranges -0.0662 to 0.1896, ending at -0.0506					

In M4 the reported coefficient is on $\ln RE^{var}$ (variable renewables). Bootstrap confidence intervals use 2,000 residual resamples and are preferred to the delta method because η_{RE} is a ratio of estimates. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Widening the dependent variable (M2) to include crude oil and coking coal degrades the model materially. The elasticity is little changed, but the electricity consumption coefficient collapses to -0.054 and loses all significance. Since electricity demand must raise power-sector fuel imports, this is direct evidence that the wider aggregate is contaminated by fuels unrelated to electricity generation, and it vindicates the restriction to power-sector fuels.

5.6 Decomposing renewables: the intermittency mechanism

Specification M4 splits renewable generation into dispatchable sources (hydropower, biomass, waste incineration and geothermal) and variable sources (solar and wind). The partition is exhaustive, so that $RE^{disp} + RE^{var} \equiv RE$. Figure 10 shows the two series: dispatchable generation is roughly flat over the sample, while variable generation grows from near zero to overtake dispatchable around 2020 and reach nearly three times its level by 2025. The result is the clearest finding in the study:

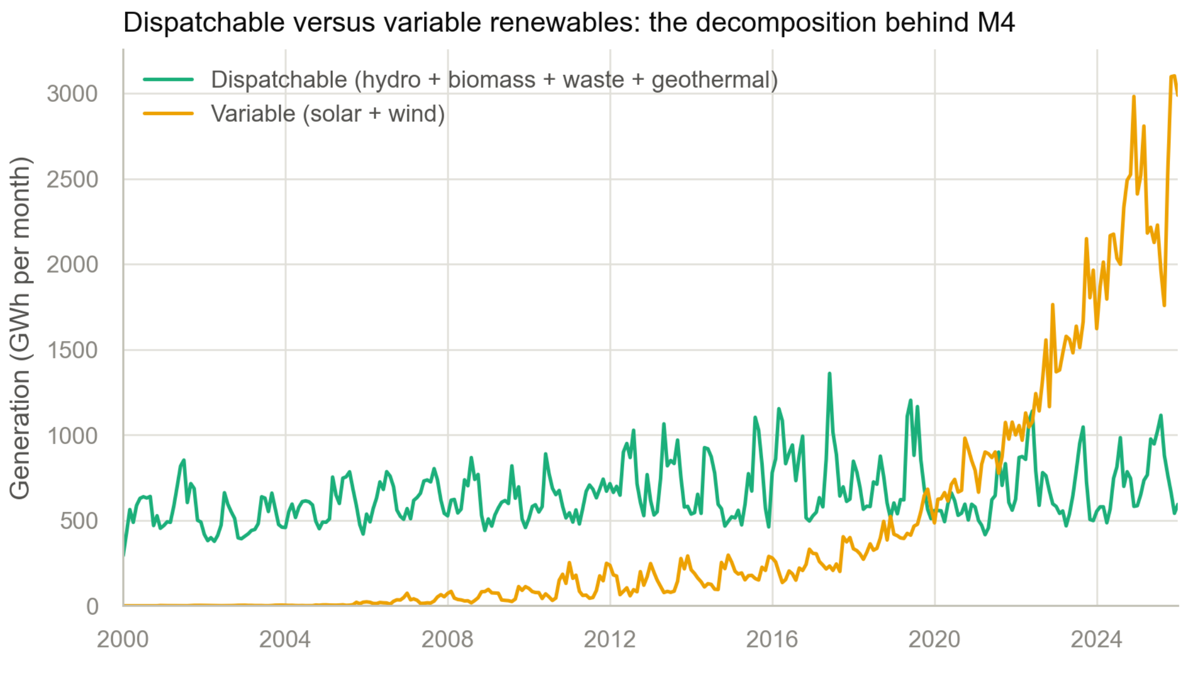


Figure 10: Dispatchable (hydropower, biomass, waste and geothermal) versus variable (solar and wind) renewable generation. The line that has grown is the one M4 shows has no measurable displacement effect. Own calculation from Energy Administration, Ministry of Economic Affairs (2026).

