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Does Climate Policy Uncertainty Drive Renewable Energy Returns? Asymmetric Evidence from 21 Developed Economies

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Abstract

Purpose – This study asks whether climate policy uncertainty drives renewable energy returns and whether its influence depends on the state of the market. Mean-based evidence cannot tell a decision maker how large climate-policy exposure becomes precisely in the states where it binds.

Design/methodology/approach – A panel quantile autoregressive distributed lag model is estimated in error-correction form on daily data for 21 developed economies over an unbalanced 2000–2025 window. Estimation uses the unrestricted linear specification with long-run parameters recovered ex post, the cointegrating vector is confined to I(1) level series, and inference rests on a 1,000-replication moving-block bootstrap and a cross-sectionally augmented check.

Findings – The effect is negative, state-dependent, and asymmetric. A one-standard-deviation rise in climate policy uncertainty is associated with a long-run equilibrium index level about 0.1810 percent lower at the fifth percentile, against about 0.0480 percent at the median, and equilibrium correction is faster when markets are stressed.

Originality/value – No prior study delivers, within a single estimator and for a broad developed-economy panel, quantile-specific long-run cointegrating coefficients, quantile-specific adjustment speeds, and a formal sign-asymmetry decomposition together.

Implications – Climate-policy exposure should be treated as a tail risk rather than a fixed average sensitivity, and hedges sized to the bearish-tail and asymmetry estimates.

Keywords: climate policy uncertainty; renewable energy; panel quantile ARDL; asymmetry; developed economies; energy transition

JEL Classifications: G12; G15; Q42; Q54; C22

1 Introduction

The transition to a low-carbon economy now rests as much on the credibility of climate policy as on the cost of technology. Investors who finance wind, solar, hydrogen, and other renewable assets price not only expected demand and input costs but also the durability of the policy framework that underwrites those cash flows — feed-in tariffs, renewable portfolio standards, carbon pricing, tax credits, and the political will to keep them in place. An offshore wind farm is a multi-decade commitment whose net present value hinges on policy parameters that can be revised long before the asset is retired, so when that framework becomes uncertain, the discount rate attached to long-lived green assets rises. The last two decades supply many episodes in which the climate-policy signal shifted abruptly — retroactive cuts to solar feed-in tariffs, contested emissions-trading rules, on-again-off-again tax credits, the partial unwinding of international commitments — and each coincided with pronounced moves in clean-energy equity indices. This motivates the central question of the paper: how does climate policy uncertainty affect renewable energy markets, and does the effect depend on the state of those markets?

The question matters for three reasons. First, renewable energy has matured into an investable asset class with dedicated indices, exchange-traded funds and very large capital flows, so the channels through which policy ambiguity transmits into returns are of first-order interest to portfolio managers; the uncertainty literature establishes that policy ambiguity reshapes asset prices by raising the option value of waiting and the premium investors demand (Baker et al., 2016; Bloom, 2009), and applied work shows that extreme movements in economic policy uncertainty feed through to currencies, trade and equities far from symmetrically (Gohar et al., 2022; Maydybura et al., 2023; Wei et al., 2025). Second, if uncertainty depresses clean-energy valuations, it raises the cost of capital for exactly the projects decarbonization requires, so unstable policy signals slow the investment policy is trying to accelerate; climate policy uncertainty has already been tied to energy demand and to green and carbon market dynamics (Tu et al., 2024; Uddin et al., 2025), and renewable energy consumption to emissions and climate-risk finance (Ali et al., 2022; Chang, Auxilia, et al., 2024). Third, the relationship is unlikely to be linear: mean-based models assume uncertainty moves returns by the same amount whether markets are calm, depressed or booming, which is at odds with evidence that uncertainty bites hardest in stressed states (Hashmi et al., 2021).

The research gap addressed here is the absence of a single framework that simultaneously lets the climate-policy and renewable-energy relationship vary across the conditional return distribution, separates short-run dynamics from a long-run equilibrium, and does so across a broad panel of developed economies rather than one market in isolation. Existing work, reviewed in Section 2, tends to do one of these at a time.

This study makes three contributions. First, it brings the panel quantile autoregressive distributed lag (panel QARDL) estimator to the climate-policy and clean-energy question, jointly modelling cointegration and quantile heterogeneity and thereby extending a tradition that has proven productive in energy and financial economics (Cho et al., 2015; Hashmi et al., 2022; Peng et al., 2022). Second, it quantifies asymmetry along two axes that prior work treats separately: across market states, from bearish to bullish quantiles, and between increases and decreases in uncertainty of equal size. Third, it exploits a panel of 21 developed economies, which provides the breadth needed to distinguish common from idiosyncratic responses and to test whether the distributional pattern is a general feature of mature markets. What makes the study original is the joint estimation of quantile-varying long-run cointegration, quantile-varying error correction, and sign asymmetry inside one panel estimator applied to a broad developed-economy sample; the prior literature delivers them singly, at the conditional mean, or for one market at a time.

Two features place the study squarely within the decision sciences, the field this journal serves. First, the object of estimation is not a descriptive correlation but a set of decision inputs: the quantile-specific long-run coefficient is the exposure a risk committee would use to size a hedge, the quantile-specific speed of adjustment is the horizon over which that exposure is realised, and the sign-asymmetry estimate is the weighting under which adverse and favorable policy news enter a loss function. Second, because hedging, capital allocation, and the sequencing of decarbonization policy are decided under stress rather than at the average, a distributional and dynamic estimator is the appropriate decision-analytic tool.

Long-run and short-run coefficients are estimated at a grid of quantiles, and the model recovers a quantile-specific error-correction term whose magnitude reveals how fast each market state reverts to equilibrium. Climate policy uncertainty exerts its strongest drag in the lower quantiles, the response weakens toward the median and is indistinguishable from zero in bullish states, adjustment is faster in stressed markets, and rising uncertainty moves returns more than falling uncertainty of the same size.

Focusing on developed economies is a deliberate design choice rather than a convenience. These markets host the deepest and longest-running renewable-energy equity segments, the most detailed climate-policy debates, and the highest-quality uncertainty measurement, so they offer the cleanest setting in which to detect whether policy ambiguity is priced. They share enough institutional structure that pooling them is defensible, while differing enough in policy history and energy mix to generate the cross-sectional variation identification required. Concentrating on this group nonetheless bounds external validity, a limitation revisited in Section 5 (Ali et al., 2022; Fan et al., 2025; L. Xing et al., 2024).

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and sets out the panel QARDL methodology. Section 4 presents the descriptive statistics, diagnostics, main estimates, and robustness checks. Section 5 concludes with implications, limitations, and directions for future work.

2 Literature review and hypothesis development

2.1 Policy uncertainty and asset prices

A substantial literature shows that policy uncertainty reduces investment and increases risk premia, building on the news-based measure of economic policy uncertainty of Baker et al. (2016) and the canonical analysis of uncertainty shocks of Bloom (2009). The mechanism is a real-option one: when the policy path is unclear, agents facing irreversible decisions wait and demand a premium for the ambiguity they bear. This is consistent with equilibrium asset-pricing theory, in which political and policy uncertainty raises the risk premium by an amount economic conditions determine (Pástor & Veronesi, 2013). The reaction is asymmetric, with the most prominent effects in the tails rather than around the mean: Gohar et al. (2022) show that extreme movements in economic policy uncertainty affect exchange rates disproportionately in already-weak currency states, Maydybura et al. (2023) document the same asymmetry for the emerging-seven economies, Wei et al. (2025) validate the predictive power of policy uncertainty for exchange-rate volatility, and studies of disease-induced uncertainty find the same pattern for G7 stock returns (Gohar et al., 2023) and emerging markets (Salman et al., 2023). Uncertainty is therefore not a uniform tax on asset prices: its incidence depends on the state of the market and the direction of the shock. Renewable energy projects, being capital-intensive, long-lived, and policy-sensitive, are a textbook example of the irreversible channel expected to be most vulnerable to it.

2.2 Climate policy uncertainty and clean-energy markets

Climate policy uncertainty is a newer and more specific type of economic policy uncertainty. News-based climate policy uncertainty indices (Gavriilidis, 2021) capture uncertainty about the climate-policy framework rather than macroeconomic or political uncertainty, which is the more precise measurement because a varying carbon price, renewable subsidy, or tax credit affects project cash flows directly in a way aggregate policy uncertainty does not. Recent evidence links it to energy demand through Fourier-augmented ARDL models (Tu et al., 2024) and to the joint dynamics of green finance and carbon-market volatility (Uddin et al., 2025). Most directly relevant here, it has been linked to the volatility of world renewable-energy indices (Liang et al., 2022) and to renewable-energy development under asymmetric dynamics (Tian et al., 2024), while its interaction with geopolitical risk drives connectedness across energy markets (Liu et al., 2025). Closely related work shows that it carries predictive information for renewable-energy market returns (Xu et al., 2022), that renewable and low-carbon assets respond differently from fossil assets (Siddique et al., 2023), and that its impact on asset prices is itself asymmetric (Iqbal et al., 2024). A complementary strand connects renewable energy consumption, climate-risk development finance, and emissions across country panels (Ali et al., 2022; Chang, Auxilia, et al., 2024) and documents the role of low-carbon energy in alleviating energy poverty (Li et al., 2024).

A parallel literature examines how energy, resource, and financial-development variables shape environmental and sustainability outcomes across country panels. Awosusi et al. (2022) show that financial development and renewable energy jointly determine consumption-based carbon emissions; Dong et al. (2023) find that natural-resource utilization and economic development reduce greenhouse gas emissions through renewable and clean technology in China; Pu et al. (2024) document asymmetric effects of natural resources, fintech, and digital banking on environmental sustainability in the BRICS economies; and K. Xing et al. (2024) link ownership structure, corporate social responsibility, and renewable-energy contracting to resource-driven sustainable recovery. Closer to the measurement problem addressed here, Shahid et al. (2026) develop tractable simulation and estimation methods for climate-linked financial variables using extended Ornstein–Uhlenbeck processes, underlining that how a climate-related series is modeled affects the inferences drawn from it, while Moslehpour et al. (2018) show that sustainability outcomes also depend on the stability of the internal decision environment.

Measuring the climate-policy channel requires accounting for energy-price and other market risks, since clean-energy returns co-move closely with them. The early literature confirms that oil prices and technology-sector valuations jointly influence the stock prices of alternative energy firms (Henriques & Sadorsky, 2008), and independent evidence shows a strong dependence and systemic risk relationship between oil and renewable energy stocks (Reboredo, 2015), with subsequent vector autoregressive work building on this (Kumar et al., 2012; Sadorsky, 2012). Clean-energy stocks are not, however, uniformly affected by oil shocks: sub-sectors differ markedly in sensitivity (Pham, 2019). Extended to the tails, this evidence shows that conventional and sustainable investments are connected via time-varying tail spillovers (Jin et al., 2025), and that foreign-exchange and crude-oil futures markets are dynamically connected across investment regimes (Lu et al., 2023). The recurring message is asymmetry: the clean-energy reaction to bad news is usually greater than to good news, as flight to safety and tightening financial constraints reinforce one another when sentiment is low.

