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Persistent Policy Uncertainty and Green Energy Valuation: A Long-Run ARDL Analysis of the CELS Index

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Abstract

This study examines the dynamic, asymmetric influence of macroeconomic and policy uncertainty on the NASDAQ Clean Edge Green Energy Index (CELS), a key benchmark for US renewable energy stocks. Using monthly data from January 2008 to June 2025 and employing an Autoregressive Distributed Lag (ARDL) model with bounds testing, we confirm a significant and stable long-run cointegrating relationship. Our primary contribution is the clear delineation of effects across time horizons. In the short run, the CELS index is highly responsive to immediate shocks, particularly those originating from the Volatility Index (VIX) and Brent crude oil prices.

However, in the long run, the most dominant and persistent negative influence stems from the US Climate Policy Uncertainty Index. This finding suggests that while investors tolerate short-term macroeconomic volatility, sustained ambiguity regarding federal energy policy significantly depresses the long-term value of clean energy assets. We provide actionable, evidence-based guidance for policymakers, recommending the implementation of durable, cross-cycle mechanisms (such as guaranteed pricing or consistent regulatory standards) to mitigate long-term uncertainty and stabilise capital flows into the clean energy transition. The results also offer clear strategies for asset managers seeking to hedge against specific macroeconomic and policy risks in the green energy sector.

Keywords: renewable energy stocks; policy uncertainty; exchange rates; treasury yields; volatility index (vix); green energy.

JEL Code: Q40, Q42, Q54, G12, G15, C22.

Introduction

The transition toward sustainable energy systems represents one of the most critical economic and technological shifts of the twenty-first century. As global governments commit to decarbonization targets, investment in clean and renewable energy technology has grown exponentially, positioning the Clean Edge Green Energy Index (CELS) as an important barometer for market confidence in this sector (IEA, 2025; OECD/IEA, 2024).

However, the unique nature of clean energy assets, characterized by high capital intensity, reliance on long-term policy contracts, and inherent exposure to political and regulatory risk, makes them acutely sensitive to various forms of macroeconomic and policy uncertainty (Sadorsky, 2012; Lyócsa & Todorova, 2024; Pham et al., 2025). This vulnerability introduces systematic risk, potentially hindering the efficient allocation of capital necessary to achieve climate goals (Calcaterra et al., 2024; Gordo et al., 2024).

This paper addresses an essential gap in the literature by rigorously analysing the differential impacts of various uncertainty measures, specifically policy-driven uncertainty and macroeconomic volatility, on the CELS index across both the short and long run. While prior research has broadly established the link between uncertainty and asset pricing (Zaier et al., 2024; Bouri et al., 2025), there remains insufficient evidence to guide policymakers and investors on which type of uncertainty poses the most persistent threat to the financial viability of the green energy sector. Furthermore, clean energy markets are distinct from general equity markets: their returns are not only influenced by traditional financial variables such as interest rates and exchange rates (Kocaarslan & Soytas, 2019) but are critically shaped by regulatory stability and geopolitical commitment to climate mandates (Gavriilidis, 2021; Islam et al., 2023; Ghosh, 2022).

To capture these dynamics, we utilize the Autoregressive Distributed Lag (ARDL) model on monthly data spanning 2008–2025. The ARDL methodology is instrumental because it allows us to formally test for cointegration and simultaneously estimate both short-run adjustment mechanisms and long-run equilibrium relationships (Pesaran, Shin, & Smith, 2001). This approach is methodologically superior to single-equation models that fail to distinguish the transient noise of macroeconomic shocks from the lasting structural damage caused by sustained policy ambiguity (Wang et al., 2025; Yuen & Yuen, 2024). Our explanatory variables include the US Climate Policy Uncertainty (CPU) Index, the Global Policy Uncertainty (GPU) Index, Brent crude oil prices, the BIS Broad Dollar Index, the 10-year Treasury yield, and the Volatility Index (VIX), consistent with prior research (Gordo et al., 2024).

Our empirical findings reveal a strong, stable long-run relationship among these variables. The main economic contribution of this study lies in demonstrating that short-run volatility is primarily driven by traditional financial variables such as market volatility (VIX) and oil prices (Dawar et al., 2021), which impact liquidity and immediate market sentiment. In contrast, the long-run valuation of the CELS index is overwhelmingly determined by policy uncertainty (Li et al., 2025; Zaier et al., 2024). We show that sustained, high levels of US climate policy ambiguity result in a significant, structural drag on the CELS index, indicating that investors view regulatory inconsistency as a fundamental impediment to future profitability.

These findings carry two important implications for applied economics. First, for policymakers, they underscore that intermittent support is insufficient; what the green energy sector requires is credible, long-term policy commitment to stabilise investment cycles (Calcaterra et al., 2024; OECD/IEA, 2024). We suggest specific measures such as locking in regulatory frameworks or providing policy-continuity incentives to de-risk the sector. Second, for finance professionals, our results highlight the need for risk-management strategies that differentiate between hedging against financial volatility (short run) and protecting capital from regulatory obsolescence (long run), thereby informing more robust green-portfolio construction (Bouri et al., 2025; Pham et al., 2025).

1. Literature Review

Policy-Driven and Regulatory Uncertainty

The renewable energy industry works in a highly regulated environment, in which policies related to fiscal incentives, subsidy mechanisms and long-term regulatory stability influence the return on investment. Therefore, the uncertainty of the credibility or stability of climate policies can impact both market behaviour and investment decisions. As such, the Climate Policy Uncertainty (CPU) index developed by Gavriilidis (2021) captures this aspect of investment and can be used for measuring the effects of this policy uncertainty on the performance of green investment assets. Research indicates that uncertainty with climate policy can increase or decrease demand for investment depending upon if any changes in climate policy are perceived by investors as an opportunity or a risk (Zaier et al., 2024; Gürsoy et al., 2024).

