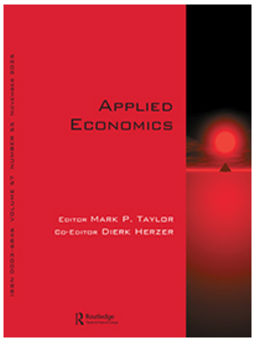

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Unpacking policy ambiguities in residential and commercial renewable energy adoption: a novel multivariate wavelet quantile regression analysis

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ABSTRACT
As the global push for clean energy accelerates, the shadow of policy ambiguity continues to cloud the path towards widespread renewable energy adoption – especially in the residential and commercial sectors where investment decisions are highly sensitive to regulatory signals. Therefore, this study addresses a gap in the literature by introducing a novel *Multivariate Wavelet Quantile Regression* approach to analyse the impact of policy ambiguities on residential and commercial renewable energy adoption in the United States. This technique quantifies the effect of each independent variable on the dependent variable across short-, medium-, and long-run frequency bands while controlling for other covariates. The study used data from 1 January 1993 to 1 January 2025 to examine this association. (a) Climate-policy uncertainty initially boosts adoption among lower- and mid-tier consumers but ultimately suppresses consumption across all tiers in the long run; (b) monetary-policy uncertainty momentarily stalls moderate adopters' renewable purchases before broadly accelerating small-scale deployment; (c) economic-policy uncertainty triggers a precautionary surge in consumption in the short run but leads to medium- and long-run declines; (d) trade-policy uncertainty drives hedging behaviour in mid- and upper-tier consumers, yielding durable gains in renewable-energy use across all tiers. The study proposes policies based on these findings.

KEYWORDS
Climate policy uncertainty; economic policy uncertainty; monetary policy uncertainty; renewable energy consumption; trade policy uncertainty

JEL CLASSIFICATION
Q42; Q54; E44; E52; F18

I. Introduction

As the environmental dangers associated with the use of non-renewable energy sources become more apparent, economies worldwide are working to move away from fossil fuel dependency and adopt renewable energy alternatives (Acheampong 2018; Ozkan, Eweade, and Usman 2024). The driving force behind this transition is the fact that renewable energy sources do not rely on hydrocarbons, which means they are less likely to contribute to environmental damage through the greenhouse gase emissions. As a result, there is a growing global push to transition to cleaner energy systems, highlighted by international environmental initiatives such as the Paris Agreement and the 2030 Sustainable Development Goals (SDGs) agenda (Abbasi et al. 2022; Addey and Nganje 2024). Despite this, the literature recognizes that various complex barriers have slowed the energy transition process, emphasizing the need for proactive strategies to overcome these obstacles (Sinha et al. 2025).

One of the primary factors influencing the adoption and consumption of renewable energy in both residential and commercial sectors is policy uncertainty, which manifests in various forms: climate, trade, economic, and monetary. These uncertainties shape investment decisions and energy consumption patterns by altering the stability of markets and creating an unpredictable regulatory environment (Shafiullah et al. 2021). Climate policy uncertainty, for example, can disrupt long-term investments in renewable energy by creating doubt over future regulations and subsidies (Addey and Nganje 2024; Işık et al. 2024). Similarly, trade policy uncertainty can impact the costs of renewable energy technologies and components, such as solar panels and wind turbines, which are subject to tariffs or trade barriers (Jamil et al. 2022; Xie, Cao, and Li 2023). Economic and monetary policy uncertainty further complicates decision-making, as fluctuations in interest rates or macroeconomic

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policies can influence financing costs for renewable energy projects, particularly for residential adopters who may be more sensitive to economic shifts. Scholars have debated the paradoxical effects of policy uncertainty on renewable energy consumption (Işık et al. 2024; Sinha et al. 2025). On one hand, such uncertainty may deter investment by introducing risk and volatility into the market, thereby slowing down the adoption of renewable energy (Athari and Kirikkaleli 2025). On the other hand, it may prompt policymakers to introduce resilience strategies, such as stronger climate policies or financial incentives, to stabilize the renewable energy market (Kilinc-Ata 2025). This dual impact suggests that the way policy uncertainty is managed plays a critical role in determining the extent to which renewable energy consumption, both residential and commercial, can thrive in uncertain policy environments.

Renewable energy consumption in the United States reached a record 8.2 quadrillion Btu in 2023, accounting for about 9% (see Figure 1) of total U.S. energy use, driven largely by the rapid expansion of solar and wind generation (EIA 2025b). Investment in renewable energy continues to surge, with U.S. wind capacity expected to grow by roughly 6 GW in 2023 and 7 GW in 2024, while solar additions and battery-storage deployments are setting new annual records (EIA 2025c). However, despite these advances, the U.S.A. has struggled to reduce its overall reliance on fossil fuels, with fossil fuel-based electricity still representing a significant portion of total energy consumption (EIA 2025a). These figures highlight that the country is significantly off track in meeting the targets outlined in SDG 7, which calls for a substantial shift towards renewable energy adoption (Kilinc-Ata, Kaya, and Barut 2025). Moreover,

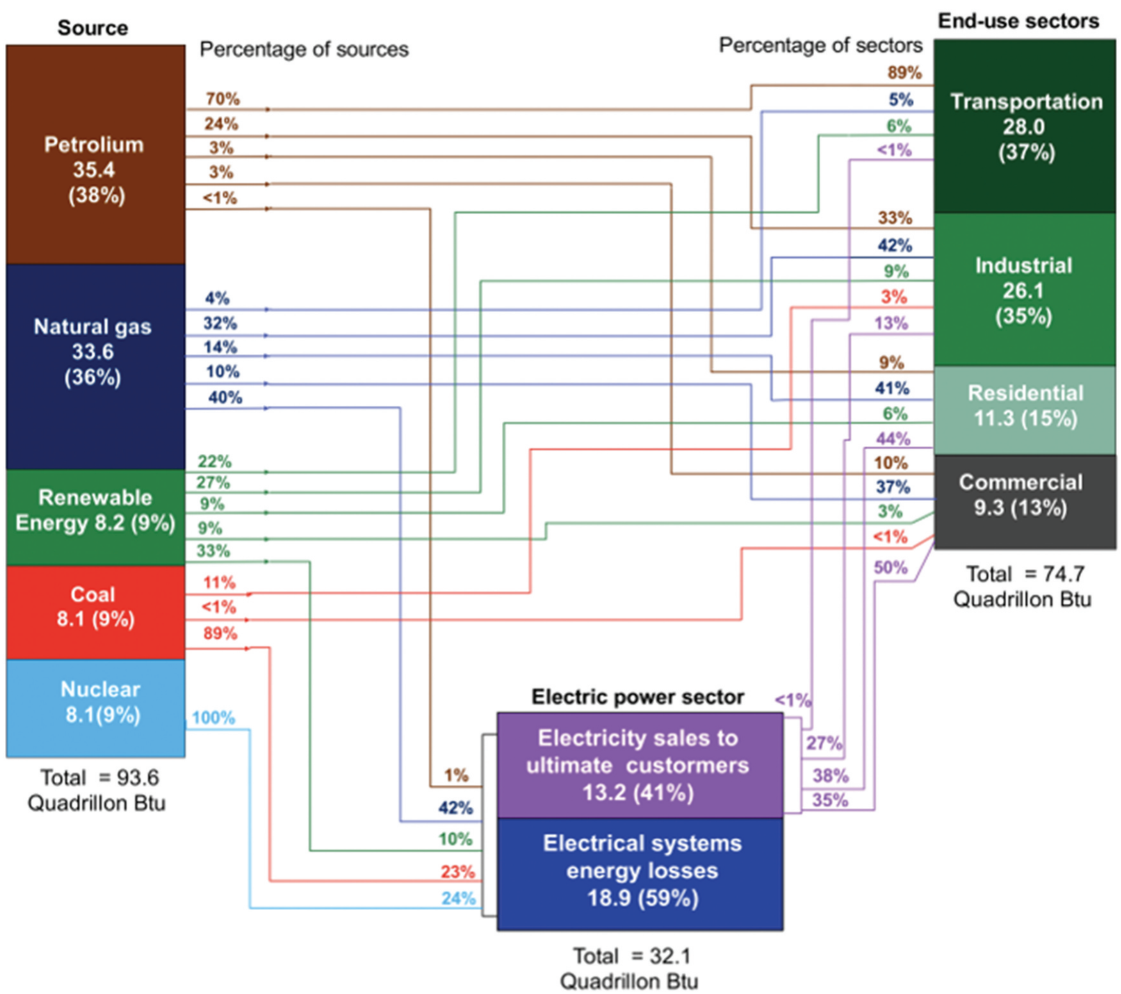

Figure 1. Energy consumption by sources, 2023 in quadrillion British thermal units (Btu).

the lack of policy coherence across different U.S. administrations has hindered long-term planning for renewable energy development. This inconsistency in environmental policymaking, combined with frequent partisan conflicts over climate-related legislation, has increased uncertainty in the U.S. climate policy landscape.

The growing uncertainties in U.S. policies, encompassing climate, trade, economic, and monetary factors, are exacerbating the challenges in developing effective risk mitigation strategies (Sinha et al. 2025). These uncertainties, in turn, are likely to slow down the progress of residential and commercial renewable energy consumption and its widespread adoption (Ding, Zhu, and Zhang 2025), ultimately impeding the clean energy transition and the realization of SDG 7 goals. The presence of uncertainty across multiple policy domains further complicates the overall risk landscape for energy transition initiatives. From an investment perspective, this situation is even more evident. Limited investment in renewable energy projects represents a key obstacle to increasing residential and commercial renewable energy consumption in the U.S. (Bakaloglou and Belaid 2022). Investment decisions are driven by anticipated returns, and the financing of renewable energy projects heavily relies on consistent, supportive policy frameworks. The increase in uncertainty related to climate, trade, economic, and monetary policies introduces greater risk, affecting firms' broader risk management strategies and raising doubts about the long-term sustainability of residential and commercial renewable energy investments (Athari and Kirikkaleli 2025; Shang et al. 2022). Therefore, the complex and multifaceted policy uncertainty in the U.S. poses significant barriers to the renewable energy transition, particularly in the residential and commercial sectors, undermining effective risk management and making it harder to attract necessary investments.