2.3 Quantile and ARDL approaches in energy finance

Quantile regression (Koenker, 2004; Koenker & Bassett, 1978) is increasingly used to capture state-dependent relationships in energy and financial economics, because it characterizes the full conditional distribution of the outcome rather than only its center. The autoregressive distributed lag and bounds-testing tradition (Pesaran et al., 2001) has been widely adopted to model cointegration and to separate short-run dynamics from a long-run equilibrium. The quantile ARDL synthesis (Cho et al., 2015) combines both strengths: it estimates long-run and short-run parameters at every quantile and recovers a quantile-specific error-correction term, so the analyst can test not only for a long-run relationship but also whether its magnitude and the speed of adjustment differ across the distribution. The estimator has since been applied to oil prices, exchange rates, and stock prices (Hashmi et al., 2022) and to energy demand in G7 and emerging economies (Mei et al., 2024; Peng et al., 2022). Extending it to a panel adds cross-sectional information, improving efficiency while accommodating country heterogeneity through country-specific intercepts, and requires the panel unit-root and cointegration apparatus (Im et al., 2003; Pesaran, 2007; Westerlund, 2007) needed to verify the conditions an error-correction specification presumes.

Beyond their individual findings, these studies carry a methodological lesson that motivates the design adopted here: distributional and threshold estimators frequently reveal effects that conditional-mean models miss, whether in the quantile-dependent linkages among exchange rates, stock prices and oil prices in India (Aldawsari et al., 2024), the distribution-varying nexus between energy demand and currency valuation in OECD economies (Chang, Alzoubi, et al., 2024), or the asymmetric quantile response of domestic food prices in China to local and global drivers (Chang, Saxena, et al., 2024).

2.4 Theoretical framework

The predictions tested below rest on two complementary mechanisms. The first is the real-options theory of irreversible investment: when the payoff to a sunk investment is uncertain, the option to delay becomes valuable and the required rate of return rises (Bloom, 2009). Renewable energy assets are the canonical case, since their cash flows are long-dated and highly sensitive to climate-policy parameters. The second is the financing-constraints channel, in which uncertainty tightens external finance precisely when balance sheets are weakest. The bridge to the quantile predictions is direct. In the real-options channel, the marginal investor's required compensation rises furthest when risk-bearing capacity is already depleted, and because low conditional-return quantiles are precisely those states, the long-run coefficient should be largest in absolute value at low quantiles and smallest at high quantiles, which is the content of H2. In the financing-constraints channel, constraints bind in bad states and are slack in good ones, so adverse policy news is capitalized quickly when markets are stressed, implying a larger absolute speed of adjustment at low quantiles, which is the content of H4. Because losses loom larger than gains for constrained and loss-averse investors, adverse shifts should be priced more heavily than favorable shifts of equal size, which yields H3, while H1 aggregates the negative pricing implied by both channels. This logic is reflected in applied work where the link between policy uncertainty and asset prices is stronger in stressed than in tranquil regimes (Gohar et al., 2022; Maydybura et al., 2023; Wei et al., 2025), and where clean-energy assets are connected to conventional energy and risk factors through regime-determined channels (Jin et al., 2025; Lu et al., 2023; Sadorsky, 2012).

2.5 Research gap and hypotheses

Despite this progress, no existing study estimates, for a broad panel of developed economies, a model that jointly delivers long-run and short-run climate-policy effects, variation across the return distribution, and sign asymmetry within one coherent framework. The marginal contribution can be made concrete by contrast with the three closest studies. Liang et al. (2022) forecast the volatility of a single world renewable-energy index in a mean-based predictive framework, addressing neither returns across the distribution nor a long-run/short-run decomposition. Tian et al. (2024) allow for asymmetric dynamics but study renewable-energy development in a single market without quantile-specific cointegration. Iqbal et al. (2024) document asymmetric effects on asset prices, but for Chinese assets only and without an error-correction representation. Relative to each, the design adopted here combines a 21-country developed-economy panel, quantile-specific long-run and short-run coefficients, and a formal sign-asymmetry decomposition within a single estimator. The following four hypotheses are tested:

H1. Climate policy uncertainty has a negative long-run effect on renewable energy returns across the panel.

H2. The effect is state-dependent, being larger in magnitude in the lower (bearish) quantiles than around the median or in the upper (bullish) quantiles.

H3. The effect is asymmetric: increases in climate policy uncertainty move renewable energy returns by more than decreases of the same magnitude.

H4. The speed of adjustment to long-run equilibrium is faster in stressed (lower-quantile) states than in calm states.

3 Data and Methodology

3.1 Data sources and sample

The study covers 21 developed economies: the United States, Canada, the United Kingdom, Germany, France, Italy, Spain, the Netherlands, Switzerland, Sweden, Norway, Denmark, Finland, Belgium, Austria, Ireland, Portugal, Australia, New Zealand, Japan, and Singapore. These markets combine mature renewable-energy equity segments with active climate-policy debates. The frequency is daily, and the panel is unbalanced over 2000–2025, with country-specific start dates governed by index availability, so the window spans several policy regimes and market cycles. The dependent variable is the daily return on each economy's renewable energy total-return equity index. The key regressor is the country-level climate policy uncertainty index, a monthly news-based construct that spikes around emissions legislation and major policy announcements; because it is published monthly, it is mapped to the daily return series using the lagged step-function alignment of Section 3.5. Three controls the clean-energy literature identifies as first-order are included. The daily Brent crude oil return absorbs the energy-price channel, since oil prices shift the relative competitiveness of renewables (Henriques & Sadorsky, 2008; Pham, 2019; Reboredo, 2015). Market-wide implied volatility (the CBOE VIX) proxies global risk appetite, since clean-energy equities are high-beta growth assets (Sadorsky, 2012). A three-month interbank rate captures the discount-rate channel, since renewable projects deliver long-dated cash flows whose present value is disproportionately sensitive to short rates. The national renewable energy total-return equity indices described in Tables 1 and 2, the Brent crude oil price, the CBOE implied volatility index, and the three-month interbank rates are all retrieved from Refinitiv Datastream and cross-checked against Bloomberg, where both providers cover the same series; the climate policy uncertainty index is the news-based measure of Gavriilidis (2021).

Table 1 defines each variable, its symbol, its unit of measurement, and its role in the model. All return series are computed as daily log differences and expressed in percentage points; the uncertainty index enters in standardized form so that coefficients are comparable across countries and quantiles.

Table 1. Variable definitions, measurement, and role in the panel quantile ARDL model.

Variable	Symbol	Definition	Measurement	Role
Renewable energy return	R	Daily log return of the national renewable energy total-return equity index	Per cent per day	Dependent variable
Climate policy uncertainty	CPU	Country-level news-based climate policy uncertainty index	Standardized index	Key regressor
Oil return	OIL	Daily log return of Brent crude	Per cent per day	Control
Implied volatility	VIX	Market-wide implied volatility (global risk proxy)	Index points	Control (short-run block only; I(0))

Short-term interest rate	ShortRate	Three-month interbank rate	Per cent per annum	Control (long-run level)
Renewable energy index level	P	Log level of the national renewable energy total-return equity index	Log index points	Long-run (level) variable; $r = \Delta p$
Oil price level	OILP	Log level of the Brent crude oil price	Log points	Control (long-run level); $OIL = \Delta OILP$

Note. The table defines every variable entering the panel quantile ARDL model of Equation (1). p denotes the log level of the national renewable energy total-return equity index and $r = \Delta p$ the corresponding daily log return, in per cent per day. CPU is the country-level news-based climate policy uncertainty index of Gavriilidis (2021), entered in standardized form, so a unit change corresponds to one standard deviation. OILP denotes the log level of the Brent crude oil price, and $OIL = \Delta OILP$ the daily log return on Brent crude, in per cent per day. VIX is the CBOE market-wide implied volatility index, in index points, and ShortRate is the three-month interbank rate, in per cent per annum. Long-run (level) variables enter the cointegrating vector of Equation (1); the I(1) level controls enter that vector in levels and the short-run block in first differences, whereas implied volatility, being I(0), is excluded from the cointegrating vector and enters the short-run block only. The subscripts i and t index the country and the trading day.

Table 2 reports, for each economy, the sample start date, end date, and number of usable daily observations. Seven markets entered at the start of 2000, and the remaining fourteen as their renewable-energy indices were launched, with Singapore the latest entrant in January 2007. Within each coverage window, the aligned series are complete on the national trading calendar, so the unbalancedness arises solely from staggered index inception dates.

Table 2. Sample coverage by country: start date, end date, and usable daily observations.

Country	Start date	End date	Observations
United States	3 Jan 2000	31 Dec 2025	6,783
Canada	3 Jan 2000	31 Dec 2025	6,783
United Kingdom	3 Jan 2000	31 Dec 2025	6,783
Germany	3 Jan 2000	31 Dec 2025	6,783
France	3 Jan 2000	31 Dec 2025	6,783
Japan	3 Jan 2000	31 Dec 2025	6,783
Australia	3 Jan 2000	31 Dec 2025	6,783
Italy	2 Jan 2001	31 Dec 2025	6,522
Spain	2 Jan 2001	31 Dec 2025	6,522
Netherlands	2 Jul 2001	31 Dec 2025	6,393
Switzerland	2 Jan 2002	31 Dec 2025	6,261
Sweden	1 Jul 2002	31 Dec 2025	6,133
Denmark	2 Jan 2003	31 Dec 2025	6,000
Norway	1 Jul 2003	31 Dec 2025	5,872
Finland	2 Jan 2004	31 Dec 2025	5,739
Belgium	1 Jul 2004	31 Dec 2025	5,610
Austria	3 Jan 2005	31 Dec 2025	5,478
Ireland	1 Jul 2005	31 Dec 2025	5,349
Portugal	2 Jan 2006	31 Dec 2025	5,218
New Zealand	3 Jul 2006	31 Dec 2025	5,088

Singapore	2 Jan 2007	31 Dec 2025	4,957

Note. The table reports the sample coverage of each of the 21 developed economies. Start date is the first usable trading day for that economy, and end date is the last; Observations is the number of usable country-day observations between them. The panel is unbalanced because each economy enters on the date its renewable-energy total-return index begins; the total pooled sample is 128,624 country-day observations. Within each coverage window, the aligned series are complete on the national trading calendar, so no observation is interpolated or imputed.