Recent research has emphasized that regulatory uncertainty for extended periods results in a structural drag on equity valuations in renewable energy (Aharon et al., 2025), because of increased financing costs and delayed capital inflow (Li et al., 2025; Calcaterra et al., 2024). Gavriilidis (2021) makes clear that climate policy uncertainty interacts with environmental policy stringency, which drives the direction and magnitude of investor responses, with inconsistent frameworks putting risk back on the table in terms of repricing. Other researchers have also found clean energy markets to be mispriced predominantly on expectation changes to policy and policy uncertainty (Cheng & Chiu., 2018; Qin et al., 2020), with adjustments occurring rapidly in valuation dynamics (Bouri et al., 2025; Pham et al., 2025). Overall, this literature points to the critical need for credible, transparent, and long-term commitments provided at the regulatory level to sustain investor confidence in renewable energy markets.

Macroeconomic and Financial Volatility Channels

Apart from ambiguity around policy, other significant macro-financial factors that influence renewable stock returns include oil prices, interest rates, exchange rates, and periods of market volatility. Oil prices serve as a cost benchmark for clean energy production, and a competitive fuel substitute to clean energy resources (Zhao., 2020; Saeed et al., 2021; Dinh., 2025) researchers have offered evidence of asymmetric effects from oil price changes (Ahmad., 2017; Bondia et al., 2016). Specifically, some research suggests oil prices serve primarily substitutionally, as in higher prices for oil will make renewables relatively more competitive (Maghyereh et al., 2019; Sadorsky, 2012). while others find complementary relationships under technology-linked conditions (Niu., 2021; Jiang et al., 2021; Dawar et al., 2021).

Another important channel of transmission is macroeconomic tightening, particularly in the form of higher Treasury yields and an increase in the value of the dollar. An increase in the value of the dollar, on average, reduces global liquidity and raises the cost of financing projects, thereby dampening renewable energy equity returns (Kocaarslan & Soytas, 2019; Gordo et al., 2024). The results point to potential sustained adverse effects on renewable equity prices as a result of monetary policy normalization; however, it should be noted that volatility spillovers would also shape market behaviour during higher risk regimes.

The VIX index, which acts as a proxy for broad-based volatility, can have a strong impact on clean energy equities (Zhang et al., 2024). Bouri et al. (2025) and Ghosh (2022) note that volatility shocks induce immediate negative shock to clean energy returns, demonstrating the tendency of investors to fly towards high-beta assets during volatility spikes. However, on longer time horizons, capital usually moves back toward green assets as capital is being rebalanced for sustainability (Pham et al., 2025). All of these findings suggest renewable equities react differently to short-term liquidity shocks versus long-term macro-financial constraints, thereby necessitating a model designed to differentiate between these two-time legs.

Characteristics of the Clean Edge Green Energy Index (CELS)

The NASDAQ Clean Edge Green Energy Index (CELS) monitors publicly traded companies that operate in clean energy technologies like solar, wind, biofuels, and advanced storage and which are typically companies with a growth emphasis and capital intensive, and are sensitive to government incentives and research grants (Lyócsa & Todorova, 2024; Pham et al., 2025). Consequently, CELS constituents have a stronger relationship with changes in interest rates, policy stability, and international equity flow compared to traditional equity indices.

Past research has shown that clean energy indices' performance often exhibits sluggish adjustment to macroeconomic news and strong downside risk transmission during episodes of financial distress (Gavriilidis, 2021; Ghosh, 2022). The CELS index is an appropriate stand-in for assessing the joint impact of climate policy and uncertainty in the macro-financial environment on renewable stock performance because it is a hybrid index of high policy exposure and high innovation dependence. Consequently, the structure of the CELS index provides a targeted lens for consideration of the sustainability finance dimension of systemic market risk.

Methodological Approaches in Renewable Finance Research

Several econometric methods have been used to study uncertainty and renewable energy markets. In earlier research, VAR and GARCH models have been used to analyse volatility spillovers (Sadorsky, 2012; Liu & Hamori, 2020). More recently, panel regressions and mixed-frequency methods have emerged to study uncertainty (Zaier et al., 2024). However, these methods do not provide a dynamic adjustment process between short- and long-run relationships. The Autoregressive Distributed Lag (ARDL) framework designed by Pesaran, Shin, and Smith (2001) remedies this limitation by permitting variables with different orders of integration (I(0) or I(1)) and jointly estimating the short- and long-run effects. Its capacity for cointegration and short-run error-correction mechanisms make ARDL particularly suitable for financial time series that have mixed integration properties and may exhibit structural breaks. The recent applications of the ARDL approach in energy finance indicate its robustness in capturing complex uncertainty interactions (Wang et al., 2025; Yuen & Yuen, 2024). For these reasons, the ARDL model is the most appropriate model for evaluating how policy and macroeconomic uncertainty affect renewable stock returns over different time horizon.

Research Gap and Contribution

Despite the growth of literature on renewable energy finance, several critical gaps remain. Most existing studies examined either policy uncertainty or macroeconomic volatility in isolation, the joint transmission of both remains largely unstudied. Further, the prior studies have rarely distinguished short-run shocks and long-run equilibrium effects, which are key to developing sustained investment and policy strategies.

This study contributes to filling these gaps in three ways. First, it jointly examines multiple uncertainty channels, including climate policy uncertainty, global uncertainty, market volatility, and macro-financial variables, within a unified ARDL framework. Second, it captures both the short-term speculative adjustments and the long-term equilibrium dynamics of renewable energy stocks, addressing the time-horizon asymmetry absent in previous models. Third, it provides actionable insights for policymakers and investors by linking empirical findings to targeted policy prescriptions and risk-management strategies. Through this comprehensive approach, the study advances the literature on uncertainty transmission and strengthens the applied relevance of renewable energy finance research.