Given the uncertainty surrounding returns, investing in renewable energy projects in the U.S.A. may lose its financial appeal, as investors struggle to accurately forecast their potential profits (Dupont et al. 2024). Therefore, assessing the impacts of policy uncertainty – spanning climate, trade, economic, and monetary policies – on residential and commercial renewable energy consumption is crucial, particularly given the complexities of managing these risks. In this context, the present study examines how unforeseen policy changes in these areas influence the factors driving residential and commercial renewable energy consumption, especially in relation to investment in energy innovation and electricity generation. This leads to the central research question of the study. Based on the above information, the following research question is formulated:

- Does policy uncertainty (climate, trade, economic, and monetary) affect residential and commercial renewable energy consumption in the same way across various quantiles and time periods?

This study offers a novel contribution compared to existing research in the literature in three key areas.

First, this study examines renewable energy consumption in the U.S. under policy uncertainty, focusing on both demand and supply-side factors. While existing literature has largely emphasized demand-side elements, this research highlights the supply-side dynamics, especially amid fluctuating climate, trade, economic, and monetary policies. Policy volatility introduces risks that impact residential and commercial adoption of renewable energy by altering investment behaviour, delaying projects, and influencing market entry. Thus, this study provides a deeper understanding of how policy uncertainty shapes energy consumption patterns, offering valuable insights into the microeconomic factors that drive broader national trends.

Second, uncertainty in the broader policy environment – encompassing climate, trade, economic, and monetary policies – interacts with multiple drivers that influence renewable energy consumption U.S. The collective impact of these policy uncertainties contributes to shaping the renewable energy market dynamics, affecting both residential and commercial sectors. While previous studies have primarily examined the effects of individual policy uncertainties on renewable energy use, this study expands by assessing how the full spectrum of policy uncertainty (across climate, trade, economic, and monetary policies) affects energy consumption patterns. Specifically, it investigates whether these uncertainties influence residential and commercial renewable energy consumption in the same way across various quantiles and time periods. This holistic approach is critical for understanding how the interplay of these policy ambiguities affects renewable energy adoption across different market segments and timeframes, offering insights for more robust policy design.

Third, this study makes a methodological contribution to the literature by introducing a novel multivariate wavelet quantile regression (MWQR) framework. This approach provides valuable insights into the energy-finance literature by simultaneously addressing key econometric challenges such as tail dependence, time-frequency effects, multivariate relationships, and asymmetric impacts. Analysing these dynamics requires an understanding of the interconnections between multiple variables, with particular emphasis on how policy uncertainty influences renewable energy consumption. In the context of energy-finance research, it is essential to identify the relationships among variables at different quantiles, especially at the extremes (or tails), and to account for asymmetric effects that can vary across the data distribution. Energy-finance analysis requires the inclusion of these essential properties to ensure robustness and provide comprehensive insights, all of which are captured effectively by the MWQR framework. Therefore, the methodological contribution of this study lies in its ability to address these important econometric challenges, which have largely been overlooked in the existing literature.

The next section is illustrated as follows: Section II presents the theoretical framework and literature review; Section III describes the data and methods; Section IV reports the results and interpretation; and Section V concludes with policy guidelines.

II. Theoretical framework and literature

Theoretical framework

Uncertainty in policy frameworks – whether stemming from shifting climate regulations, ambiguous economic directives, fluctuating monetary-policy signals, or unpredictable trade measures – elevates perceived project risk and raises the hurdle for irreversible investments in renewable energy. Under real-options theory, agents value the flexibility to wait when future policy payoffs are unclear, leading to deferred adoption and lower overall consumption. Empirically, climate policy uncertainty may induce a short-lived surge in adoption as actors 'lock in' expected benefits, but sustained ambiguity significantly curtails long-run consumption (Ding, Zhu, and Zhang 2025). Likewise, heightened economic policy uncertainty exerts a negative long-term effect on renewable energy consumption across countries by dampening investor confidence and credit flows (Ivanovski and Marinucci 2021), while monetary policy uncertainty further constrains consumption in both the short and long run through increased financing costs and tighter lending conditions (Sohail et al. 2021). Trade policy uncertainty introduces cost volatility for imported equipment, generating asymmetric consumption effects as firms and households weigh potential tariffs and supply-chain disruptions (Zuo and Majeed 2024). Residential and commercial energy consumers exhibit distinct responses to these uncertainties due to differences in investment scale, financing arrangements, and risk tolerance. Household adopters – reliant on small loans and subsidy programs – are especially sensitive to uncertainties around future energy pricing and retrofit quality, often postponing installations when policy signals falter (Bakaloglou and Belaid 2022). In contrast, commercial entities, armed with greater capital reserves and access to hedging instruments or long-term power-purchase agreements, can smooth consumption patterns by locking in financing terms and supply commitments, thereby maintaining project pipelines even amid monetary and trade policy volatility (Jamil et al. 2022). Figure 2 presents the theoretical framework.

Literature review

Policy-uncertainty measures – economic, climate, monetary, and trade – have been widely examined for their impact on renewable-energy consumption across diverse contexts. Broadly speaking, the preponderance of evidence indicates that heightened uncertainty in any of these policy domains exerts a dampening effect on investment in and use of

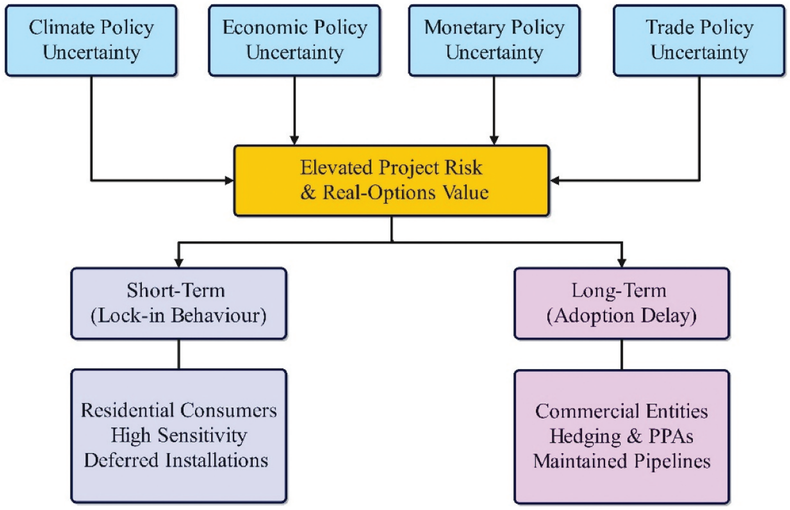

Figure 2. Theoretical framework.

both residential and commercial renewable energy technologies. For example, Feng and Zheng (2022) employ fully modified OLS on panel data from 22 countries over 1985–2015 and find that spikes in economic policy uncertainty significantly reduce aggregate renewable-energy consumption. Likewise, Ivanovski and Marinucci (2021) use nonparametric techniques across 15 high-income economies and report that higher EPU reduces CREC and RREC. Similar negative effects are confirmed by panel-quantile regressions for G7 members (Khan and Su 2022) and pooled mean group ARDL estimates for BRICS nations (Selmey and Elamer 2023).

Monetary and trade-policy uncertainties impart comparable restrictive pressures. Sohail et al. (2021) apply a nonlinear ARDL framework to U.S. data (-1990–2019) and demonstrate that greater monetary-policy uncertainty undermines REC. A global literature review by Lupu et al. (2024) further corroborates a consistently negative link between monetary-policy volatility and REC. On the trade front, Xie, Cao, and Li (2023) use panel regression techniques across 25 emerging markets (1995–2018) to show that fluctuations in TPU curb both RREC and CREC, a finding echoed in China-focused QARDL study by Zuo and Majeed (2024).

Notwithstanding this overarching consensus, a few studies point to countervailing effects. Shang et al. (2022) leverage an ARDL approach for the United States (2000–2021) and find that CPU can, under certain conditions, spur REC – perhaps reflecting anticipatory 'lock-in' behaviour before expected regulatory changes at most quantiles but CPU increase REC at lower quantiles). Similarly, Athari and Kirikkaleli (2025) use wavelet-coherence methods for China (2013–2022) and identify occasions where short-term pulses of CPU correlate with increase in REC, likely due to firms accelerating investment ahead of anticipated policy shifts. Table 1 summarizes past studies.

Research gap and contribution to the field

The literature to date exhibits both methodological and theoretical shortcomings. Although prior studies have examined how policy uncertainties – climate, economic, trade, and monetary – affect overall renewable energy consumption, they have not distinguished between commercial and residential drivers. Consequently, while the direct influence of policy uncertainty on aggregate renewable consumption is well documented, its specific effects on the residential and commercial segments remain unexplored. This study seeks to fill that gap by isolating and analysing these two consumption categories. Methodologically, existing approaches summarized in Table 2 lack the capacity to capture several vital dimensions of energy – finance interactions.

Table 1. Past studies summary.