	Coefficient	Std. err.	p
Dispatchable renewables ($\ln RE^{disp}$)	-0.0373	0.0235	0.112
Variable renewables ($\ln RE^{var}$)	-0.0032	0.0145	0.827

Dispatchable renewables display a displacement effect roughly 11.7 times larger than variable renewables, and the coefficient on solar and wind is indistinguishable from zero. Precisely the technologies at the centre of Taiwan's transition policy, and the ones that grew fifteen-fold and eight-fold respectively between 2016 and 2025, are the ones with no measurable effect on fossil fuel imports.

This replicates Marques et al. (2018) in a setting they did not examine. Their European sample retained cross-border balancing capability; Taiwan's grid has none, so intermittent output must be backed by domestic reserves that remain fuelled by imports regardless of how much solar and wind capacity is added. The result is therefore not merely a robustness check but the mechanism underlying the aggregate finding.

5.7 The elasticity is a recent phenomenon

Figure 11 plots η_{RE} estimated over rolling 96-month windows. The estimate was significantly *positive*, at +0.19, in windows ending around 2010–2011, declined steadily thereafter, and turned negative only after approximately 2022, reaching -0.051 at the end of the sample.

The positive early estimate is interpretable rather than anomalous. In that period renewable generation was overwhelmingly hydropower and was expanding alongside rapidly growing electricity demand, so renewable output and fossil fuel imports rose together: energy addition in its purest form. The transition to a negative elasticity coincides with the point at which solar and wind capacity became large enough to affect dispatch. This provides empirical justification for treating 2016 onward as the primary sample, rather than merely a convenience dictated by data availability.

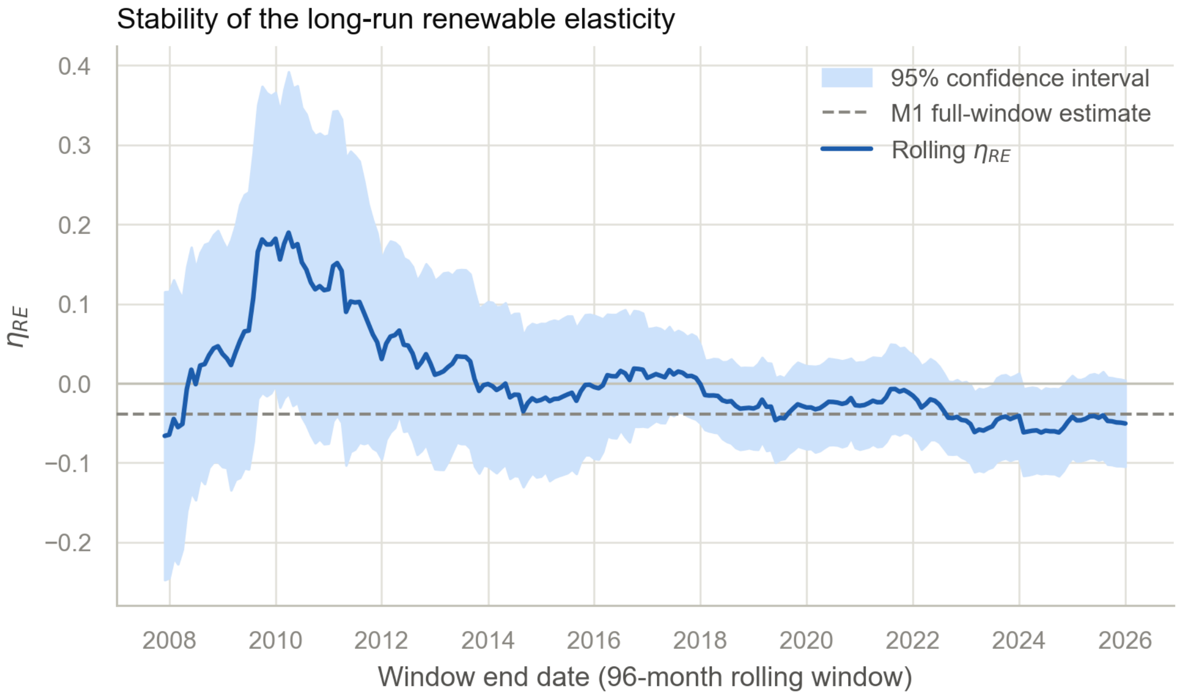


Figure 11: Long-run renewable elasticity estimated over rolling 96-month windows, with 95% confidence interval.