2. Data and Methodology

Data Description

This study employs monthly data spanning from January 2008 to June 2025. The dependent variable is the Clean Edge Green Energy Index (CELS) obtained from NASDAQ, which serves as a proxy for US renewable energy stock performance. Explanatory variables include:

- Climate Policy Uncertainty Index (CPU): US specific climate policy uncertainty index developed by Gavriilidis (https://www.policyuncertainty.com/climate_uncertainty.html);
- Brent Crude Oil Price (OIL): Extracted from the Federal Reserve Bank of St. Louis (FRED: DCOILBRENTEU);
- BIS Broad Dollar Index (BIS): Monthly trade-weighted US dollar index from the Bank for International Settlements;
- Global Policy Uncertainty Index (GPU): World-level policy uncertainty index constructed by Baker, Bloom, and Davis.
- 10-Year Treasury Yield (YIELD): Monthly US government bond yield from FRED(FRED: DGS10).
- Volatility Index (VIX): Market-wide implied volatility, from FRED.

To ensure stationarity and consistency with empirical finance literature, all asset price variables, including the NASDAQ Clean Edge Green Energy Index (CELS), Brent crude oil prices, and the BIS Broad Dollar Index, are transformed into returns. These returns are calculated as log differences of monthly closing values. Using returns instead of price levels reduces the risk of spurious regression because financial price series are often integrated of order one (I(1)), while their returns are usually stationary. This method also allows for interpreting results in percentage change terms, which provides a clearer view of market dynamics and relative changes across asset classes. Such a transformation is common in energy and financial econometrics. It ensures comparability and solid inference when examining the relationships among exchange rates, commodity prices, and renewable energy equity performance.

To capture extraordinary events, three dummy variables were introduced.

- DUM_PARIS (2016M12 onward): Represents the Paris Agreement implementation phase.
- DUM_COVID (2020M03–2020M05): Captures the initial market panic of the COVID-19 pandemic.
- DUM_UKR (2022M02-2022M06): Reflects pulse of geopolitical shocks from the Russia–Ukraine conflict**.**

These dummies are coded as 1 during the respective periods and 0 at other times. Their inclusion makes sure that results are not influenced by structural changes caused by these extraordinary events.

Econometric Framework

The analysis proceeds in several steps, fist one stationarity testing. Initially, all variables undergo testing for stationarity through the Augmented Dickey-Fuller (ADF) and KPSS tests. The results demonstrate that none of the variables are integrated of order two, I(2), which is necessary to use the Autoregressive Distributed Lag (ARDL) framework. Some variables are stationary at level, and others are stationary at I(1), which satisfies the condition of mixed orders of integration.

Table 1: Stationarity testing

Variable	Level Stationary (ADF)?	Level Stationary (KPSS)?	First Difference Stationary (ADF)	First Difference Stationary (KPSS)
CELS	No	No	Yes	Yes
BIS	No	No	Yes	Yes
CPU	No	No	Yes	Yes
GPU	Yes	No	N/A	Yes
OIL	Yes	Yes	N/A	N/A
VIX	Yes	Yes	N/A	N/A
YIELD_10Y	No	No	Yes	Yes

Source: Authors' own calculation

To evaluate the short- and long-run empirical effects of policy-related and macroeconomic uncertainty on renewable energy equity returns, we utilize the Autoregressive Distributed Lag (ARDL) bounds testing approach outlined by Pesaran et al. (2001). The ARDL model is attractive to its application in time-series financial data and allows for integration of the variables of interest that may have different orders of integration; I(0) and I(1). The ARDL model estimates the short-run dynamics and the long-run equilibrium relationship among the variables simultaneously, allowing clear separation of short-run transitory fluctuations and long-run structural impacts. This is especially useful for observing how short-lived market shocks, such as increasing oil prices and volatility, differ from different effects stemming from policy uncertainty in study the performance of renewables stock.

The general ARDL specification used in this study is as follows:

$$
\begin{aligned}
\mathrm{R\_CELS\_t} = {} & \alpha 0 + \varphi 1 * \mathrm{R\_CELS\_\{t-1\}} + \beta 0 * \mathrm{R\_OIL\_t} + \gamma 0 * \mathrm{R\_BIS\_t} + \delta 0 * \mathrm{CPU\_t} \\
& + \delta 1 * \mathrm{CPU\_\{t-1\}} + \delta 2 * \mathrm{CPU\_\{t-2\}} + \delta 3 * \mathrm{CPU\_\{t-3\}} + \theta 0 * \mathrm{GPU\_t} \\
& + \theta 1 * \mathrm{GPU\_\{t-1\}} + \theta 2 * \mathrm{GPU\_\{t-2\}} + \theta 3 * \mathrm{GPU\_\{t-3\}} + \theta 4 * \mathrm{GPU\_\{t} \\
& - 4\} + \eta 0 * \mathrm{VIX\_t} + \eta 1 * \mathrm{VIX\_\{t-1\}} + \lambda 0 * \mathrm{YIELD\_10Y\_t} + \lambda 1 \\
& * \mathrm{YIELD\_10Y\_\{t-1\}} + \omega 1 * \mathrm{D\_PARIS\_t} + \omega 2 * \mathrm{D\_COVID\_t} + \omega 3 * \mathrm{D\_UKR\_t} \\
& + \varepsilon\mathrm{\_t}
\end{aligned}
$$

where: α0: Intercept term, φi: Short-run autoregressive coefficients for lagged RCELS, βj: Short-run coefficients for Brent oil returns, γk: Short-run coefficients for BIS dollar index returns, δl: Short-run coefficients for CPU (climate policy uncertainty), θm: Short-run coefficients for GPU (global policy uncertainty), ηn: Short-run coefficients for VIX, λo: Short-run coefficients for U.S. Treasury yields, ω1, ω2, ω3: Coefficients for structural break dummy variables (Paris Agreement, COVID-19, Ukraine conflict), εt: Error term at time *t*.

Estimation Procedure

The ARDL model firstly estimated using Ordinary Least Squares (OLS). However, since heteroskedasticity was detected in preliminary diagnostic tests, Newey–West HAC robust standard errors are applied to ensure consistent inference.

