Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 4, 512-531
2026
Publisher: Learning Gate
DOI: 10.55214/2576-8484.v10i4.12717

Response of total renewable energy consumption to environmental technologies and policy uncertainties: A time–frequency analysis

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Abstract: Renewable energy transition in the United States unfolds in a landscape shaped not only by technological progress but also by policy-related uncertainty. Using monthly U.S. data from 01/04/2005 to 01/11/2025, this study examines how climate policy uncertainty (CPU), monetary policy uncertainty (MP), and environmental technologies (ET) influence total renewable energy consumption (TREC) through advanced time–frequency techniques. In doing so, the study employs wavelet coherence (WTC), partial wavelet coherence (PWC), and multiple wavelet coherence (MWC) techniques. The results show that the TREC nexus is strongly time- and frequency-dependent. Baseline WTC indicates that CPU and MP are linked with TREC mainly in the short and medium run, whereas ET exhibits a more persistent medium- and long-run relationship. PWC confirms that the TREC–CPU association remains largely short-run after controlling for ET and MP, while the TREC–ET relationship continues to dominate over medium- and long-term horizons after accounting for CPU and MP. MWC further reveals that TREC is shaped not only by individual determinants but also by the joint influence of uncertainty and technology, especially at medium frequencies. We formulate policies based on these findings.

Keywords: *Climate policy uncertainty, Environmental technologies, Monetary policy uncertainty, Total renewable energy consumption.*

1. Introduction

The transition toward cleaner energy in the United States has become increasingly important as climate commitments, energy-security concerns, and decarbonization goals continue to intensify. In this setting, total renewable energy consumption (TREC) is no longer shaped only by market demand or resource availability but also by the broader technological and policy environment in which energy decisions are made. This is particularly relevant in the United States, where renewable expansion has progressed alongside recurrent policy shifts, macro-financial instability, and changing expectations about the pace of the low-carbon transition [1, 2]. As a result, a more meaningful question is not simply whether renewable energy is expanding but how innovation and uncertainty jointly influence the scale and timing of renewable energy use.

Environmental technologies (ET) represent one of the most important structural drivers of renewable energy consumption because they improve the technical and economic conditions needed for clean-energy adoption. Through cleaner production systems, energy-saving processes, storage advancements, and innovation in renewable applications, environmental technologies can lower

History: Received: 5 February 2026; Revised: 2 April 2026; Accepted: 6 April 2026; Published: 17 April 2026
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transition costs and strengthen the long-term feasibility of renewable-energy deployment [3, 4]. This channel is especially relevant in the United States, where technological capability and commercialization remain central to industrial and environmental strategy [3]. Even so, the impact of ET should not be assumed to be immediate or automatic because its influence depends on diffusion speed, complementary infrastructure, and the ability of firms and utilities to integrate innovation into the energy system [4].

Monetary policy uncertainty (MP) is another factor that can materially affect renewable energy consumption because renewable projects are highly capital-intensive and sensitive to borrowing conditions. When monetary policy becomes uncertain, firms and investors face greater difficulty in evaluating future financing costs, which can delay renewable-energy investment and weaken project execution [5]. This mechanism is particularly important in the United States because the renewable-energy sector depends heavily on long-horizon capital, credit-market depth, and investor confidence [6]. In this sense, MP may shape TREC indirectly but strongly through the cost of capital, lending conditions, and investment timing, making monetary instability a relevant constraint on the clean-energy transition [7, 8].

Climate policy uncertainty (CPU) adds a further layer of complexity because renewable-energy decisions depend strongly on expectations about carbon regulation, subsidies, tax incentives, and long-term transition commitments. In the U.S. context, electoral turnover, regulatory reversals, and legal disputes have often created uncertainty about the future direction of climate policy, thereby influencing the incentives for renewable-energy investment and deployment [2]. A growing body of evidence suggests that CPU can weaken renewable-energy demand by reducing policy credibility and making returns to clean-energy investment less predictable, although some studies also show that climate-related uncertainty may, in some cases, accelerate the search for alternatives to fossil energy [9]. This means that the CPU should be treated as a central driver of TREC because its effect is likely to be time-varying, horizon-specific, and potentially nonlinear.