6 Discussion

6.1 Interpretation

Three findings emerge. First, fractional displacement is confirmed for Taiwan. The elasticity of -0.039 is negative, consistent with the theoretical expectation that near-zero marginal cost renewables displace fossil generation in the dispatch order, but its magnitude is negligible relative to one-for-one substitution. This aligns with York (2012) and with the finding of Karlilar Pata and Balcilar (2024) that displacing one unit of fossil capacity requires about 1.15 units of renewable capacity.

Second, intermittency is the operative mechanism, not a secondary consideration. The magnitude of the gap between dispatchable and variable renewables quantifies the system integration cost in an isolated grid. Fossil-fuelled spinning reserve must be maintained to compensate for the variability of solar and wind, and that reserve requires imported fuel whether or not it is called upon.

Third, the additionality paradox is confirmed but in a specific form. The electricity consumption elasticity of $+0.555$ is fourteen times the magnitude of the renewable elasticity. Demand growth is the dominant driver of import volumes, and renewable capacity has functioned largely to serve incremental load rather than to retire existing fossil assets.

6.2 Policy implications

If renewable expansion is chasing demand growth rather than displacing fossil fuels, supply-side capacity targets alone are insufficient for genuine decarbonization, and two priorities follow.

The first is demand-side management. With a consumption elasticity fourteen times the renewable elasticity, curbing load growth is a considerably more efficient lever on import dependence than adding capacity, and the classical case for utility-led demand-side management applies directly (Gellings, 1985).

The second is grid flexibility over headline capacity. Since variable renewables show no measurable displacement effect while dispatchable renewables do, the binding constraint is the ability to convert intermittent output into firm supply. Utility-scale storage, demand response and grid modernization address that constraint; further capacity additions without them will continue to yield elasticities near zero. The policy implication is not that solar and wind investment is misdirected, but that it is incomplete: the complementary flexibility infrastructure determines whether that investment translates into reduced import dependence.

6.3 Findings that warrant caution

Three results should be read with care rather than presented without qualification.

The error correction coefficient exceeds unity in absolute value ($\lambda_1 = -1.653$, and between -1.05 and -1.69 across specifications). This indicates overshooting rather than instability: since $|1 + \lambda_1| = 0.653 < 1$, the system converges, though it oscillates while doing so. The behaviour is consistent with the shipment lumpiness documented in Section 3, where monthly imports overshoot and revert. It is not an artefact of monthly frequency alone, since the quarterly specification also returns $\lambda_1 = -1.363$.

The fuel price coefficient is positive ($+0.047$, $p < 0.001$). Read literally, more expensive fuel is associated with larger imports, which is counterintuitive. Two explanations are plausible: prices and quantities are jointly driven by demand, producing simultaneity; and long-term contract pricing means the current benchmark price is not the price actually paid for current deliveries. The magnitude is small and the coefficient is a control rather than an object of interest, but it is reported rather than suppressed.

The consumption elasticity is unstable across specifications, at +0.555 in the primary specification, +1.362 over the full sample, and −0.054 in the all-fuel variant. The all-fuel result is explicable as contamination, as discussed above. The difference between the transition and full samples is larger than would be comfortable and suggests the demand–import relationship itself has changed over 26 years.

6.4 Limitations

Several limitations should be acknowledged.

The LNG calorific value is not drawn from the official table, because the published figure is on a volume basis while the import data are on a mass basis, and the conversion factor is unavailable. The international convention of 52 GJ/t is used instead. Since LNG constitutes 52.5% of FFI^{power} by 2025, this is the largest single measurement uncertainty in the dependent variable. Sensitivity analysis indicates the substantive conclusions are unaffected, but obtaining the official regasification factor would improve precision.