The optimal lag lengths for each variable were determined using the Akaike Information Criterion (AIC), as it balances model fit and parsimony, especially for smaller sample sizes. Multiple lag specifications were examined to ensure consistency of the long-run coefficients and stability of the error-correction term. The final specification was selected based on the minimum AIC value and theoretical coherence among variables. After estimation, a series of diagnostic tests was performed to verify model adequacy. The Breusch–Godfrey LM test confirmed the absence of serial correlation, while the Breusch–Pagan–Godfrey test verified homoscedasticity of residuals. The Jarque–Bera test indicated normality, and the Ramsey RESET test confirmed correct functional specification. To ensure the reliability of the long-run coefficients, the CUSUM and CUSUMSQ tests were applied; both plots remained within the 5% critical bounds, confirming parameter stability over the entire sample period.

The subsequent section presents the empirical findings, beginning with the ARDL bounds test results for cointegration, followed by the short-run and long-run coefficient estimates and the corresponding post-estimation diagnostics.

3. Results and Interpretation

Table 2 reports the baseline ARDL(1, 0, 0, 3, 4, 1, 1) estimation results, selected on the basis of the Akaike Information Criterion (AIC). The model explains approximately 57.6% of the variation in green energy stock returns ($R^2 = 0.576$), with a Durbin–Watson statistic close to 2, suggesting that serial correlation is not a concern. The F-statistic confirms the overall joint significance of the regressors at the 1% level. The results reveal a strong persistence effect, as the lagged dependent variable (R_CELS(-1)) is positive and highly significant ($p < 0.01$), indicating that past movements in renewable energy returns carry over into subsequent periods.

Table 2: Baseline ARDL

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R_CELS(-1)	0.2109	0.0470	4.4827	0.0000
R_OIL	-0.0032	0.0364	-0.0867	0.9310
R_BIS	-1.4778	0.4088	-3.6152	0.0004
CPU	0.0165	0.0094	1.7489	0.0820
CPU(-1)	0.0092	0.0104	0.8849	0.3773
CPU(-2)	-0.0225	0.0102	-2.2091	0.0284
CPU(-3)	-0.0210	0.0140	-1.5037	0.1344
GPU	0.0033	0.0103	0.3223	0.7476
GPU(-1)	-0.0118	0.0130	-0.9074	0.3654
GPU(-2)	0.0325	0.0166	1.9571	0.0518
GPU(-3)	0.0262	0.0155	1.6907	0.0926
GPU(-4)	-0.0300	0.0148	-2.0226	0.0445
VIX	-0.8427	0.1025	-8.2229	0.0000

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VIX(-1)	0.7105	0.0944	7.5244	0.0000
YIELD_10Y	3.5579	2.1891	1.6252	0.1058
YIELD_10Y(-1)	-4.7527	2.2288	-2.1324	0.0343
DUM_COVID	4.8674	2.5318	1.9225	0.0561
DUM_UKR	0.9879	1.8224	0.5421	0.5884
DUM_PARIS	-0.4305	1.2485	-0.3448	0.7307
Constant (C)	5.0326	1.8279	2.7532	0.0065

Source: Author's own calculation

Model statistics:

- $R^2 = 0.5763$, Adj. $R^2 = 0.5331$;
- AIC = 6.4009, SC = 6.7240, HQC = 6.5315;
- Durbin-Watson = 2.0371;
- F-statistic = 13.318 ($p = 0.0000$).

In terms of macro-financial drivers, the BIS broad dollar index (R_BIS) exhibits a large and negative effect ($\beta = -1.48$, $p < 0.01$), suggesting that a stronger US dollar significantly dampens renewable energy stock performance. This finding is consistent with the view that dollar appreciation tightens global financial conditions and raises the relative cost of renewable energy investments.

The role of climate policy uncertainty (CPU) is more nuanced. While the contemporaneous coefficient of CPU is weakly positive ($p < 0.10$), its lagged effects are negative and significant at conventional levels (CPU(-2): $\beta=-0.0225$, $p < 0.05$). This pattern suggests that climate policy shocks initially create speculative gains but subsequently suppress market sentiment and investment flows into green equities.

The global policy uncertainty index (GPU) displays mixed dynamics. While GPU(-2) is marginally positive ($p \approx 0.05$), GPU(-4) turns negative and significant ($\beta = -0.0300$, $p < 0.05$). This alternating effect points to the presence of short-term speculative adjustments, followed by longer-term adverse impacts of global policy uncertainty on green energy markets.

Market risk plays a decisive role. The VIX has a strong negative contemporaneous effect ($\beta = -0.84$, $p < 0.01$), while its one-month lagged value is strongly positive ($\beta = 0.71$, $p < 0.01$). This asymmetry reflects investors' initial withdrawal from risky assets during volatility spikes, followed by a corrective rebound as markets adjust.

Bond market dynamics also matter: the 10-year U.S. Treasury yield exerts a mixed influence, with the contemporaneous coefficient being positive but statistically insignificant, whereas the lagged effect is negative and significant ($\beta = -4.75$, $p < 0.05$). This result highlights the delayed tightening impact of rising bond yields on green energy stocks.

Regarding structural shocks, the COVID-19 dummy is marginally significant at the 10% level, with a positive effect on returns. This result is consistent with the post-pandemic green recovery narrative, where policy stimulus and investor attention to sustainability boosted renewable energy stocks. In contrast, the Russia–Ukraine conflict and the Paris Agreement announcement dummies do not show significant standalone effects, suggesting that markets either quickly priced in these shocks or perceived them as less decisive for green equity performance relative to ongoing macro-financial drivers.

Taken together, the ARDL results underscore that green energy stocks are highly sensitive to global financial conditions, climate policy-related uncertainty, and market volatility. The dynamics highlight both the short-run speculative responses and longer-term adjustment mechanisms, confirming that renewable energy equities are not insulated from broader macro-financial and policy risks.