Investigator(s)	Nation(s)/Region	Period	Method(s)	Finding(s)
Feng and Zheng (2022)	22 countries	1985–2015	FMOLS	EPU $\downarrow$ REC
Shang et al. (2022)	United States	2000–2021	ARDL	CPU $\downarrow$ REC
Ivanovski and Marinucci (2021)	15 high-income economies	1997–2017	Non-parametric analysis	EPU $\downarrow$ CREC
Sohail et al. (2021)	United States	1990–2019	NARDL	MPU $\downarrow$ REC
Zuo and Majeed (2024)	China	2000–2021	QARDL	TPU $\downarrow$ CREC & RREC
Xie et al. (2023)	25 emerging markets	1995–2018	Panel regressions	TPU $\downarrow$ RREC & CREC
Shafiullah et al. (2021)	United States	1986–2019	Nonparametric Methods	EPU $\downarrow$ REC
Selmey and Elamer (2023)	BRICS	1991–2023	PMG-ARDL	EPU $\downarrow$ REC
Khan and Su (2022)	G7 countries	2000–2020	Panel quantile regressions	EPU $\downarrow$ REC
Qamruzzaman (2024)	U.S.A. & China	2000–2021	NARDL	EPU & TPU $\downarrow$ REC
Athari and Kirikkaleli (2025)	China	2013–2022	Wavelet coherence	CPU $\uparrow$ REC
Lupu et al. (2024)	Global (literature review)	2000–2023	Qualitative review	MPU $\downarrow$ REC
Liu et al. (2025)	30 economies	1995–2022	PNARDL	MPU $\downarrow$ REC
Khan and Su (2022)	European Union	1998–2017	TVP-FAVAR	EPU $\downarrow$ REC
Zuo and Majeed (2024)	China	2000–2022	QARDL	TPU $\downarrow$ REC
Khan and Su (2022)	G7 countries	2000–2021	QQR	EPU $\downarrow$ REC.
Appiah-Otoo (2021)	20 countries	2000–2018	IV-GMM	EPU $\downarrow$ REC

Table 2. Comparison of existing methods with the proposed technique.

	Tail-dependence	Effect	Asymmetry	Time-Frequency	Multivariate
Ordinary Least Square	X	√	X	X	√
Autoregressive distributed lag	X	√	X	X	√
Quantile Regression	√	√	√	X	√
Quantile-on-Quantile Regression	√	√	√	X	√
Time-Varying Quantile Regression	√	√	√	X	√
Quantile Causality	√	X	√	X	X
Wavelet Quantile-on-Quantile Regression	√	√	√	√	X
Multi-Frequency Quantile Regression	√	√	√	√	X
Wavelet Quantile Regression	√	√	√	√	X
Multivariate Wavelet Quantile Regression	√	√	√	√	X
Multivariate Quantile-on-Quantile Granger Causality	√	X	√	X	√
Multivariate Wavelet Quantile Regression	√	√	√	√	√

III. Data, model and methods

Data and model

This study examines the impact of policy uncertainty on disaggregated renewable-energy consumption – commercial (CREC) and residential (RREC) – while controlling for other covariates. The dependent variables are CREC and RREC; the independent variables are four policy-uncertainty measures: climate (CPU), economic (EPU), trade (TPU), and monetary (MPU). The data for MPU, TPU, EPU and CPU are gathered from https://www.policyuncertainty.com/. While RREC and CREC are gathered from https://www.eia.gov/totalenergy/data/monthly/index.php#renewable. The study used monthly data spanning from 1 January 1993 to 1 January 2025. The series are transformed using log differences, which approximate growth rates, help stabilise variance, promote stationarity, and allow coefficients to be interpreted as elasticities. The trend of the log difference is shown in Figure 3.

Since this study examines disaggregated renewable energy consumption (commercial and residential), we specify two distinct models. In the first model, we analyse the effect of policy uncertainty on residential renewable energy consumption while controlling other policy uncertainties.

$$RREC = f(CPU, M\bar{P}U, T\bar{P}U, E\bar{P}U). \tag{1}$$

$$RREC = f(MPU, C\bar{P}U, T\bar{P}U, E\bar{P}U). \tag{2}$$

$$RREC = f(EPU, M\bar{P}U, T\bar{P}U, C\bar{P}U). \tag{3}$$

$$RREC = f(TPU, M\bar{P}U, C\bar{P}U, E\bar{P}U). \tag{4}$$

In the second model, we analyse the effect of policy uncertainty on commercial renewable energy consumption while controlling other policy uncertainties.

$$CREC = f(CPU, M\bar{P}U, T\bar{P}U, E\bar{P}U). \tag{5}$$

$$CREC = f(MPU, C\bar{P}U, T\bar{P}U, E\bar{P}U). \tag{6}$$

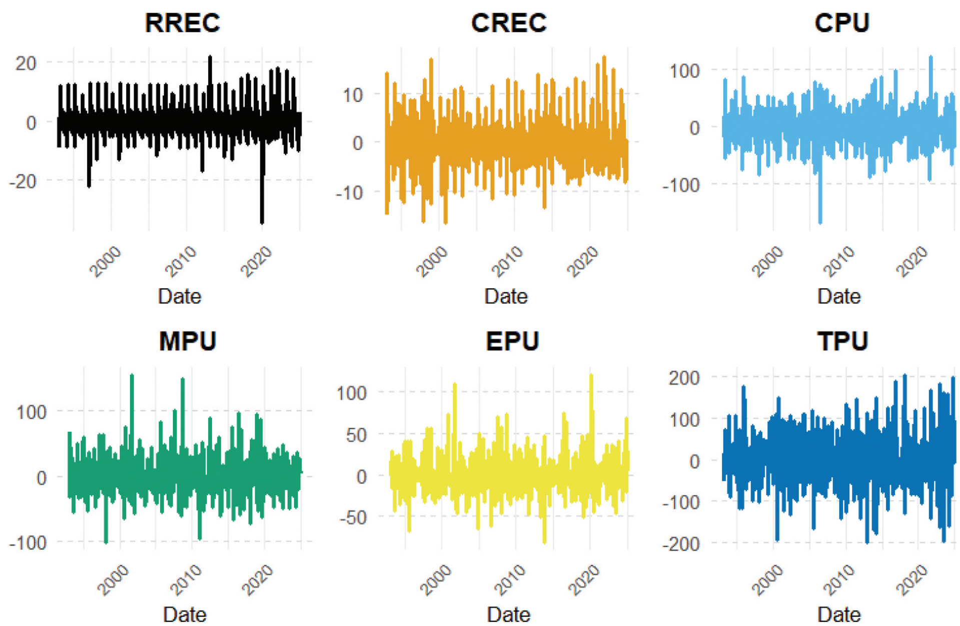

Figure 3. Trend of first difference.

$$CREC = f(EPU, M\bar{P}U, T\bar{P}U, C\bar{P}U). \quad (7)$$

$$CREC = f(TPU, M\bar{P}U, C\bar{P}U, E\bar{P}U). \quad (8)$$

Proposed methodology

The conventional quantile regression as defined by Koenker and Bassett (1978) for two series is defined in the following way:

$$\phi_\tau(Y \mid X) = \beta_0(\tau) + \beta_1(\tau)X \quad (9)$$

Where $\phi_\tau(Y \mid X)$ represents the conditional quantile of the dependent variable Y given the independent variable X at quantile τ. $\beta_0(\tau)$ represents the intercept at quantile τ. slope parameter at quantile τ is denoted by $\beta_1(\tau)$.

Though the traditional quantile regression explains the effect of independent variable on conditional distribution of the dependent variable, it does not give information regarding various period (Magazzino and Giolli 2021; Matar et al. 2021). Therefore, Adebayo and Özkan (2024) suggested the wavelet quantile regression (WQR). The WQR is an advancement over the traditional quantile regression, as it explores the effect of independent variable X on dependent variable Y with focus on both quantiles and periods.

The maximal overlapping discrete wavelet transform (MODWT) of Percival and Walden (2000) is used to decomposed X and Y. We used MODWT using the least-asymmetric Daubechies filter of length 8 (LA(8)) as the baseline. Let $X[i]$ a signal with a length of T, where $T = 2^J$ for an integer J. Consider $h_1[i]$ as the low-pass filter and $g_1[i]$ as the high-pass filter. At the initial stage, $X[i]$ undergoes convolution with $h_1[i]$ to yield the approximation coefficients denoted as $\alpha_1[i]$ of length N, and with $g_1[i]$ to produce the detail coefficients signified as $d_1[i]$ of length N. This procedure can be explained as follows:

$$\alpha_1[i] = h_1[i] * s[i] = \sum_k h_1[i-k]s[k] \quad (10)$$

$$d_1[i] = g_1[i] * s[i] = \sum_k g_1[i-k]s[k] \quad (11)$$

A comparable process is applied to filter $\alpha_1[i]$, employing adjusted filters $h_2[i]$ and $g_2[i]$, which are derived from the dyadic up-sampling of $h_1[i]$ and $g_1[i]$. This recursive process is carried out iteratively. For values of J ranging from 1 to $J_0 - 1$, where $J_0 \leq J$, the coefficients of the estimated is computed below:

$$\alpha_{j+1}[i] = h_{j+1}[i] * \alpha_j[i] = \sum_k h_{j+1}[i-k]\alpha_j[i] \quad (12)$$

$$d_{j+1}[i] = g_{j+1}[i] * \alpha_j[i] = \sum_k g_{j+1}[n-k]\alpha_j[j] \quad (13)$$

Where, $\alpha_{(j+1)}[i]$ represent approximation coefficients obtained at the $(j+1)-$th level of decomposition. $h_{(j+1)}[i]$ is the low-pass filter that has been adjusted for the $(j+1)-$th level. $\alpha_j[i]$ are the approximation coefficients at the $j-$th level. $d_{(j+1)}[i]$ represents the detail coefficients obtained at the $(j+1)-$th level of decomposition. $g_{(j+1)}[i]$ stands for the high-pass filter at the $(j+1)-$th level. $h_{(j+1)}[i] = U(h_j[i])$ and $g_{(j+1)}[i] = U(g_j[i])$ indicate that the filters used in each subsequent level are obtained through up-sampling the previous filters h_j and g_j. The up-sampling operation (U) involves inserting zeros between each consecutive pair of elements in the time series, effectively doubling the length of the filter and adapting it for use at the next decomposition level.