Temperature is not controlled. Seasonal dummies capture the average summer but not an unusually hot one, so the consumption coefficient carries some climate noise. Monthly temperature data from the Central Weather Administration would address this at low cost.

The analysis uses generation rather than capacity data, which limits direct comparability with Karlilar Pata and Balcilar (2024), whose 1.15 figure is capacity-based.

Nuclear power enters as a share rather than in logarithms, departing from the original specification, and its coefficient is therefore a semi-elasticity rather than an elasticity.

Finally, the transition sample spans 121 months, of which 119 are usable after lagging, against 25 estimated parameters. The bounds test critical values are simulated at that effective sample size precisely because asymptotic approximations are unreliable here, but the statistical power to distinguish a small negative elasticity from zero remains limited. This is the reason η_{RE} sits at the boundary of conventional significance while the control variables are estimated precisely, and it is why the substantive interpretation rests on the magnitude of the estimate and the consistency of its sign across ten specifications rather than on a single p value.

7 Conclusion

This study asked whether renewable energy development has reduced Taiwan's fossil fuel import dependence. Using monthly data from 2000 to 2026 and an ARDL bounds testing framework, it finds a stable long-run relationship in which the elasticity of power-sector fossil fuel imports with respect to renewable generation is -0.039. The sign is correct and consistent across every specification estimated, but the magnitude is negligible: renewable generation tripled over the transition period while power-sector fossil fuel imports rose by 6.3%.

The decomposition identifies why. Dispatchable renewables displace imported fossil fuel; variable solar and wind, the technologies driving Taiwan's transition, show no measurable displacement effect. In an island grid without cross-border balancing, intermittent output must be backed by fossil-fuelled reserve capacity, and that reserve requires imported fuel regardless of how much solar and wind capacity is installed. The rolling-window evidence shows displacement emerging only after approximately 2022, with renewable expansion before then representing energy addition rather than substitution.

Taiwan's transition is therefore not on the trajectory its capacity targets imply. The gap is not primarily a shortfall in renewable deployment but a shortfall in the demand-side and flexibility infrastructure required to convert that deployment into displaced imports. Capacity targets measure inputs; import dependence measures outcomes, and the two have not yet been connected.

References

Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society: Series B*, *37*(2), 149–163. https://doi.org/10.1111/j.2517-6161.1975.tb01532.x

Central Bank of the Republic of China (Taiwan). (2026). Monthly average exchange rate of the new taiwan dollar against the us dollar (series bp01m01) [Statistical database, monthly averages]. https://www.cbc.gov.tw/en/cp-370-935-6E1AC-2.html

Chuang, M. C., & Ma, H. W. (2013). An assessment of taiwan's energy policy using multi-dimensional energy security indicators. *Renewable and Sustainable Energy Reviews*, *17*, 301–311. https://doi.org/10.1016/j.rser.2012.09.034

Climate Change Administration, Ministry of Environment. (2022). Net zero roadmap: Taiwan 2050 net-zero. https://www.cca.gov.tw/en/climatetalks/net-zero-roadmap/1891.html

Diewert, W. E. (1976). Exact and superlative index numbers. *Journal of Econometrics*, *4*(2), 115–145. https://doi.org/10.1016/0304-4076(76)90009-9

Efron, B. (1979). Bootstrap methods: Another look at the jackknife. *The Annals of Statistics*, *7*(1), 1–26. https://doi.org/10.1214/aos/1176344552

Energy Administration, Ministry of Economic Affairs. (2024a). Energy supply overview (2024). https://www.moeaea.gov.tw/ECW/populace/content/Content.aspx?menu_id=14435

Energy Administration, Ministry of Economic Affairs. (2024b). Unit calorific values of energy products (effective from 2024) [Net calorific values; for energy-statistics use only]. https://www.moeaea.gov.tw/