Table 3: F-Bounds test

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	23.38436	10%	1.99	2.94
k	6	5%	2.27	3.28
		2.5%	2.55	3.61
		1%	2.88	3.99

Source: Author's own calculation

The bounds test (Table 3) strongly rejects the null hypothesis of no long-run relationship among the variables. The computed F-statistic (23.38) exceeds the 1% upper bound critical value (3.99), indicating the existence of a stable long-run cointegration between clean energy stock returns (R_CELS) and the selected macroeconomic and uncertainty indicators.

Table 4: ARDL Long-Run form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R_OIL	-0.003997	0.046151	-0.087	0.9311
R_BIS	-1.872640	0.531193	-3.525	0.0005***
CPU	-0.022641	0.017032	-1.329	0.1854
GPU	0.025711	0.018141	1.417	0.1581
VIX	-0.167540	0.075198	-2.228	0.0271**
YIELD_10Y	-1.514119	0.717284	-2.111	0.0361**
C (Constant)	6.377331	2.367297	2.694	0.0077***

Source: Author's own calculation

$$\text{EC=R\_CELS} - (-0.0040 * \text{R\_OIL} - 1.8726 * \text{R\_BIS} - 0.0226 * \text{CPU} + 0.0257 * \text{GPU} - 0.1675 * \text{VIX} - 1.5141 * \text{YIELD\_10Y} + 6.3773)$$

In the long run (Table 4), the results reveal that the BIS Broad Dollar Index exerts a significant negative impact on clean energy returns (–1.87, $p < 0.01$), suggesting that a stronger US dollar diminishes the relative attractiveness of green investments. Similarly, the 10-year Treasury yield (–1.51, $p < 0.05$) and the market volatility index (VIX) (–0.17, $p < 0.05$) negatively influence clean energy performance, underscoring the sector's sensitivity to interest rate conditions and global risk sentiment. In contrast, crude oil prices (–0.004, n.s.), the Climate Policy Uncertainty (CPU) index (–0.023, n.s.), and the Global Policy Uncertainty (GPU) index (+0.026, n.s.) do not exhibit statistically significant long-run effects.

Table 5: ECM table

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CPU)	0.0165	0.0082	2.0078	0.0461**
D(CPU(-1))	0.0435	0.0095	4.5792	0.0000***
D(CPU(-2))	0.0210	0.0086	2.4398	0.0156**
D(GPU)	0.0033	0.0116	0.2857	0.7755
D(GPU(-1))	-0.0287	0.0120	-2.3881	0.0179**
D(GPU(-2))	0.0037	0.0117	0.3201	0.7493
D(GPU(-3))	0.0300	0.0108	2.7827	0.0059***
D(VIX)	-0.8427	0.0845	-9.9761	0.0000***
D(YIELD_10Y)	3.5579	2.0675	1.7209	0.0869*

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DUM_COVID	4.8674	3.4824	1.3977	0.1639
DUM_UKR	0.9879	2.6989	0.3660	0.7148
DUM_PARIS	-0.4305	0.5484	-0.7849	0.4335
CointEq(-1)	-0.7891	0.0566	-13.9325	0.0000***

Note: ***p<0.01, **p<0.05, p<0.10.
Source: Author's own calculation.

Model statistics:

- R-squared = 0.7076;
- Adj. R-squared = 0.6894;
- Durbin-Watson = 2.037;
- AIC = 6.3329 | SC = 6.5429 | HQ = 6.4178.

The results of the error correction model (ECM) are reported in Table 5. The coefficient of the error correction term (CointEq(-1)) is -0.789 and statistically significant at the 1% level, which indicates a strong adjustment mechanism. Specifically, nearly 79% of short-run deviations from the long-run equilibrium are corrected within a month, implying a rapid speed of adjustment in renewable energy stock returns following shocks.

In the short-run dynamics, several variables exhibit significant effects. First, climate policy uncertainty (CPU) has a positive and significant influence on renewable energy returns. The coefficients of D(CPU), D(CPU(-1)), and D(CPU(-2)) are all positive and statistically significant, suggesting that increases in policy uncertainty tend to boost renewable stock returns, possibly reflecting investors' perception of renewable energy as a hedge against regulatory risks. This finding is consistent with prior evidence that climate-related policy shocks alter capital flows into the green sector.

Global policy uncertainty (GPU) shows a more complex pattern. While the contemporaneous and second lag terms of GPU are insignificant, D(GPU(-1)) enters with a negative and significant coefficient, and D(GPU(-3)) shows a positive and significant effect. This asymmetric response indicates that global policy shocks may initially depress renewable energy stock performance but tend to be offset in later periods, reflecting delayed portfolio reallocations by global investors.

Market volatility (VIX) exerts a strong negative effect on renewable stock returns, with a coefficient of -0.843 significant at the 1% level. This underscores the sensitivity of green equity markets to financial uncertainty, consistent with the broader literature on the safe-haven failure of renewable stocks during periods of heightened volatility.

The 10-year US Treasury yield (YIELD_10Y) is positive but only marginally significant at the 10% level, implying that rising long-term interest rates may weakly enhance renewable stock returns. This counterintuitive finding may reflect capital reallocation dynamics or the increasing attractiveness of renewable investments under tightening monetary conditions.

Regarding the structural dummy variables, none of the three events, COVID-19, the Ukraine conflict, and the Paris Agreement, show statistically significant effects in the short-run. Although the coefficients are in the expected directions (positive for COVID-19 and Ukraine conflict, negative for Paris Agreement), the results suggest that the impact of these events is already captured by broader uncertainty and volatility measures, rather than exerting direct isolated effects on renewable stock returns.

Overall, the short-run results confirm that climate policy uncertainty and market volatility are the key drivers of renewable energy stock performance, while the significant and sizeable ECM coefficient highlights the existence of a robust long-run equilibrium relationship.