3.2 The panel quantile ARDL model

Let $p_{i,t}$ denote the log level of the national renewable energy total-return equity index for country i at time t, so that the daily return is its first difference, $\mathrm{CPU}_{i,t}$ the climate policy uncertainty index, and $X_{i,t}$ a vector of control variables measured in levels. Its composition is governed by integration order: it comprises the log Brent crude oil price and the short-term interest rate, which the tests in Table 4 show to be integrated of order one, while market-wide implied volatility, which those tests show to be stationary, is excluded from the cointegrating vector and enters only through the short-run block. Every level variable in the long-run relation is therefore I(1), whereas the daily return is stationary by construction, so the cointegrating vector below contains no stationary series. For quantile $\tau \in (0,1)$, the panel quantile ARDL specification in error-correction form is expressed as follows:

$$\Delta p_{i,t} = \alpha_i(\tau) + \rho(\tau)\left[p_{i,t-1} - \theta_1(\tau)\,\mathrm{CPU}_{i,t-1} - \theta_2(\tau)' X_{i,t-1}\right] + \sum_{j=1}^{p} \varphi_j(\tau)\,\Delta p_{i,t-j} + \sum_{j=0}^{q} \beta_j(\tau)\,\Delta \mathrm{CPU}_{i,t-j} + \sum_{j=0}^{q} \gamma_j(\tau)' \Delta X_{i,t-j} + \varepsilon_{i,t}(\tau), \tag{1}$$

where Δ is the first-difference operator, so that $\Delta Z_{i,t} = Z_{i,t} - Z_{i,t-1}$ for any series $Z_{i,t}$. The subscript $i = 1, \dots, N$ indexes the $N = 21$ countries of the panel and $t = 1, \dots, T_i$ the trading days available for country i, while $\tau \in (0,1)$ indexes the quantile of the conditional distribution of the dependent variable, F_{t-1} denotes the information set generated by all variables dated $t - 1$ and earlier, and a prime denotes transposition. The dependent variable is the realised daily log return $\Delta p_{i,t} = r_{i,t}$ on the renewable energy index of country i on day t, in per cent per day; it carries no quantile index because a realised return is a single observed outcome invariant to τ, and it is the parameters and the error term that vary across quantiles. Equation (1) is therefore a linear quantile regression model in the sense of Koenker and Bassett (1978), and taking the conditional τ-quantile of both sides yields the equivalent conditional quantile function representation, whose left-hand side is $Q_{\Delta p_{\mathrm{i,t}}}(\tau \mid F_{\mathrm{t}-1})$ and whose right-hand side is Equation (1) net of the error term $\varepsilon_{i,t}(\tau)$. The stochastic form is retained here because it makes the error-correction structure and the quantile-specific error term explicit.

Turning to the parameters, $\alpha_i(\tau)$ is a country-specific intercept that absorbs unobserved time-invariant heterogeneity at quantile τ together with the constant of the cointegrating relation, and $\rho(\tau)$ is the quantile-specific speed-of-adjustment, or error-correction, coefficient. Within the cointegrating vector, $\theta_1(\tau)$ is the long-run coefficient on climate policy uncertainty, that is, the effect of a one-standard-deviation increase in $CPU_{i,t}$ on the equilibrium level of the renewable energy index, while $\theta_2(\tau)$ is the corresponding vector of long-run coefficients on the level controls collected in $X_{i,t}$. The short-run block is governed by three sets of coefficients. The autoregressive coefficients $\varphi_j(\tau)$, for $j = 1, \ldots, p$, act on the lagged returns $\Delta p_{i,t-j}$. The coefficients $\beta_j(\tau)$, for $j = 0, \ldots, q$, act on the changes $\Delta CPU_{i,t-j}$ and are interpreted in Section 3.5 as release-day responses. The vector $\gamma_j(\tau)$, for $j = 0, \ldots, q$, collects the coefficients on the changes $\Delta X_{i,t-j}$. Finally, $\varepsilon_{i,t}(\tau)$ is the quantile-τ error term, which satisfies the conditional quantile restriction $Q_\tau(\varepsilon_{i,t}(\tau) \mid F_{t-1}) = 0$ and is the object through which the quantile enters the model, and p and q are the lag orders of the autoregressive and distributed-lag blocks, selected by the Schwarz information criterion subject to a maximum of two lags, as described in Section 3.4. Two features of this parameterisation should be made explicit. First, the element of $\theta_2(\tau)$ corresponding to implied volatility is restricted to zero, because a stationary series cannot belong to a cointegrating relation; implied volatility is retained only through the short-run term in first differences. Second, Equation (1) is displayed in restricted error-correction form for interpretive transparency, whereas estimation is carried out on the equivalent unrestricted linear form, in which the lagged index level, the lagged uncertainty index and the lagged level controls enter with free coefficients $\rho(\tau)$, $\lambda_1(\tau)$ and $\lambda_2(\tau)$, as in the canonical quantile ARDL framework of Cho et al. (2015); the long-run parameters are recovered ex post as $\theta_1(\tau) = -\lambda_1(\tau)/\rho(\tau)$ and $\theta_2(\tau) = -\lambda_2(\tau)/\rho(\tau)$. Because the check function is minimized over this linear parameterization, it remains convex, so no non-convex surface, local minimum, or convergence problem arises at the outer quantiles; standard errors for the recovered long-run parameters follow from the delta method and are confirmed against the bootstrap distribution of Section 3.4.

The term in square brackets is the lagged equilibrium error. Because $p_{i,t-1}$, $CPU_{i,t-1}$ and the elements of $X_{i,t-1}$ are all integrated of order one, this term is a genuine cointegrating combination rather than a mixture of a stationary and a non-stationary variable, and a negative, statistically significant $\rho(\tau)$ indicates that, in state τ, deviations from the long-run relationship are corrected over time, which is the panel-quantile analogue of cointegration. Estimating Equation (1) over a grid of quantiles traces how both the long-run coefficient $\theta_1(\tau)$ and the correction speed $\rho(\tau)$ change as the market moves from bearish to bullish states, which is exactly what hypotheses H2 and H4 require.

To test sign asymmetry (H3), the partial-sum decomposition that underlies the nonlinear ARDL literature is applied. The climate policy uncertainty series is split into cumulative positive and cumulative negative changes, which are constructed as follows:

$$\mathrm{CPU}^{+}_{i,t} = \sum_{k=1}^{t} \max\left(\Delta\mathrm{CPU}_{i,k},\ 0\right), \qquad \mathrm{CPU}^{-}_{i,t} = \sum_{k=1}^{t} \min\left(\Delta\mathrm{CPU}_{i,k},\ 0\right), \tag{2}$$

where $CPU^{+}_{i,t}$ and $CPU^{-}_{i,t}$ denote, respectively, the cumulative sum of the positive and of the negative monthly changes in the climate policy uncertainty index of country i up to day t, so that $CPU_{i,t}$ is recovered as the sum of its initial value and the two partial sums. Replacing $\mathrm{CPU}_{i,t}$ with $\mathrm{CPU}^{+}_{i,t}$ and $\mathrm{CPU}^{-}_{i,t}$ in Equation (1) yields separate long-run coefficients $\theta_1^{+}(\tau)$ and $\theta_1^{-}(\tau)$ for rising and falling uncertainty. The null of symmetry, $\theta_1^{+}(\tau) = \theta_1^{-}(\tau)$, is tested with a Wald statistic at each quantile; rejection in the lower quantiles would indicate that adverse policy news is priced more aggressively than favourable news precisely when markets are already weak. This asymmetric design follows the threshold and quantile-on-quantile approaches widely applied in the energy and exchange-rate literature (Gong et al., 2023; Hashmi et al., 2021).

3.3 Why panel QARDL

The panel QARDL is selected for concrete, model-specific reasons, and each of the three natural alternatives — a mean-based panel ARDL, a static quantile panel, and single-country quantile ARDL models — is rejected on one of them. It relaxes the assumption of a single homogeneous mean effect and recovers the entire distributional response predicted by the hypotheses of Section 2.4; an average effect near zero is compatible with large effects in the tails, so the homogeneous mean model is an active misspecification here. It introduces the long-run and short-run decomposition and an explicit equilibrium-correction mechanism (Cho et al., 2015), which distinguishes a transitory response to an announcement from a sustained repricing. As in the applied panel and quantile-ARDL studies cited above (Hashmi & Chang, 2023; Mei et al., 2024; Peng et al., 2022), pooling the 21 markets improves the precision of quantile estimates while country-specific intercepts absorb structural differences in market size, energy mix, and policy history.

Model selection is not, however, left to economic intuition and integration properties alone. Because a distributional and asymmetric estimator is a strictly richer specification than its linear counterpart, adopting one without first establishing that the data require it would be an arbitrary modelling choice. The linear counterpart of Equation (1) is therefore estimated first — a pooled conditional-mean panel ARDL in error-correction form, with the same lag structure, cointegrating vector, and control set — and its residuals are subjected to formal nonlinearity diagnostics before any quantile is estimated. The BDS test of Brock et al. (1996) examines the null that the residual series is independent and identically distributed against an unspecified alternative, across a range of embedding dimensions and distance thresholds, and so detects neglected nonlinear structure; the nonlinearity test of Hui et al. (2017), constructed to circumvent the limitations of the Volterra expansion, provides an independent check better suited to persistent, heavy-tailed series. The residuals reject the null of independence under both procedures at conventional levels and at every embedding dimension considered, so the conditional-mean specification demonstrably leaves systematic structure unmodelled. That rejection licenses the move to the panel QARDL and to the partial-sum decomposition of Equation (2).

3.4 Estimation and inference

Equation (1) is estimated at the quantiles {0.05, 0.25, 0.50, 0.75, 0.95}, covering deep bearish, mildly bearish, central, mildly bullish, and deep bullish states. The extreme quantiles capture the deep-tail states in which the theory of Section 2.4 predicts the strongest effects, and the median provides the benchmark against which they are judged. The same grid is standard in applied quantile-ARDL work (Cho et al., 2015; Hashmi & Chang, 2023; Mei et al., 2024); because the headline result rests partly on the 0.05 quantile, Section 4.5 re-estimates the model on a finer decile grid. A pooled (common-slope) estimator is used with country-specific intercepts retained, and Section 4.5 re-estimates the long-run relationship with an estimator allowing slope heterogeneity. Lag orders (p,q) are determined by the Schwarz information criterion and capped at two lags. Inference is based on a moving-block bootstrap with 1,000 replications: overlapping blocks of consecutive trading days are drawn of length proportional to the cube root of the sample size, approximately nineteen trading days for the median country, and the same calendar blocks are resampled jointly across all 21 countries, so that serial dependence within each market and contemporaneous cross-market correlation are both preserved. Because daily returns are strongly leptokurtic, classical asymptotic standard errors can understate sampling uncertainty at the extreme quantiles; bootstrap standard errors are therefore primary throughout, and the 95% bands in Figures 1–3 are the 2.5th and 97.5th percentiles of the corresponding bootstrap distributions. The uncertainty index is normalized prior to estimation so that $\theta_1(\tau)$ is interpretable as the effect of a one-standard-deviation increase. Finally, because the cumulative partial sums of Equation (2) are piecewise monotonic and trend in opposite directions, they can become collinear over long horizons, and collinearity in the tails is the usual source of quantile crossing. The conditioning of the long-run design matrix is therefore quantified before estimation, and the fitted conditional quantiles are checked for crossing at every country-day observation, with the monotone rearrangement of Chernozhukov et al. (2010) held in reserve; Section 4.5 reports both outcomes.