Against this backdrop, the United States offers a strong case for examining how ET, MP, and CPU shape TREC. The country is one of the world's largest energy markets and a major arena for renewable-energy investment, environmental innovation, and climate-policy debate, which makes it an appropriate setting for evaluating whether technological progress can sustain renewable-energy use under conditions of policy and macro-financial uncertainty. Building on this motivation, the present study investigates the effects of ET, MP, and CPU on TREC in the United States using a wavelet-based framework that captures heterogeneous relationships across time horizons. Beyond the standard wavelet coherence analysis, the study also employs partial wavelet coherence and multiple wavelet coherence to strengthen inference in the presence of potentially omitted influences. Partial wavelet coherence makes it possible to isolate the time–frequency association between TREC and a given explanatory variable after filtering out the effect of another relevant factor, while multiple wavelet coherence evaluates how TREC co-moves with a set of drivers taken jointly. In this way, these approaches help reduce omitted-variable bias arising from shared policy, financial, and technological shocks, and they provide a more reliable account of whether the observed coherence reflects an independent effect or the combined influence of correlated determinants. By doing so, the study moves beyond single-factor explanations of renewable-energy demand and offers a broader understanding of how innovation and uncertainty jointly shape the U.S. clean-energy transition.

The rest of the paper proceeds in the following manner. Section 2 discusses the theoretical background and related literature. Section 3 introduces the data and methodological approach. Section 4 reports the empirical results. Section 5 concludes the paper and sets out the policy implications.

2. Theoretical Underpinning and Literature Review

2.1. Theoretical Underpinning

The relationship between CPU, MP, and TREC can be explained by real options theory and the credit channel theory. Real options theory suggests that when investment is costly and difficult to reverse, uncertainty encourages investors to delay decisions until policy conditions become clearer [10].

ISSN: 2576-8484
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DOI: 10.55214/2576-8484.v10i4.12717

This is highly relevant for renewable energy because such projects require large upfront capital and depend on stable climate and financial policies. Similarly, the credit channel theory shows that monetary uncertainty can raise borrowing costs and tighten credit conditions, thereby discouraging investment in renewable energy projects [11]. Thus, higher CPU and MP are expected to weaken TREC by delaying green investment and reducing financing availability [12].

The effect of ET on TREC can be understood through the induced innovation hypothesis and the Porter hypothesis. The induced innovation hypothesis argues that technological progress responds to economic and policy incentives and helps lower the cost of cleaner energy adoption [13]. Similarly, the Porter hypothesis states that environmental improvements can be strengthened when innovation is stimulated by supportive regulatory and technological conditions [14]. In this context, ET is expected to increase TREC by improving efficiency, lowering transition costs, and supporting renewable energy diffusion over time [3]. Therefore, the theoretical expectation is that CPU and MP reduce TREC, whereas ET promotes it.

2.2. Literature Review

2.2.1. Environmental Technologies and Total Renewable Energy Consumption

The literature on environmental technologies generally suggests that ET promotes TREC, although the strength of the effect depends on innovation diffusion, supporting regulation, and energy-system readiness. A major strand of studies argues that technological progress in environmental and renewable-energy fields lowers transition costs and improves the feasibility of renewable adoption. For example, Johnstone et al. [3] show that renewable-energy policies stimulate technological innovation, while [4] find that environmental patents act as an effective mechanism for increasing renewable energy consumption. In a similar vein, Li et al. [15] report that environmental technology significantly enhances renewable energy transition, Godil et al. [16] show that patent-based technological innovation is essential for scaling renewable energy, and Javed et al. [17] argue that environmental-related technological innovation strengthens renewable energy consumption in OECD countries. Related evidence in Khaoula et al. [18] also indicates that green technology supports cleaner energy use when combined with environmental policy instruments. The dominant argument, therefore, is that ET should increase TREC, but its actual contribution depends on how quickly innovation is commercialized and embedded into production, storage, and grid systems.