Energy Administration, Ministry of Economic Affairs. (2026). Energy statistics query system (e-stat) [Monthly series on energy imports by country of origin, electricity generation, electricity consumption and energy indicators]. https://www.esist.org.tw/database/

Gellings, C. (1985). The concept of demand-side management for electric utilities. *Proceedings of the IEEE*, *73*(10), 1468–1470. https://doi.org/10.1109/PROC.1985.13318

Hung, M.-F., & Huang, T.-H. (2015). Dynamic demand for residential electricity in taiwan under seasonality and increasing-block pricing. *Energy Economics*, *48*, 168–177. https://doi.org/10.1016/j.eneco.2015.01.010

Jacobson, M. Z. (2021). The cost of grid stability with 100% clean, renewable energy for all purposes when countries are isolated versus interconnected. *Renewable Energy*, *179*, 1065–1075. https://doi.org/10.1016/j.renene.2021.07.115

Karlilar Pata, S., & Balcilar, M. (2024). Decarbonizing energy: Evaluating fossil fuel displacement by renewables in oecd countries. *Environmental Science and Pollution Research*, *31*(21), 31304–31313. https://doi.org/10.1007/s11356-024-33324-8

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics*, *54*(1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y

Lan, H.-W., & Lee, C.-F. (2011). The study on the relativity between regional power load and climate -multiple linear regression model. *Journal of the Department of Business Administration, National Kaohsiung University of Applied Sciences*. https://etds.ncl.edu.tw/cgi-bin/gs32/gsweb.cgi/ccd=MAvYPe/record?r1=1&h1=0

Marques, A. C., Fuinhas, J. A., & Pereira, D. A. (2018). Have fossil fuels been substituted by renewables? an empirical assessment for 10 european countries. *Energy Policy*, *116*, 257–265. https://doi.org/10.1016/j.enpol.2018.02.021

McNown, R., Sam, C. Y., & Goh, S. K. (2018). Bootstrapping the autoregressive distributed lag test for cointegration. *Applied Economics*, *50*(13), 1509–1521. https://doi.org/10.1080/00036846.2017.1366643

Narayan, P. K. (2005). The saving and investment nexus for china: Evidence from cointegration tests. *Applied Economics*, *37*(17), 1979–1990. https://doi.org/10.1080/00036840500278103

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326. Retrieved February 2, 2026, from http://www.jstor.org/stable/2678547

Ritchie, H., & Rosado, P. (2026). Electricity mix [Electricity production by source, World; data through 2024]. *Our World in Data*. https://ourworldindata.org/electricity-mix

Ritchie, H., Rosado, P., & Roser, M. (2026). Energy [Electricity production by source, Taiwan; data through 2024]. https://ourworldindata.org/grapher/electricity-prod-source-stacked?country=TWN

Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with python. *Proceedings of the 9th Python in Science Conference*, 92–96. https://doi.org/10.25080/Majora-92bf1922-011

Taiwan Power Company (Taipower). (2025). Wind power generation [Taipower official webpage]. https://www.taipower.com.tw/umbraco/surface/Ini/CountAndRedirectUrl?nodeId=28876

Waskom, M. L. (2021). Seaborn: Statistical data visualization. *Journal of Open Source Software*, *6*(60), 3021. https://doi.org/10.21105/joss.03021

Wolde-Rufael, Y. (2010). Bounds test approach to cointegration and causality between nuclear energy consumption and economic growth in india. *Energy Policy*, *38*(1), 52–58. https://doi.org/10.1016/j.enpol.2009.08.053

World Bank. (2026). Commodity markets outlook: Pink sheet monthly historical prices [Series used: Coal (Australia), Liquefied natural gas (Japan), Crude oil (Dubai)]. https://www.worldbank.org/en/research/commodity-markets

York, R. (2012). Do alternative energy sources displace fossil fuels? *Nature Climate Change*, *2*(6), 441–443. https://doi.org/10.1038/nclimate1451

Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics*, *10*(3), 251–270. https://doi.org/10.1080/07350015.1992.10509904