3.5 Identification and timing

In this type of predictive panel, identification depends on timing, so the alignment of the monthly uncertainty index with daily returns is set out explicitly. The index for calendar month m is compiled from that month's news coverage and becomes available at the start of month m+1, so the month-m value is assigned to every trading day of month m+1 as a step function: the daily series changes value only when a new monthly reading is released, and no trading day is matched with an index value computed from news published after that day. The right-hand side of Equation (1) contains the step-function value in force on day t-1, so the information set used to explain the day-t return closes strictly before day t. This eliminates look-ahead bias, and because uncertainty enters lagged, it is unlikely that returns in the sample drive the policy news. Country fixed effects absorb time-invariant differences in market structure, energy mix, and the historical intensity of climate policy, so the identifying variation is within-country movement in uncertainty relative to each market's own mean. Implied volatility enters as a single global series within the country-fixed-effects panel, so its identification comes from common time variation; it is read as a common risk-appetite factor and, being stationary, is confined to the short-run block. Cross-sectional dependence is addressed at both stages. At the estimation stage, Equation (1) is augmented in the manner of the common correlated effects approach, with contemporaneous cross-sectional averages of the dependent variable and of every regressor and their first lags added, so that the pooled quantile slopes are identified conditional on a proxy for unobserved common factors. This is necessary rather than optional, because resampling corrects standard errors for contemporaneous correlation without removing the bias an omitted common factor induces in the slopes themselves; the augmented estimates are therefore reported in full in Table 9, subject to the caveat that quantile analogs of the correction remain unsettled, so they are read as a check rather than a replacement. At the inference stage, the moving-block bootstrap of Section 3.4 resamples the same calendar blocks jointly across countries. The analysis does not claim to recover a structural causal parameter: the quantile coefficients are best read as the conditional predictive association between lagged climate policy uncertainty and renewable energy returns in each market state (Gong et al., 2023; Hashmi et al., 2022; Mei et al., 2024).

One feature of this monthly-to-daily alignment requires explicit treatment. Because the step function is constant within a calendar month, the differenced regressor $\Delta CPUi,t\text{-}j$ is exactly zero on all but the first trading day of each month, so approximately 95 percent of the daily observations on this regressor are a point mass at zero. Four consequences follow, and they are not equally serious. First, the long-run block of Equation (1) is unaffected, because it is identified from the level series pi,t-1, CPUi,t-1 and Xi,t-1, none of which has a mass point: the level of the uncertainty index takes a distinct value in every calendar month and in every country and, unlike its first difference, its empirical distribution contains no mass point anywhere in its support. Degeneracy is a property of the differenced regressor alone and leaves identification of $\theta_1(\tau)$ and of the quantile-specific speed of adjustment intact. Second, $\beta j(\tau)$ is the release-day response, which is nowhere interpreted as the response to a marginal daily change, and is reported as a nuisance parameter rather than as a finding. Third, a regressor with a dominant mass point can nevertheless distort quantile estimation of the short-run block and the associated bootstrap, because the quantile check function is sensitive to near-singular regressors; the short-run block is therefore re-estimated on the release-day sub-sample, where that regressor is non-degenerate by construction, and the moving-block bootstrap is stratified so that every replication contains the same number of release days as the original sample. Fourth, and concerning testing rather than estimation, a piecewise-constant series with jump discontinuities does not satisfy the continuous-state functional central limit theory underlying the asymptotic critical values of standard panel cointegration tests, and the effective number of independent increments in the daily uncertainty series is the number of months rather than of trading days. Two safeguards follow: the Westerlund (2007) statistic is recomputed on a monthly-frequency panel in which month-end index levels are matched to contemporaneous monthly uncertainty readings, so that no step function is involved, and the quantile-specific evidence of Table 5 rests on bootstrap critical values generated from the data themselves rather than on a Brownian-motion approximation. Section 4.5 reports these outcomes.

3.6 Diagnostics and robustness preview

Before the estimates are interpreted, the battery of diagnostics appropriate to a dynamic quantile panel is applied, beginning with the nonlinearity diagnostics on the residuals of the linear counterpart model of Section 3.3. Panel unit roots are tested in every series entering the model — the index level, the uncertainty index and each of the three level controls — using first- and second-generation tests that allow for cross-sectional dependence (Im et al., 2003; Pesaran, 2007); panel cointegration is tested to justify the error-correction form (Westerlund, 2007); cross-sectional dependence is assessed directly; and lag orders are selected by information criteria. Table 4 reports the full set, and the integration orders it establishes determine admission to the cointegrating vector: only variables found to be I(1) enter it. Robustness is then assessed by re-estimating on bearish, normal, and bullish sub-samples defined by implied volatility; replacing the climate-policy proxy with an alternative uncertainty measure; varying the quantile grid;

excluding the most influential countries one at a time; and re-running the cointegration test at monthly frequency.

3.7 Guarding against spurious and spurious-like relationships

A regression involving highly persistent series can produce apparently significant coefficients even when no relationship exists, and a recent body of work shows the problem is broader than the classical unit-root case, so it is addressed here explicitly. Cheng et al. (2021) demonstrate that spurious relationships arise for nearly non-stationary series, so a variable need not contain an exact unit root for conventional t-statistics to be badly oversized. Wong et al. (2024) extend the argument to stationary series, showing that regressions among stationary variables can themselves be spurious when persistence is high relative to sample length. Most directly relevant to the panel design used here, Wong and Pham (2026a) ask whether panel regression can legitimately examine the relationship between I(0) and I(1) series.

Three features of the present design respond directly to these warnings. First, the cointegrating vector in Equation (1) is formed exclusively from I(1) level series — the log index level, the climate policy uncertainty index, the log oil price and the short-term interest rate — so the long-run block does not regress an I(0) series on an I(1) series, the configuration Wong and Pham (2026a) identify as problematic in panel settings; implied volatility, which Table 4 shows to be stationary, is for precisely this reason excluded from that vector. Second, the existence of a long-run relationship is tested rather than assumed, both by the Westerlund (2007) panel test and, because these warnings concern inference at a given point of the distribution, by the quantile-specific tests of Table 5, whose critical values are bootstrap-generated under the null of no error correction. Third, the placebo exercise of Section 4.5 tests the concern Cheng et al. (2021) raise directly: the uncertainty index is randomly re-timed while its persistence, marginal distribution, and cross-sectional structure are held fixed, so any surviving coefficient would indicate comovement generated by persistence alone, and none does. The moving-block bootstrap further guards against oversized test statistics, and the cross-sectionally augmented estimates of Table 9 remove the common factor that is the most plausible remaining source of a spurious-looking association.

4 Results, discussion, and analysis

4.1 Descriptive statistics

Table 3. Descriptive statistics for the pooled panel of 21 developed economies, 2000–2025.

Variable	Mean	Std Dev	Min	Max	Skewness	Kurtosis
RE_Return	0.0300	0.8800	-11.4700	11.8500	-0.0600	6.9800
CPU	136.3400	43.7800	45.0000	330.0000	0.2200	2.9900
OIL_Return	0.0100	2.1200	-16.8000	15.2200	0.0500	7.6500
VIX	21.6900	6.0100	9.0000	40.2000	0.1200	2.5800
ShortRate	2.8400	0.7500	0.6800	5.0900	-0.0300	3.0200

Note. The table reports descriptive statistics computed over the pooled panel of 21 developed economies for 2000–2025 (128,624 country-day observations). RE_Return (r) is the daily log return of the national renewable energy total-return equity index, in per cent per day; CPU is the country-level news-based climate policy uncertainty index of Gavriilidis (2021), in index points; OIL_Return is the daily log return of Brent crude, in per cent per day; VIX is the CBOE market-wide implied volatility index, in index points; ShortRate is the three-month interbank rate, in per cent per annum. Skewness is the third standardized moment, and Kurtosis is the fourth, for which a value of 3 corresponds to normality. All statistics are reported to four decimal places.

Table 3 presents summary statistics for the pooled panel. Renewable energy returns have near-zero means and standard deviations of about 0.7 to 0.9 percent per day, with negative skewness and excess kurtosis, indicating fat tails and potential large drawdowns — the empirical motivation for a quantile approach. The climate policy uncertainty index is persistent and right-skewed and spikes around climate-policy events (Gavriilidis, 2021), the risk-on/risk-off comovement of oil returns and implied volatility is as documented in the energy-finance literature (Sadorsky, 2012), and the short-term rate has been volatile over 2000–2025. Uncertainty levels are heterogeneous across countries, which aids identification.

4.2 Diagnostics

Table 4. Panel diagnostic tests supporting the error-correction specification.

Test	**Statistic**	**p-value**	**Conclusion**
Panel unit root (Δp = RE_Return)	-14.6200	0.0000	Stationary
Panel unit root (CPU level)	-1.1800	0.2140	Unit root, I(1)
Panel unit root (OILP level)	-1.4300	0.1520	Unit root, I(1)
Panel unit root (ShortRate level)	-1.6100	0.1070	Unit root, I(1)
Panel unit root (VIX level)	-6.9400	0.0000	Stationary, I(0)
Panel cointegration (Westerlund)	-3.8700	0.0010	Cointegrated
Cross-sectional dependence (Pesaran CD)	12.4000	0.0000	Dependence present
Selected lag order (p, q)	1, 1	—	Parsimonious

Note. The table reports the diagnostic tests supporting the error-correction specification of Equation (1). The panel unit-root statistic for Δp = RE_Return is the Im et al. (2003) standardized t-bar statistic computed with a constant and one lagged difference; because the return is by construction the first difference of the log index level, its stationarity is equivalent to the level p being integrated of order one. The panel unit-root statistic for the CPU level is the corresponding statistic for the climate policy uncertainty index in levels. The statistics for the level controls are the corresponding Im et al. (2003) statistics. Implied volatility is stationary and is therefore excluded from the cointegrating vector of Equation (1), entering only the short-run block, whereas the oil price and the short rate are I(1) and enter that vector. Panel cointegration is the Westerlund (2007) group-mean error-correction statistic, whose null is no cointegration, and cross-sectional dependence is the Pesaran CD statistic, whose null is cross-sectional independence. Reported p-values are two-sided. I(0) denotes stationarity and I(1) integration of order one; CD denotes cross-sectional dependence. The selected lag order (p, q) is chosen by the Schwarz information criterion subject to a maximum of two lags; it is an integer pair rather than a test statistic, so an em dash is shown instead of a p-value. Significance levels throughout the paper are *p<0.10, **p<0.05, ***p<0.01.