2.2.2. Monetary Policy Uncertainty and Total Renewable Energy Consumption

The literature on monetary policy uncertainty presents more mixed but largely cautionary evidence because the effect of MP on TREC works mainly through financing costs, credit availability, and investment timing. One line of argument holds that tighter or more uncertain monetary conditions discourage renewable energy investment by raising borrowing costs for capital-intensive projects. This view is strongly supported by Sohail et al. [6], who find that monetary policy uncertainty has negative short- and long-run effects on renewable energy consumption in the United States. Similarly, Chen and Lin [8] show that monetary tightening reduces renewable energy production in the U.S., while [7] reports that tighter monetary conditions reduce U.S. renewable energy consumption through uncertainty channels. At the sectoral level, Sleibi [19] finds that contractionary monetary policy harms several clean-energy segments, and Lupu et al. [5] show that contractionary monetary policy is associated with lower renewable generation. Yet the evidence is not fully uniform, as Gordo et al. [20] find that the significance of monetary policy varies across subsamples rather than remaining constant over time. The broader conclusion is that MP tends to weaken TREC, although the size and persistence of that effect depend on policy regimes, financial structure, and renewable-energy segments.

2.2.3. Climate Policy Uncertainty and Total Renewable Energy Consumption

The literature on climate policy uncertainty is notably mixed because CPU can either delay renewable investment or, in some cases, accelerate the shift toward cleaner energy. One influential

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perspective argues that higher CPU weakens TREC by reducing policy credibility and making expected returns on renewable investments less certain. This view is supported by Setiastuti and Rajendra [2], who demonstrate that high climate-policy uncertainty adversely affects renewable energy consumption in the United States, by Tu, et al. [21], who find that CPU negatively impacts renewable energy demand both in the short and long term, and by Lin, et al. [22], who report that CPU hinders the energy transition. Related time-varying evidence from Xi et al. [23] and Huo et al. [24] shows that the impact of CPU on renewable energy consumption varies over time and across renewable energy categories. However, the literature also identifies an alternative channel, as Pata [9] finds that climate policy uncertainty can increase renewable energy consumption in the United States under certain conditions.

3. Data and Empirical Method

3.1. Data

The analysis employs monthly U.S. data spanning 01/04/2005 to 01/11/2025 to examine the effects of climate policy uncertainty (CPU), monetary policy uncertainty (MP), and environmental technologies (ET) on total renewable energy consumption (TREC). The U.S. offers an important empirical setting for this study due to its large-scale energy sector, ongoing transition toward cleaner energy sources, and substantial investment in environmental innovation. Additionally, the presence of monetary and climate-policy uncertainty provides a useful background for assessing how renewable energy consumption adjusts to both technological change and policy instability. To ensure consistency in scale and to capture dynamic changes more appropriately, all variables are transformed into log differences before estimation. This transformation reflects growth rates or percentage changes rather than levels, thereby allowing the analysis to focus on how changes in CPU, MP, and ET influence changes in TREC.

To reduce omitted-variable bias arising from shared policy, financial, and technological shocks, the study complements the baseline wavelet coherence analysis with partial wavelet coherence and multiple wavelet coherence. In the partial wavelet coherence framework, the association between TREC and one explanatory variable is examined after removing the effect of a third factor. Thus, the coherence between TREC and CPU is assessed conditional on ET and MP, the coherence between TREC and MP is evaluated conditional on CPU and ET, and the coherence between TREC and ET is examined conditional on CPU and MP. This allows the analysis to isolate the net time–frequency relationship between renewable energy consumption and each driver. In addition, the multiple wavelet coherence approach is used to examine how TREC co-moves with pairs of explanatory variables taken jointly, thereby capturing the combined influence of policy uncertainty and environmental technology on renewable energy consumption across different horizons.