After performing a J-level decomposition on Y and X and obtaining the corresponding detail coefficients, quantile regression is applied to the wavelet detail pairs, $d_j[Y]$ and $d_j[X]$, for all levels J. Therefore, wavelet quantile regression is specified as follows:

$$\phi_\tau(d_j[Y] \mid d_j[X]) = \beta_0(\tau) + \beta_1(\tau)d_j[X] \quad (14)$$

Where; $\phi_\tau(d_j[Y] \mid d_j[X])$ depicts the conditional quantile of the j-th level decomposition of the dependent variable Y given j-th level decomposition of the independent variable X at a specific quantile τ. The wavelet detail coefficient of Y and X are depicted by $d_j[Y]$ and $d_j[X]$. The quantile τ can take values between 0 and 1, representing the different quantiles of the response variable's distribution. $\beta_0(\tau)$ and $\beta_1(\tau)$ depicts the intercept parameter of the regression model and the slope parameter associated with the independent variable X.

The WQR facilitates the analysis of how the independent variable X affects the dependent variable Y across different quantiles. However, a limitation of WQR is its inability to directly incorporate additional control variables. To overcome this constraint, we extend the WQR into a Multivariate Wavelet Quantile Regression (MWQR) by introducing a set of control variables, denoted by Z, into the model. The MWQR is specified as follows.

$$\phi_\tau(d_j[Y] \mid d_j[X], d_j[Z]) = \beta_{0,j}(\tau) + \beta_{1,j}(\tau)d_j[X] + \beta_{2,j}(\tau) \cdot d_j[Z] \quad (15)$$

Here, $\phi_\tau(\cdot)$ is the conditional τ-quantile function, $d_j[X], d_j[Y], and\, d_j[Z]$ are the MODWT coefficients of $X, Y\, and\, Z$ at scale j, $\beta_{2,j}(\tau) \cdot d_j[Z]$ denotes the inner product between the vector of control-variable coefficients and the control vector at that scale and $\beta_{1,j}(\tau)$ isolates the effect of X on Y at quantile τ and horizon j, holding Z constant.

The flow of the analysis is shown in Figure 4.

IV. Findings and interpretation

Descriptive statistics and correlation result

Panel A of Table 3 reports the univariate distributional properties of the six series. RREC and CREC are relatively tame, ranging from −34.56 to 21.81 and −16.66 to 17.64, respectively, whereas CPU and TPU display much larger swings (−170.13 to 123.27 and −198.78 to 202.73). All series have means and medians clustered near zero (means between 0.00 and 0.57; medians between −2.53 and 1.72), but their standard deviations reveal that CPU (36.83) and TPU (72.17) are far more volatile. Skewness is close to zero for RREC (−0.023) and TPU (0.048), mildly negative for CPU (−0.188) and mildly positive for CREC (0.159), but are notably positive for MPU (0.634) and EPU (0.606), reflecting occasional large upward shocks in policy-uncertainty measures. Excess kurtosis is strongly positive for RREC (3.168), MPU (1.832) and EPU (1.799) – signalling fat tails and frequent extremes – mildly leptokurtic for CREC (0.422) and CPU (0.779), and essentially mesokurtic for TPU (−0.044). Finally, the Jarque – Bera statistics reject normality with the exception of TPU. Panel B reports pairwise Pearson correlations between the studied variables.

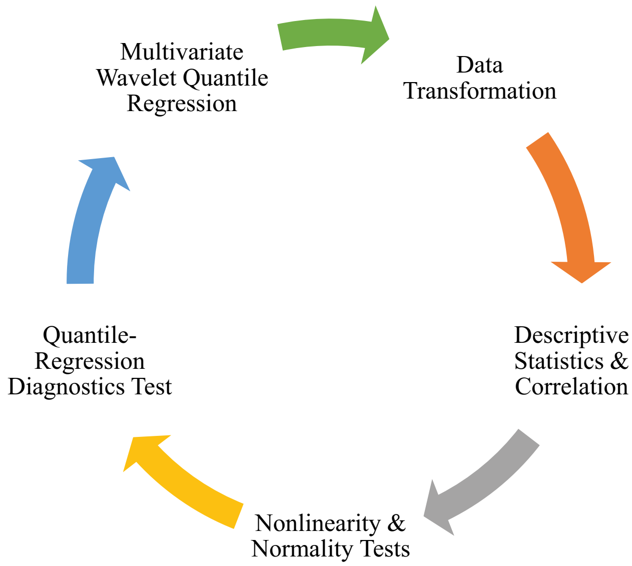

Figure 4. Flow of analysis.

Stationarity Test result

This study introduces the wavelet quantile Zivot–Andrews (WQZA) test to examine the stationarity properties of the series. Figure 5 reports the results of the WQZA. Across all six series, the statistics lie well below the 10% critical line, indicating strong rejection of a unit root across all periods and quantiles, with break dates clustered for CPU, CREC, RREC, TPU, MPU and EPU.

Diagnostic test results

In Panel A of Table 4, the Bartels rank test, the robust Jarque – Bera test and the SJ test of normality uniformly reject the null hypothesis of normality for RREC, CREC and CPU, MPU and EPU, indicating significant departures from a normal distribution in these series. The bootstrap symmetry test and the difference-sign test further corroborate the presence of skewness in MPU and EPU, while the Mann – Kendall rank and runs tests confirm that the temporal ordering of observations is not purely random for RREC, CREC, CPU and TPU. In Panel B, Tsay's test and Keenan's quadratic nonlinearity test provide strong evidence of nonlinear dynamics in RREC, CREC and CPU, whereas the White neural-network and Teraesvirta tests do not systematically detect nonlinearity in MPU, EPU or TPU. Collectively, these diagnostic results imply that modelling this association using standard linear methods with normally distributed errors would be inappropriate, and that more flexible, nonlinear specifications are warranted.

Multivariate Wavelet quantile Regression (RREC model)

Figure 6 analyzes the effect of each policy uncertainty on residential renewable-energy consumption

Table 3. Descriptive statistics and correlation.

	RREC	CREC	CPU	MPU	EPU	TPU
Panel A: Descriptive Statistics						
Minimum	−34.56	−16.66	−170.13	−101.91	−81.28	−198.78
Maximum	21.814	17.636	123.268	155.256	119.832	202.726
1. Quartile	−3.975	−3.186	−23.211	−21.933	−15.093	−50.248
3. Quartile	3.436	3.553	25.977	20.244	14.681	50.527
Mean	0.000	0.184	0.402	0.409	0.195	0.566
Median	−0.144	−0.004	1.722	−2.530	−1.899	−0.778
SE Mean	0.313	0.294	1.880	1.718	1.314	3.683
LCL Mean	−0.616	−0.394	−3.294	−2.970	−2.389	−6.675
UCL Mean	0.616	0.762	4.098	3.787	2.778	7.807
Variance	37.7	33.2	1356.7	1134.0	663.1	5207.8
Stdev	6.139	5.758	36.833	33.675	25.750	72.165
Skewness	−0.023	0.159	−0.188	0.634	0.606	0.048
Kurtosis	3.168	0.422	0.779	1.832	1.799	−0.044
JB	163.89***	4.7357*	12.5004***	81.164***	76.898***	0.1597
Panel B: Correlation Result						
	RREC	CREC	CPU	MPU	EPU	TPU
RREC	1	0.7409	−0.0565	0.0254	0.0880	0.0971
CREC	0.7409	1	−0.0614	0.0087	0.0746	0.1394
CPU	−0.0565	−0.0614	1	0.1783	0.2194	0.0686
MPU	0.0254	0.0087	0.1783	1	0.5824	0.1265
EPU	0.0880	0.0746	0.2194	0.5824	1	0.2843
TPU	0.0971	0.1394	0.0686	0.1265	0.2843	1

***$p<1\%$ and *$p<10\%$.

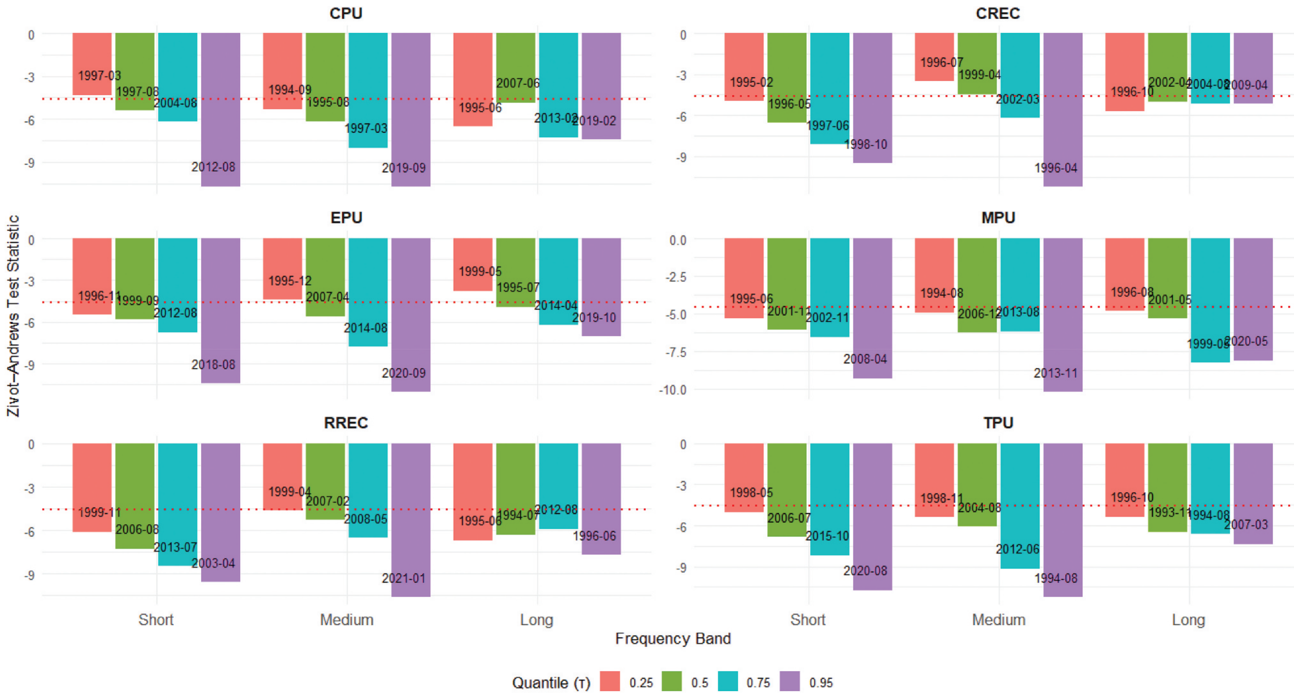

Figure 5. Wavelet quantile zivot andrew Test result.