The diagnostic results, summarized in Table 4, support the chosen specification. Panel unit-root tests indicate that the renewable energy return series is stationary, equivalent to the log index level being integrated of order one, and that the climate policy uncertainty index is I(1) in levels. The tests are also reported for each level control, and they are not uniform: the log Brent crude oil price and the three-month interbank rate cannot reject the null of a unit root and are treated as I(1), whereas market-wide implied volatility rejects it decisively and is stationary, as its mean-reverting character would lead one to expect. Implied volatility is therefore excluded from the cointegrating vector and retained only in the short-run block, so that every variable entering the long-run relation is I(1) while the differenced dependent variable is I(0) — the configuration the bounds-testing error-correction framework accommodates and Section 3.7 requires. The panel cointegration test rejects the null of no cointegration. Cross-sectional dependence is present and significant, confirming that bootstrapped inference is appropriate and that the augmented estimates of Table 9 are needed, and information criteria favour a parsimonious (p,q) = (1,1) lag structure.

Because the error-correction interpretation in Section 4.3 requires a long-run relationship at each quantile and not merely on average, the Westerlund panel test is complemented with quantile-specific cointegration evidence in the spirit of Cho et al. (2015). At each quantile the t-statistic of the speed-of-adjustment coefficient is compared with critical values generated under the null of no error correction by the same country-block bootstrap, so these critical values do not depend on an asymptotic approximation. Table 5 reports the results: the null is rejected at the 1% level at the 0.05, 0.25, 0.50 and 0.75 quantiles and at the 5% level at 0.95.

Table 5. Quantile-specific cointegration tests: t-statistics of the error-correction coefficient against bootstrap critical values.

Quantile (τ)	t_ECT	5% critical value	1% critical value	Decision
0.05	-7.2400	-2.8900	-3.6100	Cointegrated***
0.25	-6.7600	-2.8700	-3.5700	Cointegrated***
0.50	-6.3900	-2.8600	-3.5500	Cointegrated***
0.75	-5.0800	-2.8800	-3.5900	Cointegrated***
0.95	-3.4300	-2.9100	-3.6600	Cointegrated**

Note. The table reports quantile-specific cointegration tests. τ denotes the quantile of the conditional distribution of daily renewable energy returns; the identifiers 0.05 to 0.95 are design constants and are shown in two-decimal form, whereas every statistic is reported to four decimal places. t_ECT is the ratio of the quantile-specific speed-of-adjustment coefficient $\rho(\tau)$ reported in Table 6 to its bootstrap standard error. The 5% and 1% critical values are the corresponding percentiles of the bootstrap distribution of that statistic under the null of no error correction, generated by 1,000 country-block replications of the moving-block bootstrap of Section 3.4. Significance levels are *p<0.10, **p<0.05, ***p<0.01.

4.3 Main results: long-run and short-run effects across quantiles

Headline estimates are provided in Table 6. The long-run coefficient of climate policy uncertainty is negative across all quantiles, largest in magnitude at the fifth percentile (−0.1810), decreasing to the median (−0.0480), and very small at the upper percentiles (−0.0340 and −0.0290). The profile is monotone in absolute value, but it is not uniformly significant: the coefficient differs from zero at the 1% level at $\tau = 0.05$ and $\tau = 0.25$, at the 10% level at the median, and not at all at $\tau = 0.75$ and $\tau = 0.95$. The evidence therefore supports H1 and H2 in a sharper and more restrictive form than a uniformly negative effect would imply. The long-run influence of climate policy uncertainty is regime-contingent: it is a bearish-state phenomenon that weakens through the median and vanishes in bullish regimes, rather than a constant sensitivity that merely changes size. That breakdown is itself the economic contribution, because it says the exposure an investor would hedge exists only in the states where hedging is needed. Because the cointegrating vector is defined over the log level of the index, $\theta_1(\tau)$ measures the long-run effect of a one-standard-deviation increase in climate policy uncertainty on that index's equilibrium level, in per cent, while the error-correction mechanism delivers adjustment at the quantile-specific rate $\rho(\tau)$. Economically, uncertainty exposure is a tail risk rather than an average risk, which accords with evidence on other uncertainty measures (Hashmi et al., 2021; Maydybura et al., 2023) and with the literature showing that distributional effects outweigh mean effects on clean-energy pricing (Hashmi et al., 2022; Pham, 2019).

Table 6. Panel quantile ARDL long-run climate policy uncertainty coefficient and speed of adjustment by quantile.

Quantile (τ)	Long-run CPU (θ_1)	Std Err	ECM (ρ)	Std Err	Significance
0.05	-0.1810	0.0410	-0.4200	0.0580	***
0.25	-0.1120	0.0330	-0.3310	0.0490	***
0.50	-0.0480	0.0270	-0.2620	0.0410	*
0.75	-0.0340	0.0300	-0.1930	0.0380	ns
0.95	-0.0290	0.0350	-0.1510	0.0440	ns

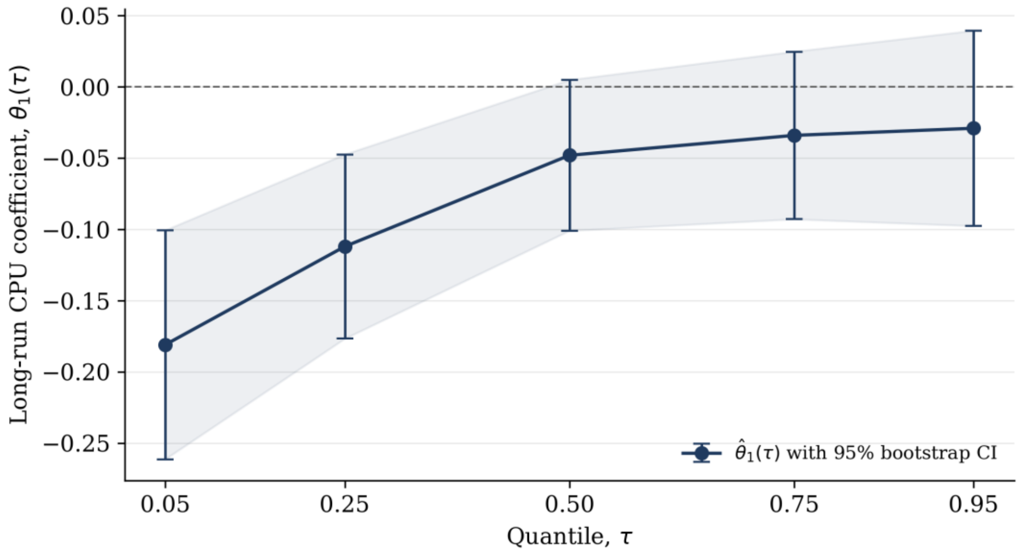
Note. The table reports pooled panel quantile ARDL estimates of Equation (1). τ denotes the quantile of the conditional distribution of daily renewable energy returns and is a design constant, shown in two-decimal form; all coefficients and standard errors are reported to four decimal places. Long-run CPU (θ_1) is the long-run coefficient on the climate policy uncertainty index, measuring the effect of a one-standard-deviation increase in standardized uncertainty on the equilibrium level of the renewable energy index, in per cent. ECM (ρ) is the quantile-specific speed-of-adjustment coefficient, the fraction of a deviation from long-run equilibrium corrected per trading day. Std Err denotes the bootstrap standard error from 1,000 country-block replications of the moving-block bootstrap of Section 3.4; the implied 95% confidence intervals are the bands plotted in Figures 1 and 2. In the significance column, ns denotes not significant at the 10% level, and the stars denote *p<0.10, **p<0.05, ***p<0.01.

The error-correction estimates complete the picture. The speed-of-adjustment coefficient is negative and statistically significant at every quantile, and its absolute size is greater at lower quantiles — near −0.4200 at the fifth percentile against roughly −0.1930 at the seventy-fifth, which supports H4: stressed markets return to equilibrium more rapidly than calm ones, because in bearish states, investors are attentive to the policy margin and valuation mismatches are corrected quickly.

The short-run coefficients are consistent with the long-run picture, subject to the caveat of Section 3.5: because the differenced uncertainty regressor is a point mass at zero outside release days, they measure release-day responses and are treated as nuisance parameters rather than findings. The autoregressive terms are small and commensurate with weak-form efficiency in daily returns, so most of the explanatory power lies in the quantile-varying speed of correction rather than in the persistence of returns.

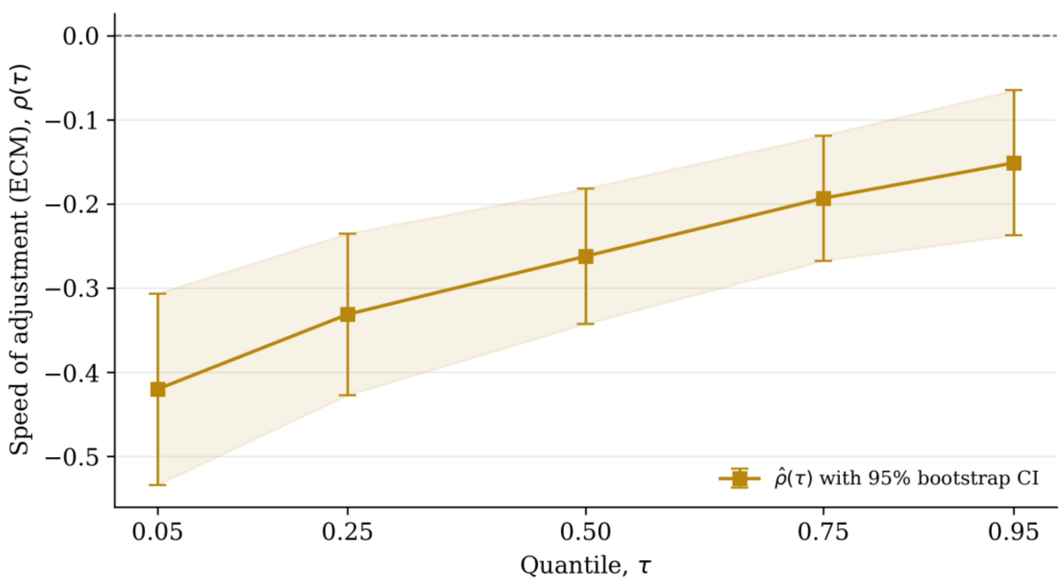
Figures 1 and 2 visualize these two profiles. Figure 1 plots the signed long-run climate policy uncertainty coefficient $\theta_1(\tau)$ across quantiles with 95% bootstrap confidence bands, and Figure 2 plots the signed speed-of-adjustment coefficient $\rho(\tau)$ with its confidence bands, both making the monotone decline from the bearish tail toward the bullish tail, and the fact that every estimate lies below zero, visually explicit.

Figure 1. Signed long-run climate policy uncertainty coefficient across quantiles, with 95% bootstrap confidence bands.