The abbreviations, descriptions, measurement approaches, and corresponding data sources for all study variables are provided in Table 1.

Table 1.
Measurement and Source.

Abbreviation	Sign	Measurement	sources
ET	Environmental Technologies	Index	Investing [25]
TREC	Total Renewable energy consumption	Trillion Btu	EIA [26]
MP	Monetary Policy Uncertainty	Index	PU [27]
CPU	Climate Policy Uncertainty	Index	PU [27]

Figure 1 presents descriptive statistics. CPU and MP exhibit the largest maximum values, 192.89 and 176.74, respectively, along with very large standard deviations of 48.79 and 48.99, indicating that these two variables are the most volatile in the sample. They also record the most extreme negative minimum values, -170.95 for CPU and -134.51 for MP, suggesting wide fluctuations over time. ET shows a more moderate range, with a maximum of 37.23, a minimum of -40.82, and a standard deviation of 10.31, while TREC is the least volatile variable, as reflected by its smaller maximum of 19.84, minimum of -15.21, and standard deviation of 5.51. In terms of central tendency, the mean values are positive for TREC, MP, and CPU, whereas ET has a slightly negative mean, implying weaker average performance relative to the others. The skewness values are small for all variables, suggesting limited asymmetry, although ET is slightly left-skewed. Kurtosis remains low across the series, indicating that none of the variables display extremely sharp peaks or excessively heavy tails overall.

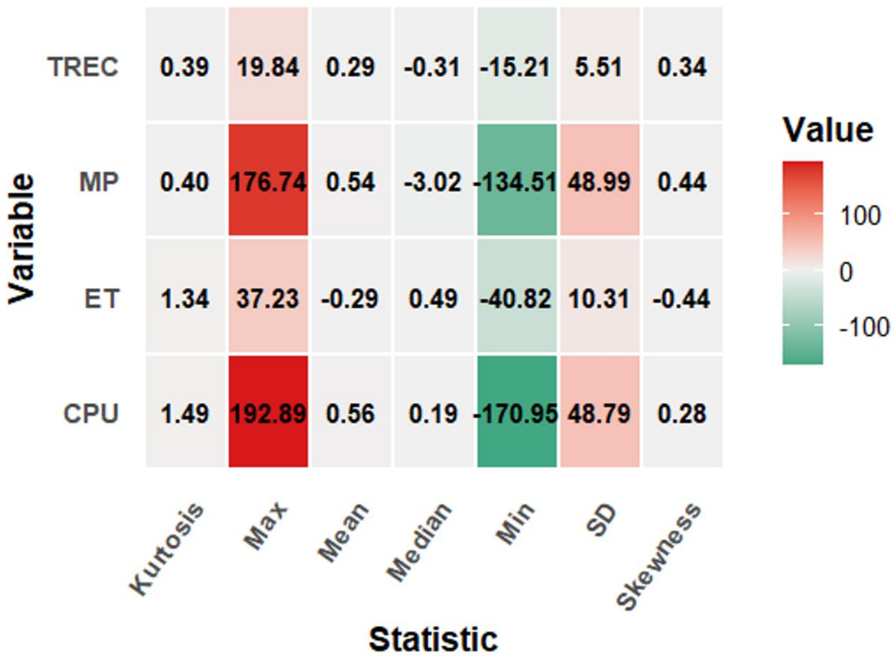

Figure 1.
Descriptive Statistics.

Figure 2 discloses the correlation results. The correlation results show that its association with the other variables is generally weak, indicating no serious linear dependence. TREC is weakly and positively correlated with MP at 0.07 and with ET at 0.03, while it has a very small negative correlation with CPU at -0.04. These low coefficients suggest that changes in total renewable energy consumption are only marginally linked with movements in MP, ET, and CPU, which supports the view that multicollinearity is unlikely to be a concern from the TREC side.