Table 4. Diagnostic test results.

Panel A: Normality test results

	Bartels Test	Robust Jarque Bera Test	Test of Normality SJ Test	Bootstrap Symmetry Test	Difference Sign Test	Mann-Kendall Rank Test	Runs Test
RREC	8.4016***	186.47***	6.3207***	0.6585	−1.5006	−0.2081	10.731***
CREC	9.4021***	8.2723**	3.0111***	0.8813	−2.3834**	−0.2988	7.8691***
CPU	8.4704***	6.6127**	0.3185	−0.9335	−0.6179	0.2415	6.8471***
MPU	3.6141***	73.076***	2.7986***	2.3495**	−0.0882	0.1197	2.8615**
EPU	3.5288***	78.355***	3.5816***	2.2116**	−0.2648	0.2853	2.2483**
TPU	8.3435***	0.1957***	−0.3186	0.4807	1.1476	0.3569	6.8471***

Panel B: Nonlinearity test results

	Tsay Test	White Nn Test	Keenan Test	Teraesvirta Nn Test
RREC	2.985***	0.3551	31.983***	0.3082
CREC	2.067***	0.1499	0.6211	0.2860
CPU	1.540***	0.0319	0.1126	0.0404
MPU	1.198	0.0494	0.5728	0.0595
EPU	1.094	0.1341	1.0553	0.1668
TPU	1.011	0.2090	2.4852	0.2882

*** $p< 1\%$, ** $p< 5\%$ and *$p< 10\%$.

(RREC), adjusting for the influence of the other uncertainty measures.

Panel A depicts how variations in CPU influence RREC once MPU, TPU, and EPU are held constant. In the short-term, CPU has a modestly positive yet weak effect at the very low end (τ = 0.05) and among mid-range adopters (τ≈0.60–0.80), suggesting that some households accelerate small-scale investments to 'lock in' anticipated benefits before policy shifts. In the medium term – particularly at the upper tail (τ = 0.90–0.99) – CPU's effect turns significantly negative, indicating that larger or later-stage projects are postponed when uncertainty peaks. Over the long run, CPU uniformly depresses RREC across all quantiles, reflecting the cumulative deterrent effect of sustained policy ambiguity on investment decisions. In the U.S. context, this pattern arises because residential solar and other distributed renewables depend critically on stable federal and state incentives. This outcome corroborates the findings of Addey and Nganje

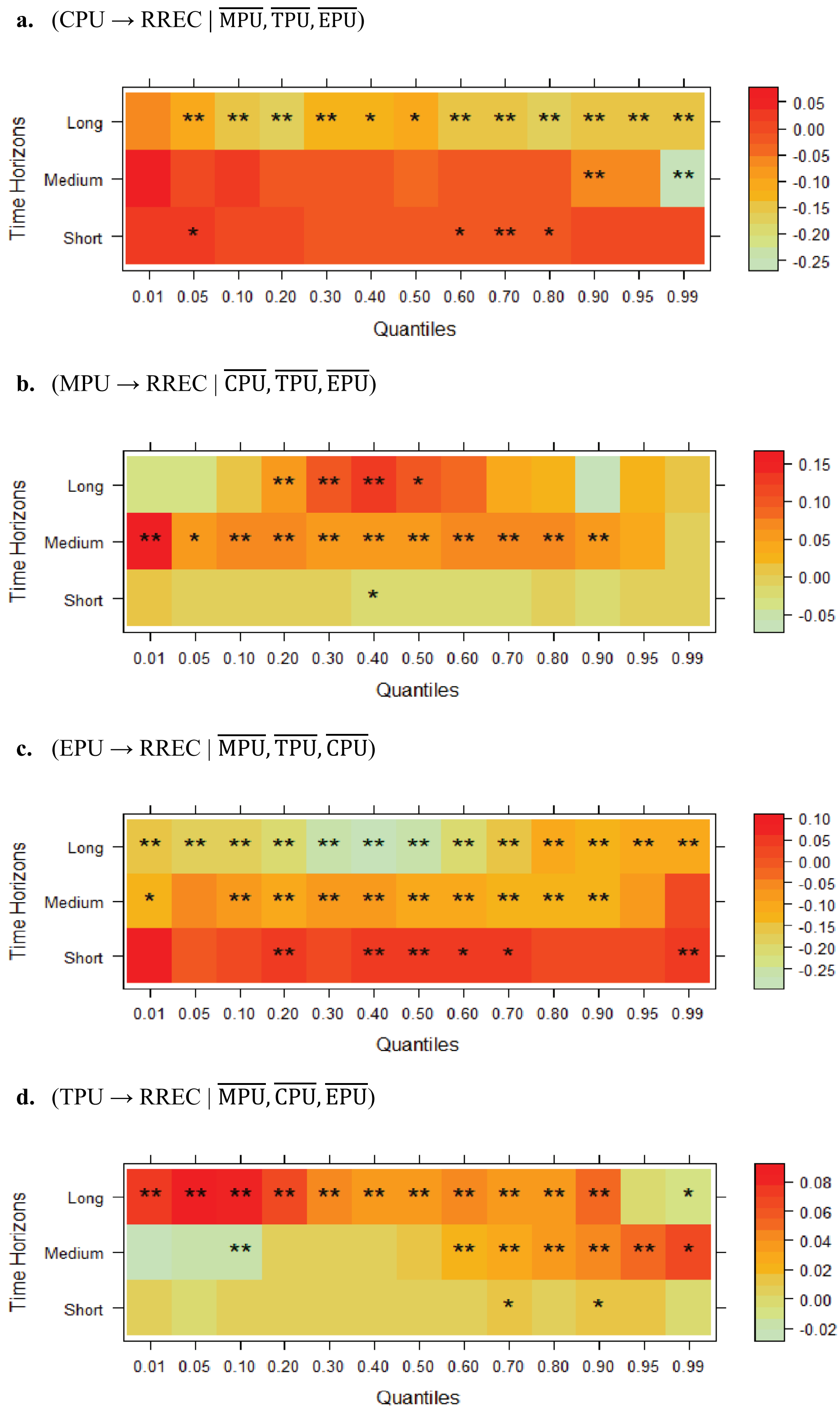

Figure 6. Multivariate wavelet quantile regression results (RREC model). The heatmaps display the estimated slope coefficients in ascending order, ranging from light green to red. The vertical and horizontal axes represent time horizons and quantiles, respectively.

(2024) who reported that spikes in climate policy volatility initially spur precautionary investments but ultimately hinder renewable uptake when uncertainty persists.

Panel b illustrates the impact of MPU on RREC after accounting for CPU, TPU, and EPU. In the short run, MPU's effect on RREC is significantly negative only at quantile $\tau = 0.40$, suggesting that moderate adopters briefly postpone projects when interest-rate outlooks are most uncertain. In the medium horizon, MPU coefficients turn positive and significant from $\tau = 0.01$ through $\tau = 0.90$, indicating that once households assess the shock, they accelerate installations to lock in lower borrowing costs or hedge against inflation under an ambiguous Fed policy. Over the long run, the persistence of a stimulative effect at lower quantiles ($\tau = 0.10$–0.50) but its attenuation at higher quantiles aligns with structural VAR evidence that interest-rate uncertainty bolsters small-scale renewable investments while larger projects revert to baseline once rate paths clarify; thus, affirming the perspective of Hashmi, Syed, and Inglesi-Lotz (2022).

Panel C illustrates the impact of EPU on RREC, controlling for CPU, TPU, and MPU. In the short run, spikes in EPU are associated with significantly higher residential RREC at mid-lower quantiles ($\tau \approx 0.20$–0.70) and again at the extreme upper tail ($\tau = 0.99$), suggesting that both the most risk-averse small adopters and late-moving large-scale consumers rush to lock in subsidies and favourable net-metering rules before anticipated policy reversals. Over the medium term, however, this pattern reverses: EPU exerts a significantly negative effect from $\tau = 0.01$ through $\tau = 0.90$, indicating that once the initial precautionary demand subsides, sustained ambiguity deters installations across most of the distribution (Khan and Su 2022). In the long run, the negative impact extends to all quantiles ($\tau = 0.01$–0.99), underscoring that protracted policy uncertainty ultimately suppresses residential renewable-energy uptake across every household segment in the United States.