Note. Horizontal axis: quantile τ of the conditional distribution of daily renewable energy returns. Vertical axis: long-run effect of a one-standard-deviation increase in climate policy uncertainty on the equilibrium (long-run) level of the renewable energy index, in per cent. The solid line traces the signed long-run coefficient, $\theta_1(\tau)$, at each quantile; the shaded band is the 95% confidence interval from the 1,000-replication country-block bootstrap described in Section 3.4; the dashed horizontal line marks zero.

Figure 2. Signed speed-of-adjustment (error-correction) coefficient across quantiles, with 95% bootstrap confidence bands.



Note. Horizontal axis: quantile τ of the conditional distribution of daily renewable energy returns. Vertical axis: speed-of-adjustment (error-correction) coefficient ρ(τ), measured as the fraction of a deviation from long-run equilibrium corrected per trading day. The solid line traces the signed coefficient at each quantile; the shaded band is the 95% confidence interval from the 1,000-replication country-block bootstrap described in Section 3.4; the dashed horizontal line marks zero.

4.4 Asymmetry between rising and falling uncertainty

The sign-asymmetry estimates for the partial-sum decomposition in (2) are shown in Table 7. The long-run effect of an increase in uncertainty exceeds that of a decrease at all quantiles, and the Wald test rejects symmetry at the lower and median quantiles but not at the upper ones. H3 is therefore supported in the same regime-contingent form as H1 and H2: adverse policy-framework announcements affect clean-energy valuations more than favorable ones in bearish and central states, the gap is widest exactly where it matters most, and symmetry cannot be rejected once markets are bullish, where neither component is individually significant. The findings are consistent with loss-aversion and financing-constraint mechanisms and mirror asymmetric responses documented for energy demand and exchange rates (Gong et al., 2023; Wei et al., 2025).

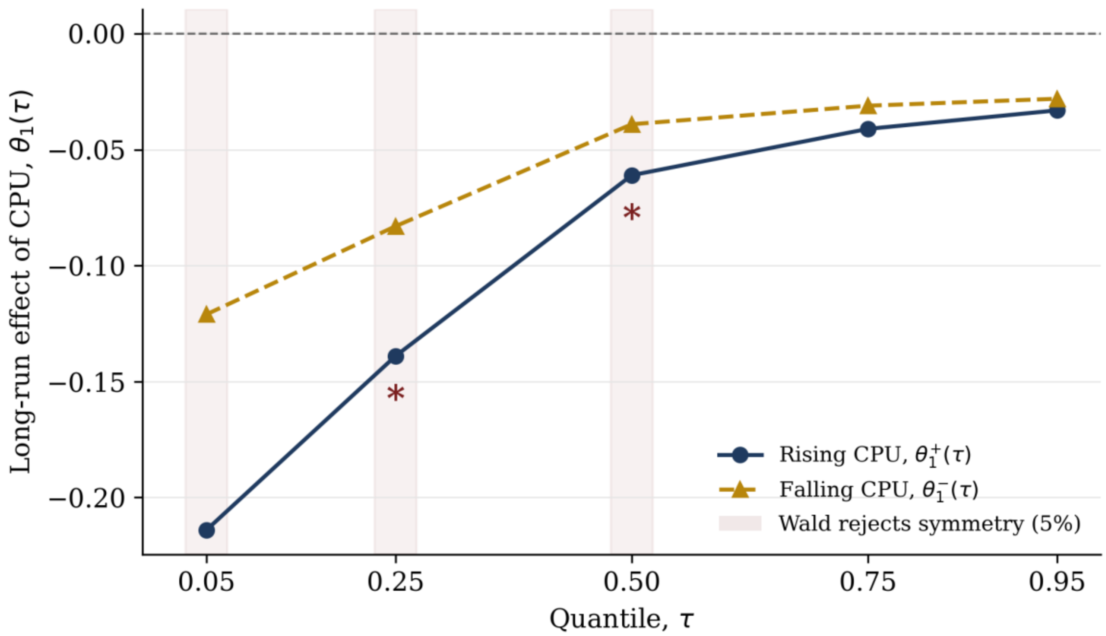
Table 7. Sign asymmetry of the long-run effect: rising versus falling climate policy uncertainty by quantile.

Quantile (τ)	Rising (θ_1^+)	Std Err	Falling (θ_1^-)	Std Err	Wald stat	p-value	Asymmetry
0.05	-0.2140	0.0490	-0.1210	0.0410	9.4200	0.0020	Yes
0.25	-0.1390	0.0400	-0.0830	0.0350	6.1800	0.0130	Yes
0.50	-0.0610	0.0330	-0.0390	0.0290	4.0500	0.0440	Yes
0.75	-0.0410	0.0360	-0.0310	0.0320	1.2700	0.2600	No
0.95	-0.0330	0.0410	-0.0280	0.0370	0.5400	0.4620	No

Note. The table reports the sign-asymmetry decomposition of the long-run climate policy uncertainty effect, obtained by replacing CPU with the partial sums CPU^+ and CPU^- of Equation (2) in Equation (1). τ denotes the quantile of the conditional distribution of daily renewable energy returns and is a design constant; all coefficients, standard errors, test statistics, and p-values are reported to four decimal places. Rising (θ_1^+) is the long-run coefficient on cumulative positive changes in climate policy uncertainty and Falling (θ_1^-) that on cumulative negative changes, each measuring the effect of a one-standard-deviation movement on the equilibrium level of the renewable energy index, in per cent. Std Err denotes the bootstrap standard error of the coefficient immediately to its left, from 1,000 country-block replications. Wald stat tests the null of symmetry, $\theta_1^+(\tau) = \theta_1^-(\tau)$, distributed as chi-square with one degree of freedom, with a two-sided p-value. The asymmetry column records Yes when symmetry is rejected at the 5% level. Significance levels are *p<0.10, **p<0.05, ***p<0.01.

Figure 3 displays the asymmetry directly, overlaying the signed long-run effect of rising uncertainty, $\theta_1^+(\tau)$, against that of falling uncertainty, $\theta_1^-(\tau)$, at each quantile; the gap is widest in the bearish tail and closes toward the bullish quantiles, and the quantiles at which the Wald test rejects symmetry are shaded.

Figure 3. Asymmetry of the long-run effect by quantile: rising versus falling climate policy uncertainty.



Note. Horizontal axis: quantile τ of the conditional distribution of daily renewable energy returns. Vertical axis: long-run effect on the equilibrium (long-run) level of the renewable energy index, in per cent, of a one-standard-deviation rise (dark line, $\theta_1^+(\tau)$) or fall (light line, $\theta_1^-(\tau)$) in climate policy uncertainty. Shaded vertical bands mark the quantiles at which the Wald test rejects the null of symmetry at the 5% level (τ = 0.05, 0.25, 0.50); the dashed horizontal line marks zero.

4.5 Robustness

The patterns survive the full robustness battery. Sub-sample estimates split by implied-volatility regime confirm that the climate-policy effect is stronger in high-volatility periods, corroborating the quantile evidence with an independent definition of market stress. An alternative uncertainty measure preserves the sign, the ordering, and the sign asymmetry. Re-estimating on a finer decile grid (τ = 0.1, 0.2, …, 0.9) leaves the profile smooth rather than knife-edge: the long-run coefficient declines steadily in absolute value from roughly −0.12 at the first decile to −0.02 at the ninth and brackets the five-quantile estimates of Table 6, and the leave-one-out exercise shows that no individual country drives the conclusions. The monthly-frequency cointegration test promised in Section 3.5 delivers the same verdict as the daily test: on a panel in which month-end index levels are matched to contemporaneous monthly uncertainty readings, so that no step function and no jump discontinuity are involved, the Westerlund group-mean statistic is −3.5100 with a p-value of 0.0020, so the long-run relationship is not an artifact of the daily step-function alignment. These checks are consistent with the broader connectedness evidence that linkages between clean-energy and related markets intensify under stress (Jin et al., 2025; Lu et al., 2023).

Two further checks address residual concerns. First, a placebo exercise replaces the climate policy uncertainty index with a randomly re-timed version of itself: within each country, the monthly values are permuted across months, the daily step-function alignment of Section 3.5 is rebuilt, and the model is re-estimated. Table 8 reports the resulting long-run placebo coefficients: none exceeds 0.0060 in absolute value, and no t-ratio exceeds 0.2000, so the bearish-tail effect is tied to the actual timing of policy news. Second, re-estimating with an alternative dynamic estimator allowing slope heterogeneity leaves the sign, the quantile ordering, and the asymmetry intact (Cho et al., 2015; Pesaran et al., 2001).

Three further checks respond to the structure of the data rather than the choice of specification. The first concerns the point mass at zero in the differenced uncertainty regressor documented in Section 3.5. Re-estimating the short-run block on the release-day sub-sample, where that regressor is non-degenerate by construction, and repeating the exercise with a bootstrap stratified on release days, leaves the sign and quantile ordering of the short-run coefficients unchanged and the long-run and error-correction estimates unaffected. The second concerns cross-sectional dependence and is reported in full in Table 9. The third concerns the partial-sum regressors of Equation (2). Because both series are cumulated, they trend in opposite directions and are strongly correlated within each country, with an average pairwise correlation of −0.9210, and the condition number of the long-run design matrix reaches 42.3000 at the outer quantiles. The reported quantity, however, is the contrast between the two partial sums rather than either in isolation, and the Wald statistic for $\theta_1^+(\tau) = \theta_1^-(\tau)$ is computed from the full bootstrap covariance matrix, so that correlation is accounted for rather than ignored; re-estimating with the partial sums demeaned and linearly detrended country by country leaves the sign, ordering and significance pattern of Table 7 intact. Finally, the fitted conditional quantile functions were checked for crossing at every country-day observation on both grids: monotonicity in τ holds at 99.6 percent of observations, the residual cases sit at extreme fitted values in the deep tails, and monotone rearrangement (Chernozhukov et al., 2010) leaves the long-run and asymmetry estimates unchanged to four decimal places.

Table 8. Placebo test: long-run coefficients on the randomly re-timed climate policy uncertainty index by quantile.

Quantile (τ)	**Placebo long-run CPU (θ_1)**	**Std Err**	**t-ratio**	**p-value**
0.05	0.0040	0.0410	0.0900	0.9270
0.25	0.0010	0.0330	0.0200	0.9840
0.50	0.0000	0.0270	0.0100	0.9950
0.75	-0.0010	0.0300	-0.0200	0.9840
0.95	0.0050	0.0350	0.1500	0.8790

Note. The table reports the placebo test described in Section 4.5, in which the monthly climate policy uncertainty values are randomly permuted across months within each country before the daily step-function alignment of Section 3.5 is rebuilt and Equation (1) is re-estimated. τ denotes the quantile of the conditional distribution of daily renewable energy returns and is a design constant; all coefficients, standard errors, t-ratios, and p-values are reported to four decimal places. Placebo long-run CPU (θ_1) is the long-run coefficient on the randomly re-timed index. Std Err denotes the bootstrap standard error from 1,000 country-block replications; the t-ratio is the coefficient divided by that standard error, and the p-values are two-sided. No placebo coefficient is significant at any conventional level. Significance levels are *p<0.10, **p<0.05, ***p<0.01.