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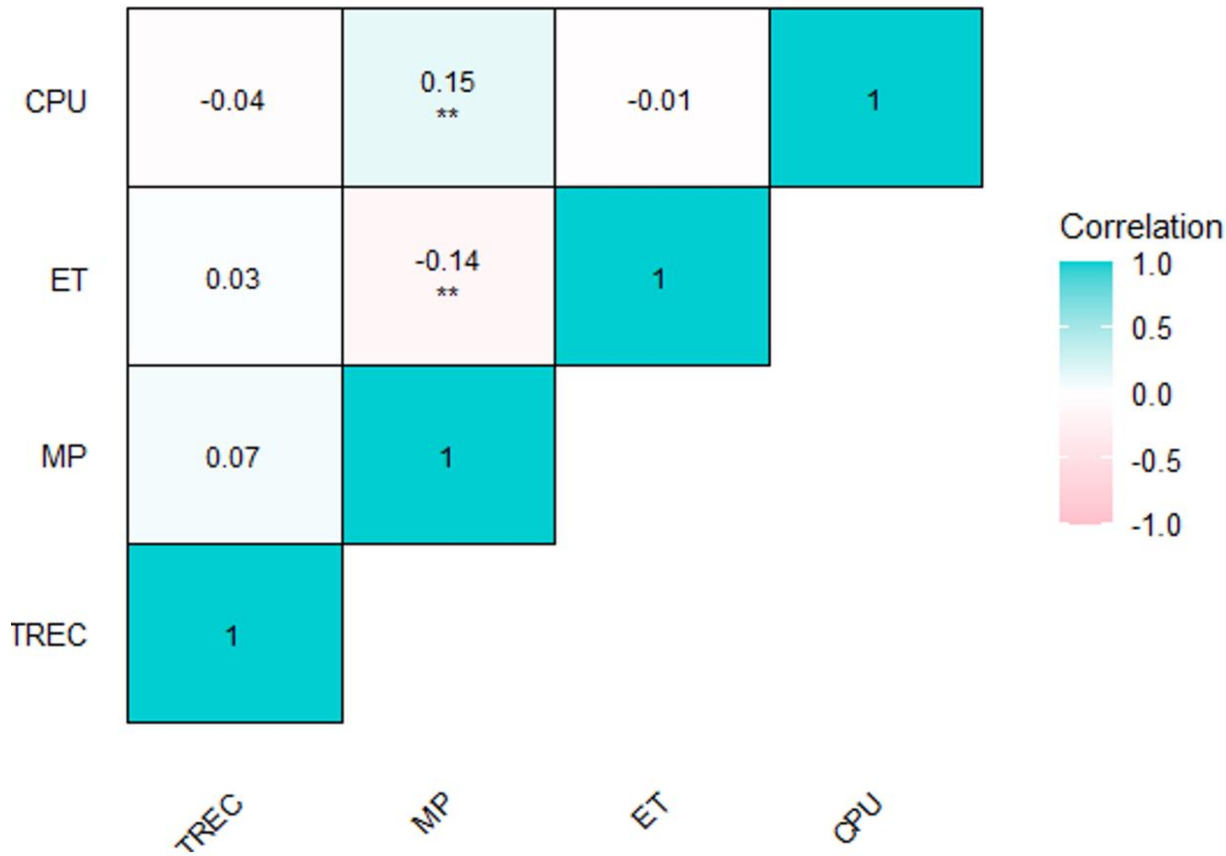

Figure 2.
Correlation Result.
Note: ** denotes 5%

3.2. Empirical Method

To examine the time–frequency behavior of the variables, the study employs a set of wavelet-based techniques that capture localized variation and dynamic dependence across different horizons. These methods are useful because they allow relationships among variables to vary jointly over time and frequency, which offers richer insight than conventional time-domain approaches. The wavelet framework has been widely used for non-stationary time-series analysis because it can simultaneously identify short-, medium-, and long-run dynamics within the same empirical setting.