Panel D illustrates the impact of TPU on RREC, controlling for CPU, EPU, and MPU. In the short run, TPU significantly boosts RREC only for moderate- and high-quantile adopters ($\tau = 0.70$ and 0.90), suggesting that mid-sized and large consumers rush to purchase solar panels and related equipment before expected tariff hikes or supply-chain disruptions drive up costs; thus, echoing the viewpoint of Jamil et al. (2022). Over the medium horizon, TPU depresses uptake among the smallest adopters ($\tau = 0.10$) – who are most price-sensitive to sudden import-cost spikes – but continues to stimulate investment for quantiles $\tau \geq 0.60$ as larger or more credit-worthy households and installers accelerate capacity additions to hedge against protracted trade risks (Mouffok et al. 2025; Sun et al. 2022). In the long run, persistent trade-policy ambiguity yields a positive and significant effect across all quantiles ($\tau = 0.01$–0.99), indicating that, regardless of scale, U.S. households ultimately turn to residential renewables as a durable hedge against ongoing import volatility and potential energy-price shocks.

Multivariate wavelet quantile regression (CREC model)

In Figure 7, the study examines how each policy uncertainty affects commercial renewable-energy consumption (CREC), controlling for all other uncertainty measures.

Holding EPU, MPU, and TPU constant, Panel A uncovers that CPU's influence on U.S. CREC differs markedly across quantiles. In the short run, elevated CPU significantly boosts CREC at the 1st percentile ($\tau = 0.01$), around the median ($\tau \approx 0.50$–0.70) and the extreme upper tail ($\tau = 0.99$), implying that both the most risk-averse small adopters and the largest corporate buyers rush to lock in tax credits and favourable net-metering before any policy rollback (Fuss et al. 2009; Karlilar Pata and Balcilar 2024). In the medium term, CPU briefly suppresses uptake among the smallest firms at $\tau = 0.05$ but remains significantly positive from $\tau = 0.50$ through $\tau = 0.99$, as well-capitalized companies continue to hedge against future compliance costs by securing stable financing and subsidies. Over the long horizon, however, CPU's effect flips to uniformly negative and significant across all quantiles ($\tau = 0.01$–0.99), indicating that sustained policy ambiguity ultimately discourages commercial investment in renewables throughout the sector; thus, corroborating the viewpoint of Fuss et al. (2009).

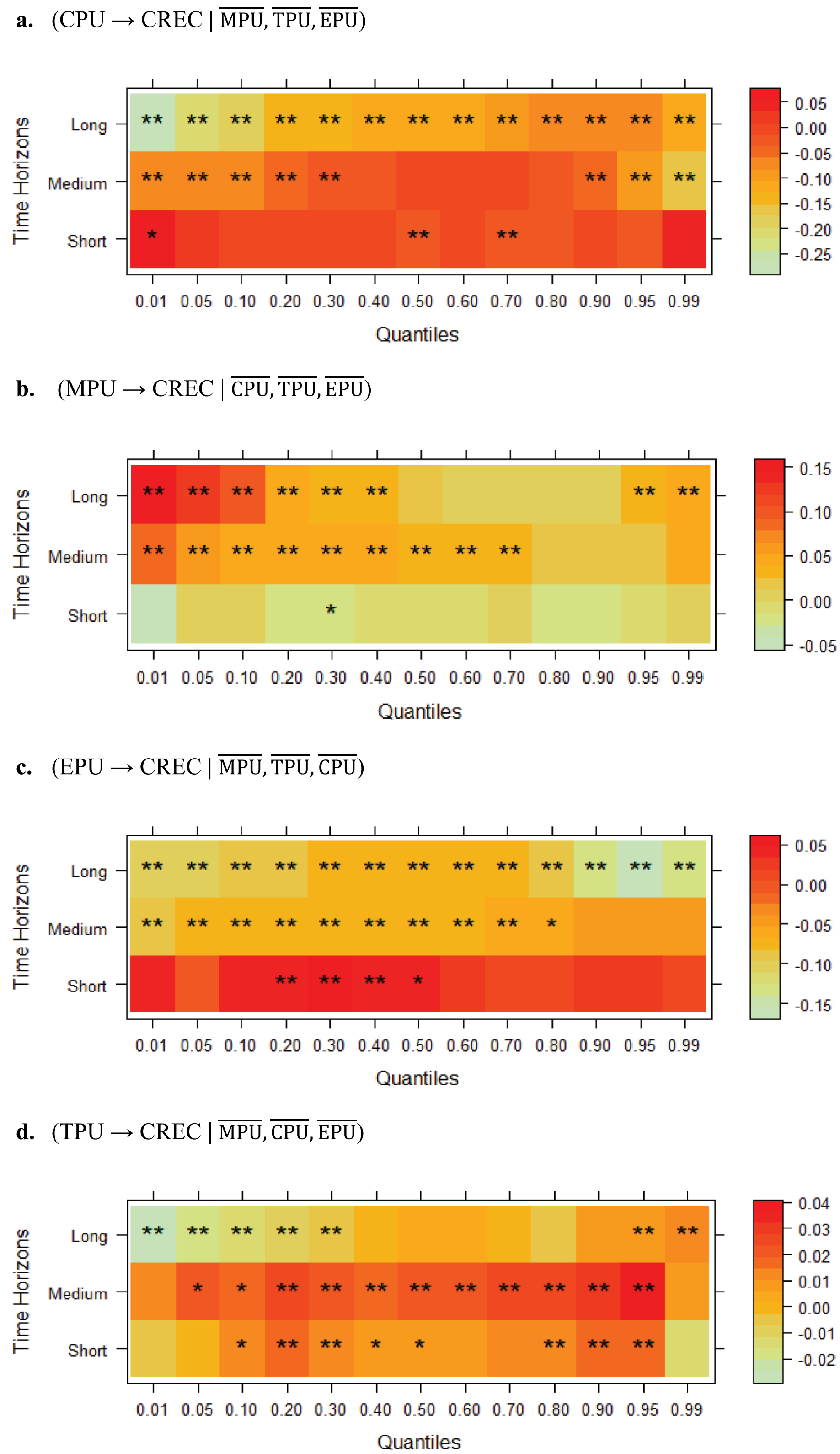

Figure 7. Multivariate wavelet quantile regression results (CREC model). The heatmaps display the estimated slope coefficients in ascending order, ranging from light green to red. The vertical and horizontal axes represent time horizons and quantiles, respectively.

Panel b reveals that, conditional on CPU, EPU, and TPU, MPU affects U.S. commercial renewable-energy consumption (CREC) in a non-uniform way. In the short run, heightened MPU prompts a statistically significant increase in CREC at $\tau = 0.30$, suggesting that mid-sized firms accelerate small-scale installations to lock in financing before potential rate hikes – consistent with industry analyses showing that hedging strategies in renewable markets boost investment appeal amid borrowing-cost volatility.[1] Over the medium horizon, MPU exerts a robust positive effect from $\tau = 0.01$ through $\tau = 0.60$, aligning with empirical findings that tighter monetary policy regimes – driven by uncertainty around the Fed's future path – encourage commercial adopters to expand capacity as they hedge against volatile financing conditions (Lupu et al. 2024). In the long run, this stimulative impact persists at low quantiles ($\tau = 0.01$–0.50) and re-emerges among the largest consumers at $\tau = 0.95$ and 0.99, reflecting that both cash-constrained businesses and well-capitalized firms ultimately treat renewable investments as durable hedges against prolonged interest-rate uncertainty – a dynamic also observed in the U.S. wind industry, where policy expiration-induced uncertainty expedited investment timing and 'bunched' wind farm projects around anticipated policy renewals (Chen 2025).

Panel C illustrates that, even after controlling for CPU, MPU, and TPU, EPU exerts heterogeneous effects on U.S. CREC. In the short run, increases in economic policy uncertainty (EPU) elicit a significantly positive effect on U.S. CREC at intermediate quantiles ($\tau \approx 0.30$–0.70), indicating that mid-sized commercial adopters temporarily accelerate installations to 'lock in' existing incentives before anticipated policy reversals (Lei et al. 2022). However, over the medium horizon, EPU's coefficient turns significantly negative from $\tau = 0.01$ through $\tau = 0.90$—suggesting that once initial precautionary demand dissipates, sustained policy ambiguity erodes firms' willingness to commit capital, raises financing costs, and complicates investment planning (Khan and Su 2022). This deterrent effect persists and even strengthens in the long run, with EPU decreasing CREC across virtually the entire distribution ($\tau = 0.01$–0.99), reflecting how protracted uncertainty about tax credits, depreciation schedules, and carbon-pricing regimes undermines the predictability on which commercial renewable-energy projects depend (Khan and Su 2022).

Panel D demonstrates TPU's differentiated impact on U.S. CREC once CPU, MPU, and EPU is held constant. In the short run, TPU's coefficient is positive and significant at $\tau = 0.20$, 0.30, and 0.40, as mid-sized developers rush to import panels and equipment ahead of anticipated tariff hikes – consistent with Qamruzzaman (2024), who finds that short-run trade-policy uncertainty stimulates moderate-quantile renewable demand in the U.S. and China. TPU's stimulative effect re-emerges at $\tau =$ 0.70, 0.90, and 0.95, echoing Gao et al. (2024) nonlinear assessment of U.S. data, which reports upper-quantile surges in commercial renewable uptake under heightened TPU. Over the medium horizon, TPU remains a robust positive driver of CREC from $\tau = 0.05$ through $\tau = 0.70$ and again at $\tau = 0.95$—reflecting broad-based hedging against supply-chain disruptions as firms lock in favourable input costs – another pattern documented by Qamruzzaman (2024). In the long run, however, TPU's effect turns significantly negative at the lowest quantiles ($\tau = 0.01$–0.40) and at the uppermost tail ($\tau = 0.95$–0.99), indicating that protracted tariff risk ultimately deters both resource-constrained small adopters and the largest corporate investors – a long-run asymmetry also observed by Qamruzzaman (2024).

The summary of the MWQR is depicted in Appendix A and B respectively.