Diagnostic Tests

Table 6: Breusch–Godfrey LM test

Test Statistic	Value	Prob.	Decision (5% level)
F-statistic	1.461702	0.1428	Fail to reject H_0 → No serial correlation
Obs*R-squared	18.86457	0.0918	Fail to reject H_0 → No serial correlation

Source: Author's own calculation

To ensure that the ARDL model is free from residual autocorrelation, the Breusch–Godfrey LM test (Table 6) was conducted with up to 12 lags. The results show that the null hypothesis of no serial correlation cannot be rejected, as both the F-statistic (1.46, p = 0.143) and the Obs*R-squared statistic (18.86, p = 0.092) are statistically insignificant at conventional levels. This shows that the residuals do not have serial correlation. This means that the model is well-specified over time.

Moreover, the Durbin-Watson statistic (≈2.02) provides evidence that there is no first-order autocorrelation. Overall, both findings indicate that the ARDL specification is a good representation of the data-generating process, and there were no systematic patterns in the residuals generated from the ARDL model.

Table 7: Ramsey RESET test

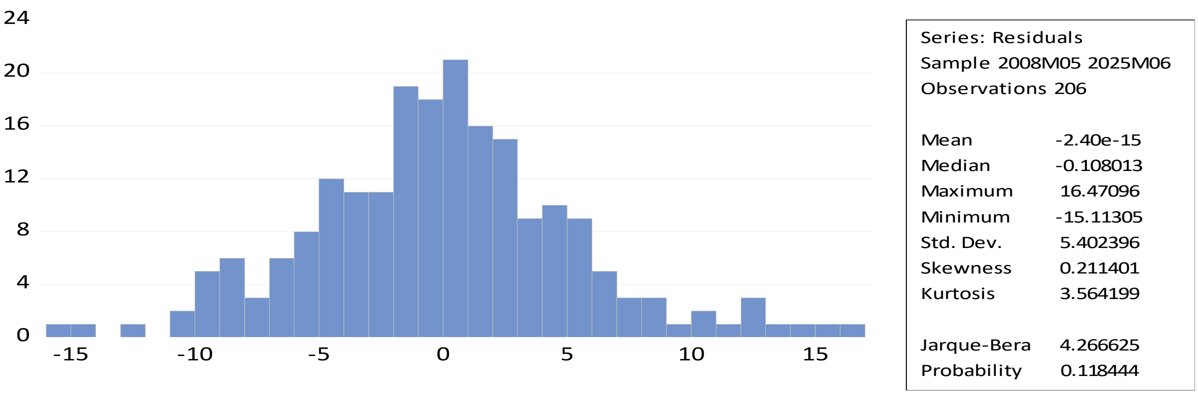
Test Statistic	Value	df	Probability
t-statistic	0.2174	185	0.8281
F-statistic	0.0473	(1,185)	0.8281
Likelihood Ratio (LR)	0.0526	1	0.8186

Source: Author's own calculation

The Ramsey RESET test (Table 7) was implemented to test for any specification errors in the context of the ARDL model. From the test results for the ARDL model, we found the t -statistic (0.2174, p = 0.8281), F-statistic statistics (0.0473, p = 0.8281), and the likelihood ratio statistics (0.0526, p = 0.8186) are statistically insignificant. This implies we are unable to reject the null hypothesis of correct model specification.

In other words, the ARDL model does not suffer from omitted variables bias or incorrect functional form. In summary, the results confirmed our initial findings that the model is correctly specified and the model accounts quite well for the short-run and long-run dynamics of renewable energy stock returns.

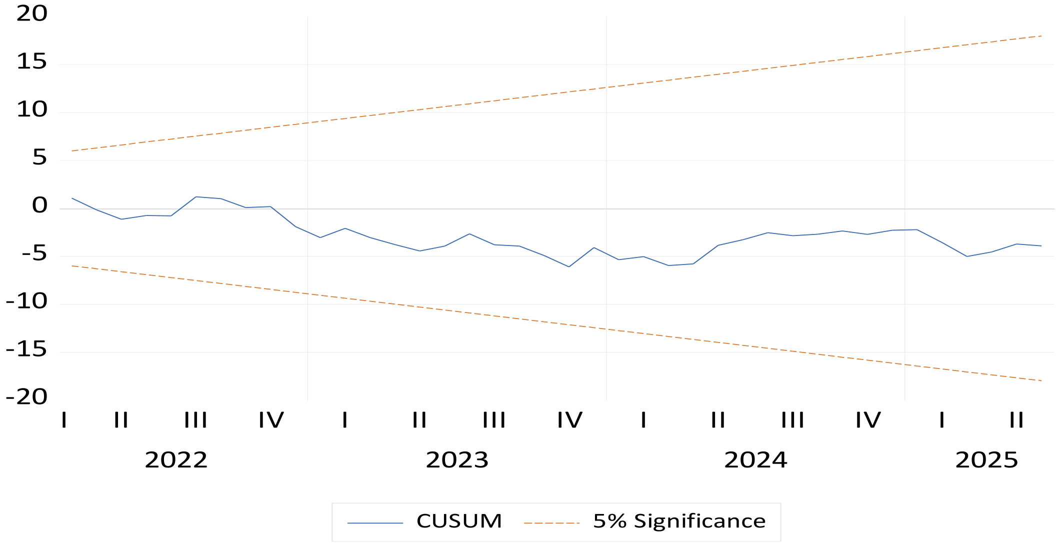
Figure 1: Normality of residuals



The Jarque-Bera (JB) test was used to check if the residuals of the ARDL model are normally distributed. As highlighted in Figure 1, The JB test result was a JB statistic of 4.2666 and a p-value of 0.1184, which is above the 5 % significance level, thus we cannot reject normality of the residuals.