The wavelet power spectrum is used to identify the localized variance of a series across time and frequency. It shows where a variable exhibits strong fluctuations and whether such volatility is concentrated in the short, medium, or long run. Following Torrence and Compo [28], let $x(t)$ denote a time series and $W_x(u,s)$ its continuous wavelet transforms, where u is the time position and is the scale. The wavelet power spectrum is defined as follows

$$WPS_x(u,s) = |W_x(u,s)|^2 \tag{1}$$

where $|W_x(u,s)|^2$ measures the local power or intensity of variation in the series at time u and scale s.

The wavelet coherence method is applied to examine the strength of co-movement between two series in the time–frequency domain. It is often interpreted as a localized correlation coefficient because it captures the degree of association between two variables across time and scale [29]. For two time series $x(t)$ and $y(t)$, the squared wavelet coherence is expressed as follows:

$$R_{xy}^2(u,s) = \frac{\left|S\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{S(s^{-1}|W_x(u,s)|^2)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)} \tag{2}$$

where $W_{xy}(u,s) = W_x(u,s)W_y(\bar{u},s)$ is the cross-wavelet transform, $W_y(\bar{u},s)$ denotes the complex conjugate of $W_y(u,s)$, and $S(\cdot)$ is the smoothing operator in both time and scale. This measure ranges between 0 and 1, with larger values indicating stronger dependence between the two series at a given time and frequency [29].

The partial wavelet coherence approach extends standard wavelet coherence by controlling for the effect of a third variable. It is used to isolate the net co-movement between two variables after removing the influence of another common factor [30]. For variables $x(t)$, $y(t)$, and $z(t)$, the squared partial wavelet coherence is written as follows:

$$RP_{xy|z}^2(u,s) = \frac{\left|R_{xy}(u,s) - R_{xz}(u,s)R_{yz}^*(u,s)\right|^2}{(1-|R_{xz}(u,s)|^2)\left(1-\left|R_{yz}(u,s)\right|^2\right)} \tag{3}$$

where $R_{xy}(u,s)$, $R_{xz}(u,s)$, and $R_{yz}(u,s)$ denote the wavelet coherence terms, and $*$indicates the complex conjugate

The multiple wavelet coherence framework is used to assess how one dependent variable co-moves jointly with more than one explanatory variable across time and frequency. It can be regarded as the wavelet-domain counterpart of multiple correlation because it measures the combined explanatory power of several predictors at each time, scale location [31]. For a dependent variable $y(t)$and two regressors $x_1(t)$ and $x_2(t)$, the squared multiple wavelet coherence can be written as follows:

$$RM_{y|x_1,x_2}^2(u,s) = 1 - \frac{M_{yy}^d(u,s)}{M_{yy}(u,s)} \tag{4}$$

where $M_{yy}(u,s)$ is the wavelet-domain auto-spectrum of y, and $M_{yy}^d(u,s)$ is the determinant-based residual component after accounting for the joint influence of $x_1$and x_2

The wavelet Granger causality approach suggested by Adebayo et al. [32] is used to examine predictive causality across different frequency bands after decomposing the original series into wavelet scales. This allows causal relationships to differ across short-, medium-, and long-run horizons rather than imposing a single average causal structure. After decomposition, the causality test is implemented on the scale-specific components using a standard Granger-type specification. For a given scale j, the model is written as follows:

$$y_t^{(j)} = \alpha_0 + \sum_{k=1}^{p} \alpha_k y_{t-k}^{(j)} + \sum_{k=1}^{p} \beta_k x_{t-k}^{(j)} + \varepsilon_t^{(j)} \tag{5}$$

where $y_t^{(j)}$and $x_t^{(j)}$ are the wavelet-decomposed components of the variables at scale j, $p$is the lag length, and $\varepsilon_t^{(j)}$ is the error term. Variable x is said to Granger-cause y at scale j if the null hypothesis H_0: $\beta_1 = \beta_2 = \cdots = \beta_p = 0$ is rejected

4. Results and Discussion

4.1. Nonlinearity Test

Next, we examine the nonlinearity test of the studied variables (see **Fig. 3**). The BDS results show that, across all variables and wavelet scales, the test statistics remain well above the critical benchmark indicated by the dotted line for embedding dimensions 2 to 6. This means the null hypothesis of independent and identically distributed series is rejected for TREC, MP, ET, and CPU at all scales, confirming the presence of nonlinearity and dependence in the data. The rejection is especially strong at higher scales such as D4 and D5, where the statistics are consistently largest, suggesting that nonlinear dynamics are more evident in the medium- and long-run components of the series.