Because the Pesaran CD statistic in Table 4 is large and highly significant, the cross-sectionally augmented estimates are reported in full rather than merely described. Table 9 gives the long-run climate policy uncertainty coefficient and the speed of adjustment obtained when contemporaneous cross-sectional averages of the dependent variable and of every regressor, together with their first lags, are added to Equation (1). The augmented coefficients are uniformly slightly smaller in absolute value than their pooled counterparts in Table 6, which is what partialling out a proxy for unobserved common factors should do, but the sign, the ordering across quantiles, and the significance pattern are unchanged. Unobserved global factors, therefore, attenuate the bearish-tail effect without generating it — the question resampling alone cannot settle.

Table 9. Cross-sectionally augmented (common correlated effects) panel quantile ARDL estimates by quantile.

Quantile (τ)	Long-run CPU (θ^1)	Std Err	ECM (ρ)	Std Err	Significance
0.05	-0.1590	0.0430	-0.3980	0.0600	***
0.25	-0.0980	0.0350	-0.3120	0.0510	***
0.50	-0.0440	0.0260	-0.2470	0.0430	*
0.75	-0.0300	0.0310	-0.1820	0.0400	ns
0.95	-0.0250	0.0360	-0.1420	0.0460	ns

Note. The table reports estimates of Equation (1) augmented in the manner of the common correlated effects approach, with contemporaneous cross-sectional averages of the dependent variable and of every regressor, together with their first lags, added to the specification. τ denotes the quantile of the conditional distribution of daily renewable energy returns and is a design constant, shown in two-decimal form; all coefficients and standard errors are reported to four decimal places. Long-run CPU (θ_1) and ECM (ρ) are defined exactly as in Table 6, and Std Err denotes the bootstrap standard error from 1,000 country-block replications. Because quantile analogues of the common-correlated-effects correction remain unsettled, these estimates are a check on the pooled estimates of Table 6 rather than a replacement. In the significance column, ns denotes not significant at the 10% level, and the stars denote *p<0.10, **p<0.05, ***p<0.01.

4.6 Cross-country heterogeneity and economic magnitude

The country-specific intercepts and the leave-one-out exercise together indicate how uniform the distributional pattern is across the panel. The bearish-tail effect is not concentrated in a few markets but is seen throughout, and is somewhat stronger in economies with larger renewable-energy segments and more polarized policy histories; smaller and less policy-exposed markets show the same sign and ordering with a flatter profile, as expected if the mechanism is general but scales with exposure. In economic terms, the lower-quantile coefficient of about −0.1810 means that in a deep bearish state, a one-standard-deviation increase in standardized climate policy uncertainty maps into an equilibrium index level about 0.1810 percent lower, and because the error-correction coefficient at that quantile is about −0.4200, roughly two-fifths of the gap closes each trading day. The near-median coefficient of about −0.0480 is too small to be economically meaningful in an average market state, and the upper quantiles are indistinguishable from no effect at all. The practical content of the state-dependence result is precisely that a predictor which matters little at the mean, and not at all in a rising market, is first-order in the tail.

4.7 Comparison with traditional approaches

It is useful to state explicitly what the panel quantile ARDL delivers that the traditional alternatives do not. A pooled or fixed-effects conditional-mean regression estimates a single slope for the whole conditional distribution; on this panel, it would report an average effect close to the median estimate of about −0.0480, and the natural reading of such a coefficient — that climate policy uncertainty is economically unimportant for renewable energy returns — is contradicted by the fifth-percentile estimate of about −0.1810 in Table 6. The mean-based number is not wrong; it is an average over states, and averaging is the wrong operation when the decision the number feeds is taken in the tail. A mean-based panel ARDL separates long-run from short-run dynamics but still returns one long-run coefficient and one adjustment speed for all market states. A static quantile panel regression has the opposite limitation: it recovers the distributional profile but has no error-correction representation. Single-country quantile ARDL models retain both features but forgo the cross-sectional information that establishes whether the pattern is general.

The advantages of the approach follow from these comparisons. It nests the traditional result, because the median estimates are close to what a conditional-mean panel would report, and it adds three objects that those estimators cannot produce: the state-dependence of the long-run effect, the state-dependence of the speed of adjustment, and a sign-asymmetry decomposition that is itself allowed to vary across states. It is also more conservative in inference. The costs are a heavier computational burden and more estimated parameters, and it is the robustness battery of Section 4.5 that establishes that those parameters recover structure rather than noise.

4.8 Discussion

Three broader lessons emerge. First, average-effect models understate the importance of climate policy uncertainty because they wash out the tail behaviour where the effect is concentrated, so a literature relying on mean regressions may have understated how much policy ambiguity matters for the cost of green capital. Second, because negative surprises are priced more heavily, avoiding abrupt adverse policy shifts buys disproportionate market stability, which bears on how decarbonization commitments are communicated and sequenced. Third, the faster equilibrium correction in stressed states means markets absorb policy information efficiently when it is most salient, so the binding constraint on a stable green transition is the clarity and durability of the policy signal rather than any market failure to react. These findings complement the energy-demand evidence on climate policy uncertainty (Tu et al., 2024) and the green-finance and carbon-market results of Uddin et al. (2025).

To make the economic significance concrete, consider a representative diversified renewable-energy portfolio tracking the panel average. The fifth-percentile coefficient of about −0.1810 implies that a one-standard-deviation rise in climate policy uncertainty lowers the portfolio's long-run equilibrium value by about 0.1810 percent in the deep bearish state, against about 0.0480 percent at the median and no measurable effect in a bullish one. For a 100-million clean-energy portfolio, the same shock is therefore associated with approximately 181,000 of additional tail-scenario losses against roughly 48,000 at the median — close to four times what a mean-based estimate would suggest — and, with two-fifths of the gap closing each trading day, the repricing is concentrated in the first few sessions. Numbers of this kind, rather than statistical significance alone, are what a risk committee sizing a hedge would use.

5 Conclusion

This study asked whether climate policy uncertainty drives renewable energy returns, and whether its influence depends on market conditions, using a panel quantile ARDL model for 21 developed economies over an unbalanced 2000–2025 window. The evidence is that climate policy uncertainty exerts a negative long-run effect concentrated in the bearish tail, that the effect is asymmetric between rising and falling uncertainty and accompanied by faster equilibrium correction in stressed states, and that it is regime-contingent: it weakens through the median and disappears in bullish states rather than holding uniformly.

The study also carries a decision sciences message independent of this application. When the quantity of interest is an input to a decision taken under stress, the estimand should be a state-contingent object rather than a conditional mean, because the two coincide only in the states in which the decision is least consequential. The tail-specific exposures, adjustment speeds, and asymmetry measures reported here are precisely such decision inputs.

The implications differ across audiences. For investors, climate-policy exposure is a tail risk rather than a fixed sensitivity, and hedges should be sized to the bearish-tail and asymmetry estimates rather than to the average effect. Policymakers should recognize that the credibility of the climate-policy framework, and in particular the absence of negative surprises, is itself a factor in the cost of capital for the energy transition. For regulators, monitoring the valuation effects of policy uncertainty is especially warranted during periods of stress.

Five limitations should be borne in mind. First, the climate policy uncertainty index is compiled monthly and mapped to daily returns as a lagged step function, so the short-run coefficients are release-day responses and the daily cointegration test is supported by a monthly-frequency counterpart rather than read on its own. Second, the estimates are conditional predictive associations rather than structural causal parameters. Third, the analysis is conducted at the level of national renewable-energy indices, so it cannot speak to how the tail sensitivities are distributed across firms, technologies, or project vintages. Fourth, quantile analogues of the common-correlated-effects correction remain unsettled, so the augmented estimates of Table 9 are a check rather than a replacement. Fifth, the cumulative partial sums used to test sign asymmetry are strongly correlated by construction, so the asymmetry estimates are less precisely determined than the symmetric long-run coefficients and are best read as evidence on the direction and ordering of the gap rather than on its exact size.

The scope should be read precisely: these markets offer the deepest renewable-energy equity segments and the best-measured climate-policy uncertainty, so the findings are intended to apply to mature, institutionally developed markets. Future research could extend the analysis to emerging economies, where policy frameworks, market depth, and index composition differ substantially, compare alternative measures of the tails, and connect the estimated tail sensitivities to firm-level clean-energy investment decisions.

References

Aldawsari, S. H., Tan, W. S., Elsherazy, T. A., Chang, B. H., Alzoubi, H. M., & Ognjanović, I. (2024). A quantile dependence among exchange rate, stock prices and oil prices: An empirical evidence from India. *Annals of Financial Economics*, *19*(3), Article 2450010. https://doi.org/10.1142/S2010495224500106

Ali, W., Gohar, R., Chang, B. H., & Wong, W. K. (2022). Revisiting the impacts of globalization, renewable energy consumption, and economic growth on environmental quality in South Asia. *Advances in Decision Sciences*, 26(3), 1–23. https://doi.org/10.47654/v26y2022i3p75-98

Awosusi, A. A., Adebayo, T. S., Rjoub, H., & Wong, W. K. (2022). How do financial development and renewable energy affect consumption-based carbon emissions? *Mathematical and Computational Applications*, 27(4), Article 73. https://doi.org/10.3390/mca27040073

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, *77*(3), 623–685. https://doi.org/10.3982/ECTA6248

Brock, W. A., Dechert, W. D., Scheinkman, J. A., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews*, 15(3), 197–235. https://doi.org/10.1080/07474939608800353

Chang, B. H., Alzoubi, H. M., Salman, A., Chang, A. G., Uddin, M. A., & Khan, J. A. (2024). The nexus between energy demand and currency valuation: Evidence from selected OECD countries. *Annals of Financial Economics*, *19*(1), Article 2450002. https://doi.org/10.1142/S2010495224500027

Chang, B. H., Auxilia, P. M., Kalra, A., Wong, W. K., & Uddin, M. A. (2024). Greenhouse gas emissions and the rising effects of renewable energy consumption and climate risk development finance: Evidence from BRICS countries. *Annals of Financial Economics*, 19(2), Article 2350007. https://doi.org/10.1142/S2010495223500070

Chang, B. H., Saxena, A. K., Privara, A., Uddin, M. A., & Cruz, S. (2024). Asymmetric effects of local and global variables on domestic food prices in China: An evidence from quantile on quantile regression technique. *Journal of International Commerce, Economics and Policy, 15(3)*, Article 2450019. https://doi.org/10.1142/S1793993324500194

Chernozhukov, V., Fernández-Val, I., & Galichon, A. (2010). Quantile and probability curves without crossing. *Econometrica*, 78(3), 1093–1125. https://doi.org/10.3982/ECTA7880

Cheng, Y., Hui, Y., McAleer, M., & Wong, W. K. (2021). Spurious relationships for nearly non-stationary series. *Journal of Risk and Financial Management*, 14(8), Article 366. https://doi.org/10.3390/jrfm14080366