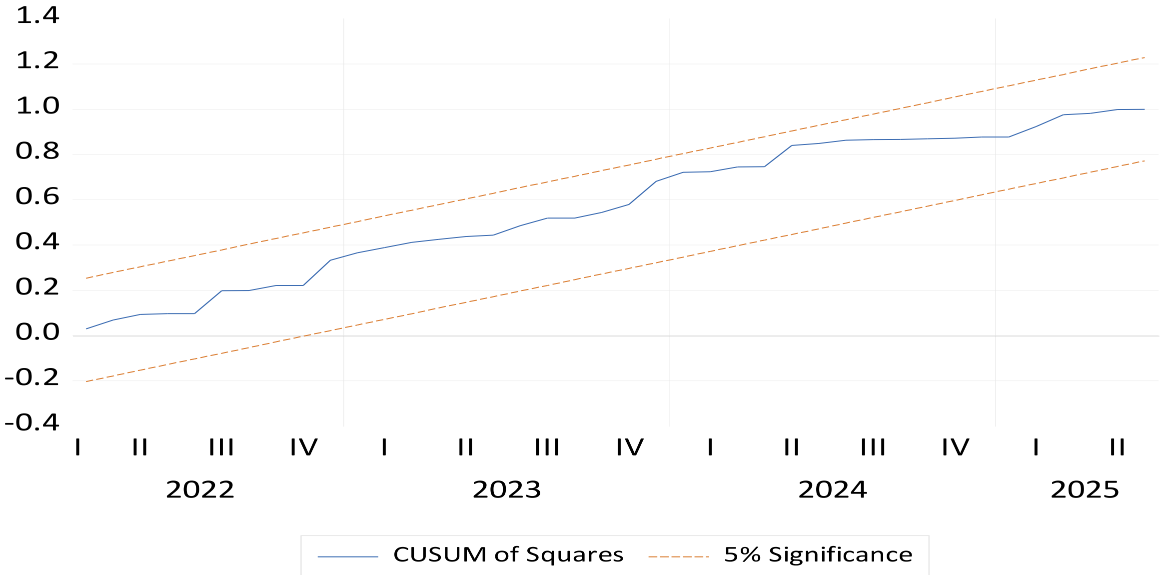
The histogram and descriptive statistics were in accordance with this finding. The residuals were well-behaved with a mean very close to zero (–2.40E–15), slight skewness (0.2114) and 3.56 for Kurtosis, which being close to the Gaussian reference of 3.0. This indicates that the residuals were roughly normally distributed, which is a necessary assumption of the ARDL framework.

Figure 2: CUSUM test



To validate the stability of the ARDL coefficients, a CUSUM test was performed. As highlighted in Figure 2, the CUSUM statistic remains comfortably within the 5% significance bounds over the sample period (2008M01-2025M06), suggesting that the estimated model does not have structural breaks or parameter instability.

Figure 3: CUSUM of Square test



We also conducted the CUSUM of Squares test in addition to the CUSUM test to determine whether the ARDL coefficients are stable. In Figure 3, we see that the CUSUM statistic has remained steadily within the 5% significance bounds throughout the entire sample period of January, 2008 to June, 2025. This means we did not experience any structural breaks or parameter instability in the estimated model. The results from the CUSUM and CUSUM of Squares tests point to the dynamic stability of the ARDL specification. This enhances the reliability of both the short-run and long-run parameter estimates, hence ensuring that the empirical relationships are time-consistent in interpretation and easily interpretable for policy purposes (Table 8a and Table 8b).

Table 8a: Robustness check

Variable	Baseline ARDL (1,0,0,3,4,1,1)	Robustness ARDL (1,0,0,3,2,1,1)
R_CELS(-1)	0.211*** (0.047)	0.205*** (0.043)
R_OIL	−0.003 (0.036)	0.021 (0.034)
R_BIS	−1.478*** (0.409)	−1.451*** (0.386)
CPU	0.016* (0.009)	0.019* (0.010)
CPU(-1)	0.009 (0.010)	0.006 (0.011)
CPU(-2)	−0.023** (0.010)	−0.020** (0.010)
CPU(-3)	−0.021 (0.014)	−0.020 (0.014)
GPU	0.003 (0.010)	−0.003 (0.010)
GPU(-1)	−0.012 (0.013)	−0.007 (0.013)
GPU(-2)	0.032* (0.017)	0.032** (0.014)
GPU(-3)	0.026* (0.016)	—
GPU(-4)	−0.030** (0.015)	—
VIX	−0.843*** (0.102)	−0.833*** (0.102)
VIX(-1)	0.710*** (0.094)	0.708*** (0.094)
YIELD_10Y	3.558 (2.189)	2.652 (2.155)
YIELD_10Y(-1)	−4.753** (2.229)	−3.773* (2.202)
DUM_COVID	4.867* (2.532)	4.797* (2.477)
DUM_UKR	0.988 (1.822)	1.424 (2.073)
DUM_PARIS	−0.430 (1.248)	−0.835 (1.197)
Constant	5.033** (1.828)	4.300** (1.857)

Source: Author's own calculation

Table 8b: Robustness check

Statistic	Baseline	Robustness
R^2	0.576	0.556
Adjusted R^2	0.533	0.516
AIC	6.4009	6.4324
Schwarz (BIC)	6.7240	6.7222
Durbin–Watson	2.0371	2.0514

Source: Author's own calculation

To check the strength of the baseline ARDL (1,0,0,3,4,1,1), we estimated an alternative model with fewer lags (1,0,0,3,2,1,1). The diagnostics indicate that the baseline model provides a slightly better fit, with a higher adjusted R^2 (0.533 compared to 0.516) and a slightly lower AIC (6.4009 versus 6.4324). Meanwhile, the robustness model shows a slightly lower Schwarz criterion (6.7222 compared to 6.7240). In both models, the Durbin–Watson statistics are close to 2 (2.0371 and 2.0514), ruling out serial correlation. These results indicate that the alternative lag structure does not materially alter the explanatory power or statistical adequacy of the model.