Wavelet quantile regression

Although the primary objective of this study is to employ the Multivariate Wavelet Quantile Regression (MWQR) to assess the effect of a key independent variable on the dependent variable while controlling for additional covariates, comparative analysis using the bivariate Wavelet Quantile Regression (WQR) model is also conducted. This approach is an advancement over the wavelet quantile regression introduced by Adebayo and Özkan (2024), as it incorporates p-values to

[1]https://montel.energy/resources/blog/how-does-renewable-energy-hedging-affect-market-stability.

show the significance of the estimates across all quantiles and time horizons.The graphical results for both the RREC model (see Figure 8) and the CREC model (see Figure 9) clearly demonstrate that, while the general patterns of WQR and MWQR may appear superficially aligned, the

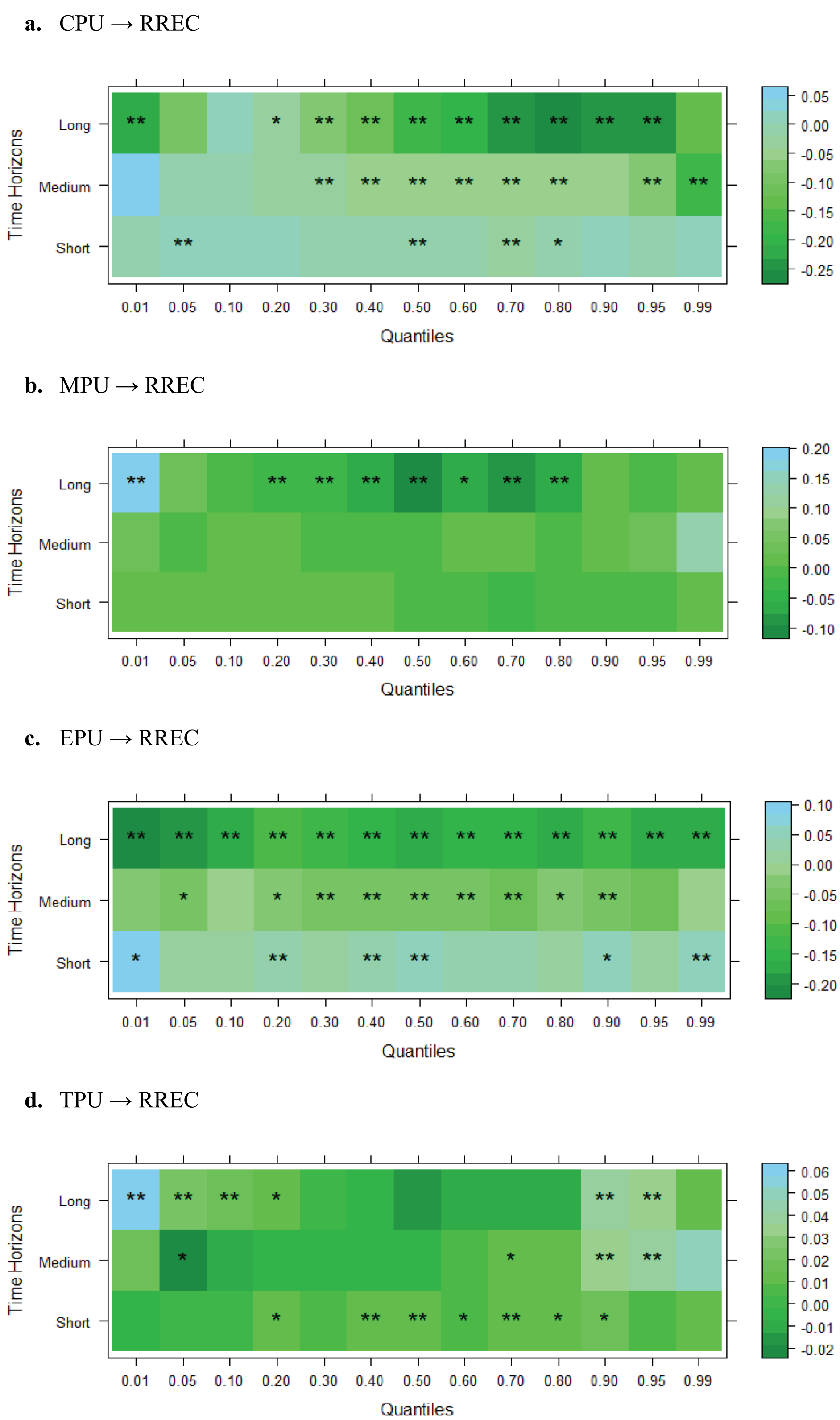

Figure 8. Wavelet quantile regression results (RREC model). The heatmaps display the estimated slope coefficients in ascending order, ranging from forestgreen to skyblue. The vertical and horizontal axes represent time horizons and quantiles, respectively.

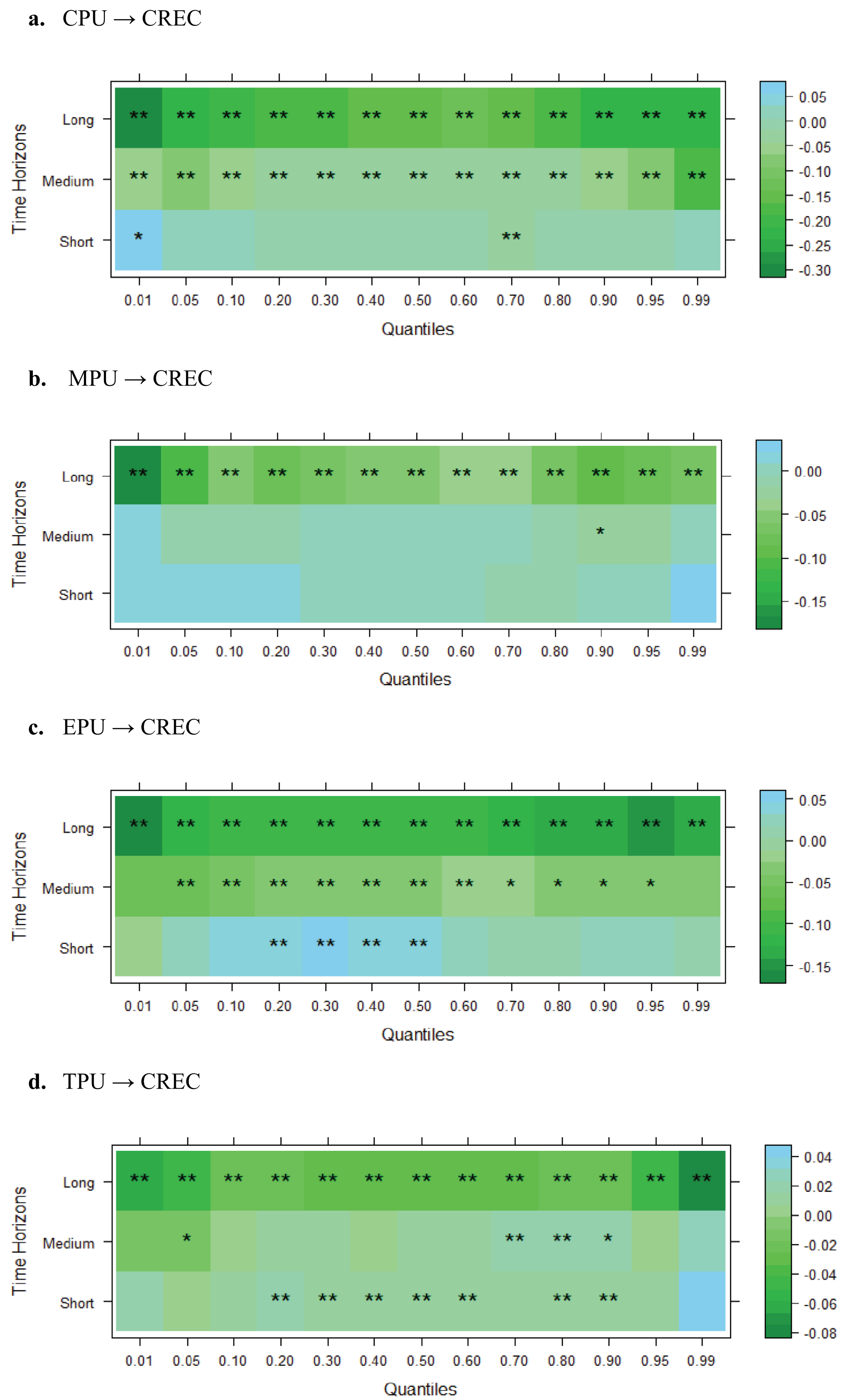

Figure 9. Wavelet quantile regression results (CREC model). The heatmaps display the estimated slope coefficients in ascending order, ranging from forestgreen to skyblue. The vertical and horizontal axes represent time horizons and quantiles, respectively.

underlying estimates differ significantly in magnitude and inference. This divergence provides a compelling justification for the use of MWQR over simpler bivariate frameworks. The key insight is that the omission of relevant covariates in bivariate models can lead to biased or misleading conclusions, particularly when dealing with complex, policy-sensitive phenomena like energy consumption. By incorporating multiple relevant variables, MWQR allows for a more comprehensive understanding of the interactions between these factors, yielding more accurate and reliable estimates.

Furthermore, the statistical significance of the estimates varies across different quantiles and time periods, underscoring the importance of considering the distributional and temporal aspects of renewable energy consumption. This variability in significance across quantiles highlights that the impact of policy uncertainties and other determinants of renewable energy consumption is not uniform across the entire distribution of energy use, but instead, may differ in both the short and long term. The use of MWQR, with its ability to model these effects, offers a substantial advantage over traditional models by capturing the complex relationships between variables at different points in the distribution and across various time horizons. This approach is critical for providing policy recommendations that account for these variations, ultimately leading to more robust and informed decision-making in energy policy.