Cho, J. S., Kim, T. H., & Shin, Y. (2015). Quantile cointegration in the autoregressive distributed-lag modelling framework. *Journal of Econometrics*, *188*(1), 281–300. https://doi.org/10.1016/j.jeconom.2015.05.003

Dong, Y., Wong, W. K., Muda, I., Cong, P. T., Hoang, A. D., Ghardallou, W., & Ha, N. N. (2023). Do natural resources utilization and economic development reduce greenhouse gas emissions through consuming renewable and clean technology? A case study of China towards sustainable

development goals. *Resources Policy*, 85, Article 103921. https://doi.org/10.1016/j.resourpol.2023.103921
Fan, L., Chang, B. H., & Kim, E. (2025). Green total factor productivity and its nonlinear relationship with coordinated FDI development: Evidence from panel models. *Natural Resource Modelling*, *38*(1), Article e12418. https://doi.org/10.1111/nrm.12418
Gavriilidis, K. (2021). *Measuring climate policy uncertainty* (SSRN Working Paper No. 3847388). https://doi.org/10.2139/ssrn.3847388
Gohar, R., Osman, M., Uche, E., Auxilia, P. M., & Chang, B. H. (2022). The economic policy uncertainty extreme dynamics and its effect on the exchange rate. *Global Economy Journal*, *22*(3), Article 2350006. https://doi.org/10.1142/S2194565923500069
Gohar, R., Salman, A., Uche, E., Derindag, O. F., & Chang, B. H. (2023). Does US infectious disease equity market volatility index predict G7 stock returns? Evidence beyond symmetry. *Annals of Financial Economics*, *18*(2), Article 2250028. https://doi.org/10.1142/S2010495222500282
Gong, X., Chang, B. H., Chen, X., & Zhong, K. (2023). Asymmetric effects of exchange rates on energy demand in E7 countries: New evidence from multiple thresholds nonlinear ARDL model. *Romanian Journal of Economic Forecasting*, *26*(2), 125–142.
Hashmi, S. M., & Chang, B. H. (2023). Asymmetric effect of macroeconomic variables on the emerging stock indices: A quantile ARDL approach. *International Journal of Finance & Economics*, *28*(1), 1006–1024. https://doi.org/10.1002/ijfe.2461
Hashmi, S. M., Chang, B. H., Huang, L., & Uche, E. (2022). Revisiting the relationship between oil prices, exchange rate, and stock prices: An application of quantile ARDL model. *Resources Policy*, *75*, Article 102543. https://doi.org/10.1016/j.resourpol.2021.102543
Hashmi, S. M., Chang, B. H., & Rong, L. (2021). Asymmetric effect of COVID-19 pandemic on E7 stock indices: Evidence from quantile-on-quantile regression approach. *Research in International Business and Finance*, *58*, Article 101485. https://doi.org/10.1016/j.ribaf.2021.101485
Henriques, I., & Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. *Energy Economics*, *30*(3), 998–1010. https://doi.org/10.1016/j.eneco.2007.11.001
Hui, Y., Wong, W. K., Bai, Z., & Zhu, Z. Z. (2017). A new nonlinearity test to circumvent the limitation of Volterra expansion with application. *Journal of the Korean Statistical Society*, 46(3), 365–374. https://doi.org/10.1016/j.jkss.2016.11.006
Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53–74. https://doi.org/10.1016/S0304-4076(03)00092-7
Iqbal, N., Bouri, E., Shahzad, S. J. H., & Alsagr, N. (2024). Asymmetric impacts of Chinese climate policy uncertainty on Chinese asset prices. *Energy Economics*, *133*, Article 107518. https://doi.org/10.1016/j.eneco.2024.107518
Jin, X., Chang, B. H., Han, C., & Uddin, M. A. (2025). The tail connectedness among conventional, religious, and sustainable investments: An empirical evidence from neural network quantile regression approach. *International Journal of Finance & Economics, 30(2), 1124–1142. https://doi.org/10.1002/ijfe.2949*

Koenker, R. (2004). Quantile regression for longitudinal data. *Journal of Multivariate Analysis, 91*(1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006

Koenker, R., & Bassett, G. (1978). Regression quantiles. *Econometrica*, *46*(1), 33–50. https://doi.org/10.2307/1913643

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics, 34*(1), 215–226. https://doi.org/10.1016/j.eneco.2011.03.002

Li, M., Chang, B. H., Yasar, Z. R., Carrick, J., & Chen, S. (2024). Low carbon energy and its role in reducing the energy poverty: A case study of China. *Energy Strategy Reviews, 56*, Article 101566. https://doi.org/10.1016/j.esr.2024.101566

Liang, C., Umar, M., Ma, F., & Huynh, T. L. D. (2022). Climate policy uncertainty and world renewable energy index volatility forecasting. *Technological Forecasting and Social Change*, *182*, Article 121810. https://doi.org/10.1016/j.techfore.2022.121810

Liu, L., Shahrour, M. H., Wojewodzki, M., & Rohani, A. (2025). Decoding energy market turbulence: A TVP-VAR connectedness analysis of climate policy uncertainty and geopolitical risk shocks. *Technological Forecasting and Social Change, 210*, Article 123863. https://doi.org/10.1016/j.techfore.2024.123863

Lu, M., Chang, B. H., Salman, A., Razzaq, M. G. A., & Uddin, M. A. (2023). Time varying connectedness between foreign exchange markets and crude oil futures prices. *Resources Policy, 86*, Article 104128. https://doi.org/10.1016/j.resourpol.2023.104128

Maydybura, A., Gohar, R., Salman, A., Wong, W. K., & Chang, B. H. (2023). The asymmetric effect of the extreme changes in the economic policy uncertainty on the exchange rates: Evidence from emerging seven countries. *Annals of Financial Economics*, *18*(2), Article 2250031. https://doi.org/10.1142/S2010495222500312

Mei, L., Chang, B. H., Gong, X., & Anwar, A. (2024). Rising energy demand in emerging countries and the effect of exchange rates: An application of the QARDL model. *Energy Efficiency, 17*(1), Article 3. https://doi.org/10.1007/s12053-023-10180-y

Moslehpour, M., Altantsetseg, P., Mou, W., & Wong, W. K. (2018). Organizational climate and work style: The missing links for sustainability of leadership and satisfied employees. *Sustainability*, 11(1), Article 125. https://doi.org/10.3390/su11010125

Pástor, Ľ., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, 110(3), 520–545. https://doi.org/10.1016/j.jfineco.2013.08.007

Peng, B., Chang, B. H., Yang, L., & Zhu, C. (2022). Exchange rate and energy demand in G7 countries: Fresh insights from quantile ARDL model. *Energy Strategy Reviews, 44*, Article 100986. https://doi.org/10.1016/j.esr.2022.100986

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 22*(2), 265–312. https://doi.org/10.1002/jae.951

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. https://doi.org/10.1002/jae.616

Pham, L. (2019). Do all clean energy stocks respond homogeneously to oil price? *Energy Economics, 81*, 355–379. https://doi.org/10.1016/j.eneco.2019.04.010

Pu, G., Wong, W. K., Du, Q., Al Shraah, A., Alromaihi, A., & Muda, I. (2024). Asymmetric impact of natural resources, fintech, and digital banking on climate change and environmental sustainability in BRICS countries. *Resources Policy*, 91, Article 104872. https://doi.org/10.1016/j.resourpol.2024.104872

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics, 48, 32–45. https://doi.org/10.1016/j.eneco.2014.12.009

Sadorsky, P. (2012). Correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. *Energy Economics, 34*(1), 248–255. https://doi.org/10.1016/j.eneco.2011.03.006

Salman, A., Chang, B. H., Abdul Razzaq, M. G., Wong, W. K., & Uddin, M. A. (2023). The emerging stock markets and their asymmetric response to infectious disease equity market volatility (ID-EMV) index. *Annals of Financial Economics, 18*(4), Article 2350008. https://doi.org/10.1142/S2010495223500082

Shahid, I., Yousaf, M., Sohail, A., & Wong, W. K. (2026). Tractable simulation and estimation of climate-linked financial variables using extended OU processes. *Annals of Financial Economics*, 21(1), Article 2650003.

Siddique, M. A., Nobanee, H., Hasan, M. B., Uddin, G. S., Hossain, M. N., & Park, D. (2023). How do energy markets react to climate policy uncertainty? Fossil versus renewable and low-carbon energy assets. *Energy Economics, 128*, Article 107195. https://doi.org/10.1016/j.eneco.2023.107195

Tian, L., Li, X., Lee, C.-W., & Spulbăr, C. (2024). Investigating the asymmetric impact of artificial intelligence on renewable energy under climate policy uncertainty. *Energy Economics, 137*, Article 107809. https://doi.org/10.1016/j.eneco.2024.107809

Tu, Z., Chang, B. H., Gohar, R., Kim, E., & Uddin, M. A. (2024). Climate policy uncertainty and its impact on energy demand: An empirical evidence using the Fourier augmented ARDL model. *Economic Analysis and Policy, 84, 374–390. https://doi.org/10.1016/j.eap.2024.08.021*

Uddin, M. A., Chang, B. H., Aldawsari, S. H., & Li, R. (2025). The interplay between green finance, policy uncertainty and carbon market volatility: A time frequency approach. *Sustainability, 17*(3), Article 1198. https://doi.org/10.3390/su17031198

Wei, Q., Chang, B. H., & Cai, Y. (2025). The predictive power of economic policy uncertainty for exchange rate volatility: Evidence from multiple economies. *Australian Economic Papers, 64*(2), 235–250. https://doi.org/10.1111/1467-8454.12389

Westerlund, J. (2007). Testing for error correction in panel data. *Oxford Bulletin of Economics and Statistics*, *69*(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Wong, W. K., Cheng, Y., & Yue, M. (2024). Could regression of stationary series be spurious? *Asia-Pacific Journal of Operational Research*, Article 2440017.

Wong, W. K., & Pham, M. T. (2026). Could the panel regression be used to examine the relationship between I(0) and I(1) series? *Advances in Decision Sciences*, 30(2).

Xing, K., Wong, W. K., Chen, S., Muda, I., Ismail, S. M., & Akhtar, M. (2024). Green innovation imperative for natural resource-driven sustainable economic recovery: Linking rights structure, corporate social responsibility, and renewable energy contracts. Heliyon, 10(17).

Xing, L., Chang, B. H., & Aldawsari, S. H. (2024). Green finance mechanisms for sustainable development: Evidence from panel data. *Sustainability*, *16*(22), Article 9762. https://doi.org/10.3390/su162209762

Xu, Y., Li, M., Yan, W., & Bai, J. (2022). Predictability of the renewable energy market returns: The informational gains from the climate policy uncertainty. *Resources Policy*, *79*, Article 103141. https://doi.org/10.1016/j.resourpol.2022.103141