Across specifications, the key relationships remain stable. The lagged dependent variable R_CELS(−1) is consistently positive and significant, highlighting return persistence. The BIS index exerts a strong and negative effect in both models, while the VIX maintains its expected role, negative in contemporaneous form and positive in its lag, indicating volatility spillovers. Climate Policy Uncertainty (CPU) continues to display heterogeneous lag effects: a positive short-term effect (CPU) and a negative impact at the second lag [CPU(-2)], with stability across models. Although the robustness specification reduces higher-order lags of GPU, GPU(-2) remains statistically significant, reinforcing the robustness of this channel. Similarly, the 10-year bond yield shows a negative lagged effect in both models, albeit with slightly reduced significance in the robustness check. The dummy variables for COVID-19 and the Ukraine war retain their expected signs, with COVID remaining significant.

Overall, the similarity in coefficients, signs, and statistical significance across the two ARDL specifications confirms that the central findings, namely the role of financial conditions, policy uncertainty, and global shocks in shaping renewable energy stock returns, are robust to alternative lag structures.

Conclusion and Policy Implications

This study examines the factors that affect US renewable energy stock returns, using the NASDAQ Clean Edge Green Energy Index (CELS) as a benchmark. It employs an ARDL modelling framework from January, 2008 to June, 2025. The analysis includes climate policy uncertainty (CPU), oil price changes, currency strength (BIS Broad Dollar Index), market volatility (VIX), global policy uncertainty (GPU), and interest rate factors (10-year US Treasury yield). This provides a detailed look at both short- and long-term influences on clean energy stock performance.

The results show several important findings. First, green stock returns are highly persistent; past returns greatly affect current performance. Second, the BIS dollar index has a strong negative effect on renewable energy stocks in both the short and long term. This supports the view that a stronger dollar can tighten global financial conditions and reduce investor interest in capital-intensive clean energy projects. Long-term interest rates and market volatility also negatively impact renewable stock returns, highlighting the sector's sensitivity to changes in global financial conditions and risk sentiment.

In contrast, crude oil prices and measures of global policy uncertainty do not show significant long-term effects, although they do affect short-term market trends. The findings on climate policy uncertainty are particularly significant: CPU shocks have a positive short-term impact on renewable energy returns. This suggests that increased policy discussions or regulatory changes can initially draw capital to the green sector as investors reposition themselves for policy-driven opportunities. However, the effects of lagged CPU show that prolonged uncertainty can negatively influence market sentiment. This indicates a complex relationship between policy developments and renewable stock performance that changes over time. The estimated error correction term is negative, highly significant, and large (–0.789). This confirms a strong and quick adjustment to long-term equilibrium aftershocks. Structural dummy variables for major events, like the COVID-19 pandemic and the Russia-Ukraine conflict, show limited direct effects when broader financial uncertainty is considered. This indicates that clean energy markets are more responsive to systemic risk conditions than to specific geopolitical events.

Overall, these findings suggest that renewable energy stock performance is influenced by macro-financial factors. Climate policy discussions have subtle effects, with short-term volatility often followed by longer-term adjustments. The evidence stresses the importance of stable economic conditions, predictable regulatory frameworks, and risk-aware investment strategies in supporting the growth of renewable energy markets.

Empirical evidence demonstrates that long-term uncertainty, especially financial and policy uncertainty, negatively impacts growth and stability for renewables investments. Therefore, authorities should take steps to enhance policy credibility, accessibility to finance and market certainty. To start with, renewable policy frameworks must be long-term and legally binding. Commitments such as feed-in tariffs for a set number of years, obligations to purchase renewables or production tax credits, must be written into law and not tied to a short-term budget cycle. These long-term and transparent commitments lower barriers to changes in policy, lower perceived investment risk by creating continuity and stability of expected returns. Next, the incentives must be tied to performance and not upon project-based approvals. Subsidies based on quantifiable performance such as verified emission reductions, efficiency improvements or technology advancements would enable policymakers to link public funding to climate objectives with minimal political discretion.

Third, it is necessary to modify financing mechanisms to mitigate macroeconomic tightening. There is significant long-run sensitivity of CELS to interest rates and the U.S. dollar that reveals renewable projects are especially exposed to higher costs of financing. Expanding domestic green bond markets, concessional credit facilities, and risk-mitigation instruments can protect renewable financing projects from global liquidity shocks.

Implications for Investors and Asset Managers

From an investment perspective, the results offer actionable insights for managing renewable portfolios under uncertainty.

First, investment horizon should direct strategy. The positive short-run effect of policy uncertainty shows that investors may seek to capitalize on tactical opportunities around policy events. However, the negative long-run effects of macro-financial tightening imply a more cautious approach to strategic allocation. Long-run investors should favour firms with diversified revenues, low leverage, and stable policy exposure. Second, active hedging against financial volatility is critical. The large negative coefficients for the USD, Treasury yields, and VIX suggest that renewable equities are sensitive to shocks to liquidity and risk sentiment. Asset managers can hedge these exposures using interest rate derivatives, volatility instruments, or allocating into more defensive green sectors, such as utilities, energy infrastructure, and storage. Third, incorporating policy uncertainty into risk modelling enhances resilience of portfolios. Following Climate Policy Uncertainty (CPU) index as a systematic risk factor allows for dynamic rebalancing, i.e., increasing exposure during stable policies and decreasing exposure during uncertain regulatory periods.

Finally, blending equity exposure with green debt instruments, including sustainability-linked bonds and infrastructure debt, can reduce portfolio volatility and smooth returns across uncertainty cycles. In short, these results stress that successful investments in renewable energy necessitate distinguishing between transitory financial turbulence and structural policy risk. Both long-term stability in policy and disciplined management of portfolios can further both financial return and the larger aim of sustainable energy transition.

Credit Authorship Contribution Statement

Akshay Sahu contributed to the conceptualization, methodology, data analysis, and writing of the manuscript. Avneesh Kumar provided supervision, guidance, and critical review of the work.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Data Availability Statement

The data supporting the findings of this study are publicly available on Mendeley Data at the following link: https://data.mendeley.com/datasets/pptbmyvv8h/1 and https://doi.org.10.17632/pptbmyvv8h.1

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