Discussion of findings

In summary, the results of the MWQR show that in the short-run there is a positive response to CPU, EPU, and TPU among lower to mid quantiles in RREC and among selected quantiles in CREC reflect an option to expand before rules or input costs shift, a pre-emption motive where households and firms accelerate small or modular projects to capture incentives or avoid tariffs while uncertainty is transient. The medium horizon reveals learning and threshold effects that raise the value of waiting when ambiguity persists. CPU turns negative at the upper tail for RREC and later becomes uniformly negative in the long run, and EPU flips from short-run pull-forward to broad medium and long-run deterrence in both sectors, all consistent with an option to defer or stage capacity until policy signals clarify and financing and regulatory risks reprice. MPU shows a different mechanism because rate uncertainty interacts with leverage and contract structures. Its medium-horizon positives for most quantiles in both sectors indicate selective option exercise to expand while locking in financing, whereas the long-run attenuation for higher quantiles in the residential case signals reversion once interest-rate paths become clearer, which lowers the option value of waiting and curbs further expansion by large projects. TPU expresses two distinct real options channels. In the residential case the long-run positive effect across all quantiles implies households treat distributed renewables as a hedge against persistent trade frictions, exercising the option to switch or expand to reduce exposure to equipment price shocks. In the commercial case the long-run negatives at the lowest and highest quantiles indicate either abandonment by resource constrained firms that face binding capital costs or deferral by the largest investors whose scale magnifies tariff and supply chain risk, while mid quantiles with positive short to medium responses reflect tactical expansion to pre-empt future constraints

V. Conclusion and policy recommendations

Conclusion

This study examines the effect of specific policy uncertainties on disaggregated renewable energy consumption (residential and commercial) while controlling for other uncertainty measures, using the United States as a case. It employs monthly data spanning from 1 January 1993 to 1 January 2025. The study introduces ***Multivariate Wavelet Quantile Regression with pvalue*** to capture the connection. The results from the study showed that policy uncertainties impact residential and commercial renewable-energy consumption differently across adopter tiers and horizons: (a) climate-policy uncertainty briefly boosts lower- and mid-tier projects but then suppresses all tiers long-term; (b) monetary-policy uncertainty momentarily stalls moderate adopters before broadly accelerating small-scale deployment; (c) economic-policy uncertainty triggers precautionary short-run surges but leads to medium- and long-run declines; (d) and trade-policy uncertainty drives mid- and upper-tier hedging, yielding durable gains across all tiers.

Analytical implications

Recent work on policy ambiguity and renewable-energy adoption spans asymmetry, co-movement, tail dependence, predictability, and multivariate dynamics, yet most approaches examine these features in isolation rather than jointly. The multivariate wavelet quantile regression framework addresses this gap by integrating time – frequency decomposition with quantile regression to track relationships across horizons and along the distribution, capturing extreme behaviours, asymmetries, and the effects of multiple policy variables within one coherent model. Its multivariate design reduces omitted-variable bias and moves beyond restrictive ceteris paribus assumptions, yielding estimates that are both context sensitive and policy relevant. Unlike wavelet quantile correlation, bivariate wavelet quantile regression, or multi-frequency quantile regression, MWQR accommodates control variables and tests the strength and significance of associations across quantiles and scales, which is essential in energy-finance settings characterized by nonlinear, asymmetric, and time-dependent responses. By exploiting high-frequency information and allowing conditional relationships to vary with both quantile position and frequency band, MWQR provides a flexible, rigorous specification that advances methodology and delivers stronger empirical insights into how policy uncertainty propagates through residential and commercial energy adoption.

Policy recommendations

This study develops targeted policy recommendations for the United States – spanning multiple time horizons and adoption tiers – and integrates existing federal and state programs to accelerate both residential and commercial renewable-energy adoption as follows:

First, stabilize the rules of the game. In both models the evidence shows that prolonged policy ambiguity, especially economic policy uncertainty and in the long run climate policy uncertainty suppresses renewable consumption across nearly the entire distribution of adopters. National and state authorities should anchor stability in the Inflation Reduction Act credit architecture, including long-dated and tech-neutral production and investment credits, transferability, elective direct pay where eligible, and phase-out schedules tied to emissions and deployment milestones rather than calendar cliffs. Pair these with clear net-metering and interconnection standards and predictable depreciation rules. Build automatic stabilizers into policy so that when uncertainty indices breach pre-set thresholds, credit rates, grant intensities, or capital write-offs extend automatically rather than approach cliff edges. Publish synchronized federal and state rulemaking calendars with minimum notice periods. For large commercial projects that are highly sensitive to long-run uncertainty, rely on safe-harbour and grandfathering so once a project qualifies, later rule changes do not apply and CFOs can lock financing with confidence.

Second, neutralize the financing channel exposed by monetary policy uncertainty. When interest-rate paths are unclear, small and mid-quantile adopters can still move forward if financing is insulated from volatility, while larger leveraged projects tend to stall. Expand fixed-rate, long-tenor instruments that delink household and SME decisions from rate swings, including PACE and on-bill repayment, green mortgages with public rate buy-downs, and credit guarantees through green banks. Ground the proposed clean energy trust fund in real-world platforms such as the Department of Energy Loan Programs Office and state green banks, using co-lending, credit enhancement, and project aggregation so the effective cost of capital remains steady during monetary uncertainty. Pair this with simplified underwriting that leverages utility bill history for lower and mid-quantile households, and with standardized tax-equity contracts and public co-investment facilities for commercial buyers. Where feasible, manage rate risk at program level with pooled swaps or caps so individual firms are not exposed to basis and timing risk.

Third, manage trade-policy uncertainty with supply-chain and pricing safeguards rather than shock tariffs that create boom-bust cycles. Replace ad hoc actions with transparent tariff corridors announced well in advance, predictable review windows, and targeted carve-outs for essential residential components. Tie recommendations to concrete precedent, including solar safeguard measures under Section 201 and subsequent exemptions for specific products such as bifacial modules, and use of time-limited exemptions linked to domestic capacity milestones so prices, remain stable while local industry scales. Support this with domestic manufacturing incentives, diversified sourcing through friend-shoring, strategic inventories of modules, inverters, and transformers, and fast-track customs procedures for renewable inputs to prevent installation bottlenecks when frictions rise.

Finally, target interventions by adopter segment because heterogeneity across the distribution is the norm. For lower and mid-quantile households that react positively in the short run but fade when uncertainty lingers, use instant point-of-sale rebates, standardized turnkey packages, and flexible community-solar subscriptions, combined with clear consumer-protection messaging that reduces perceived policy risk. For upper-quantile residential buyers and large commercial customers whose responses flip from early acceleration to long-run retrenchment, emphasize long-dated certainty tools such as firm interconnection timelines, capacity-reservation certificates, performance-based incentives that vest over time, and production credit floors indexed to equipment costs. Across both sectors, operate public uncertainty dashboards that track the four indices and trigger pre-announced adjustments such as extending application windows or raising rebate caps when volatility spikes, thereby turning today's boom-bust response into steady and resilient decarbonization momentum.

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Data availability

Data are readily available on request

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Appendices

Appendix A

Table A1. RREC results (conditional on the other three uncertainties).

Driver	Short run	Medium run	Long run	Interpretation/who moves
CPU → RREC	Weakly positive at τ≈0.05 and τ≈0.60–0.80	Turns significantly negative at upper tail τ≈0.90–0.99	Uniformly negative across τ = 0.01–0.99	Early lock-in by small and mid adopters, then deferral of larger projects; sustained climate-policy ambiguity depresses residential consumption
MPU → RREC	Significant dip at τ = 0.40 only	Broadly positive τ = 0.01–0.90	Positive persists at lower τ = 0.10–0.50, fades at higher τ	Rate-path uncertainty briefly pauses moderate adopters, then stimulates small-scale instals as households hedge financing risk; large projects normalize when paths clarify
EPU → RREC	Positive at mid-lower τ≈0.20–0.70 and at τ = 0.99	Negative τ = 0.01–0.90	Negative τ = 0.01–0.99	Precautionary pull-forward at first, then broad deterrence as economic-policy ambiguity persists; long-run suppression across all segments
TPU → RREC	Positive at τ = 0.70 and 0.90	Negative at τ = 0.10; positive for τ≥0.60	Positive across τ = 0.01–0.99	Tariff risk pulls forward medium and large adopters; smallest are price-sensitive in medium run; ultimately households hedge ongoing trade volatility by adopting

Appendix B

Table B1. CREC results (conditional on the other three uncertainties).

Driver	Short run	Medium run	Long run	Interpretation/who moves
CPU → CREC	Positive at τ = 0.01, τ≈0.50–0.70, and τ = 0.99	Small-firm dip at τ = 0.05; positive τ = 0.50–0.99	Uniformly negative τ = 0.01–0.99	Risk-averse small buyers and largest corporates lock in incentives; prolonged climate-policy ambiguity ultimately deters commercial investment
MPU → CREC	Positive at τ = 0.30	Positive τ = 0.01–0.60	Positive at low τ = 0.01–0.50 and at τ = 0.95–0.99	Mid-sized firms accelerate to secure financing; both constrained and well-capitalized firms treat renewables as a hedge under rate uncertainty
EPU → CREC	Positive at τ≈0.30–0.70	Negative τ = 0.01–0.90	Negative τ = 0.01–0.99	Mid-quantile pull-forward, then broad deterrence as economic-policy ambiguity raises planning and financing frictions
TPU → CREC	Positive at τ = 0.20, 0.30, 0.40 and at τ = 0.70, 0.90, 0.95	Positive τ = 0.05–0.70 and at τ = 0.95	Negative at τ = 0.01–0.40 and τ = 0.95–0.99	Firms hedge supply-chain and tariff risk in short to medium run; prolonged TPU deters the smallest and the very largest investors