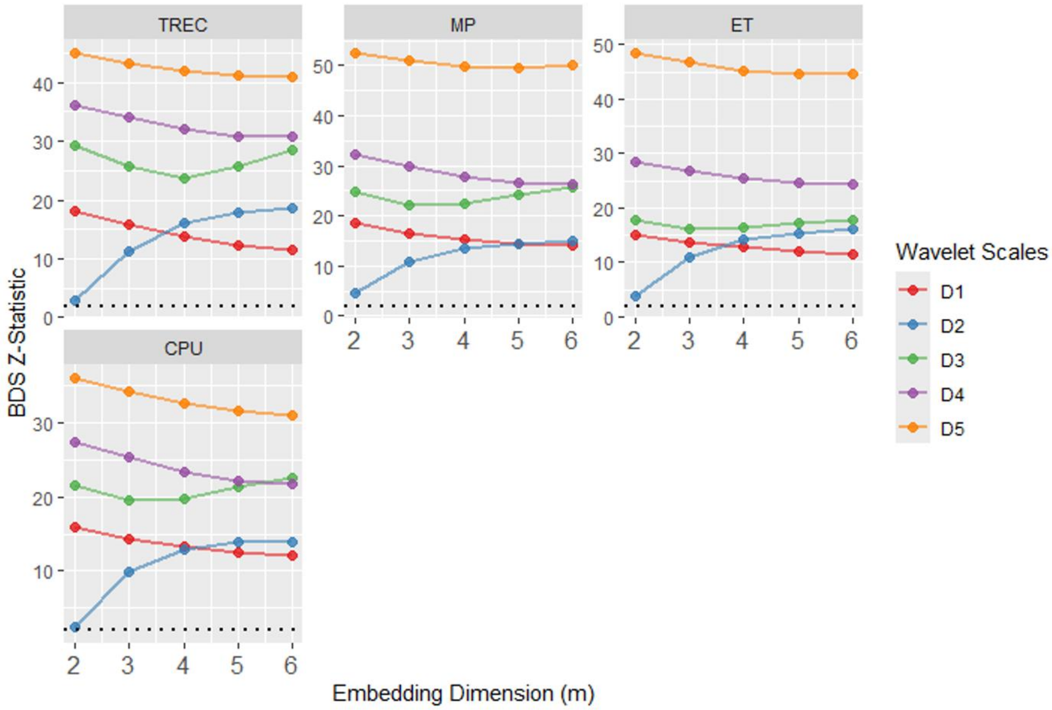

Figure 3.
Wavelet BDS.

4.2. Stationarity Test Result

Next, we check the stationarity features of the series (see Figure 4). The WZA results indicate that the null hypothesis of a unit root without a structural break is rejected for all variables because the test statistics at every MODWT detail level lie below the red critical line. This implies that CPU, ET, MP, and TREC become stationary once one endogenous structural break is taken into account. The estimated break dates differ across scales, showing that the timing of major shocks is frequency-dependent. For example, CPU records breaks around 2007-01, 2007-05, 2007-10, 2009-01, and 2022-10, while ET shows breaks around 2025-05, 2025-05, 2023-09, 2006-06, and 2012-05. MP has breaks around 2006-11, 2024-12, 2008-01, 2007-11, and 2008-06, whereas TREC records breaks around 2025-05, 2006-09, 2007-05, 2024-04, and 2008-04. Overall, the findings confirm the importance of structural changes in shaping the stochastic properties of the series.

Edelweiss Applied Science and Technology
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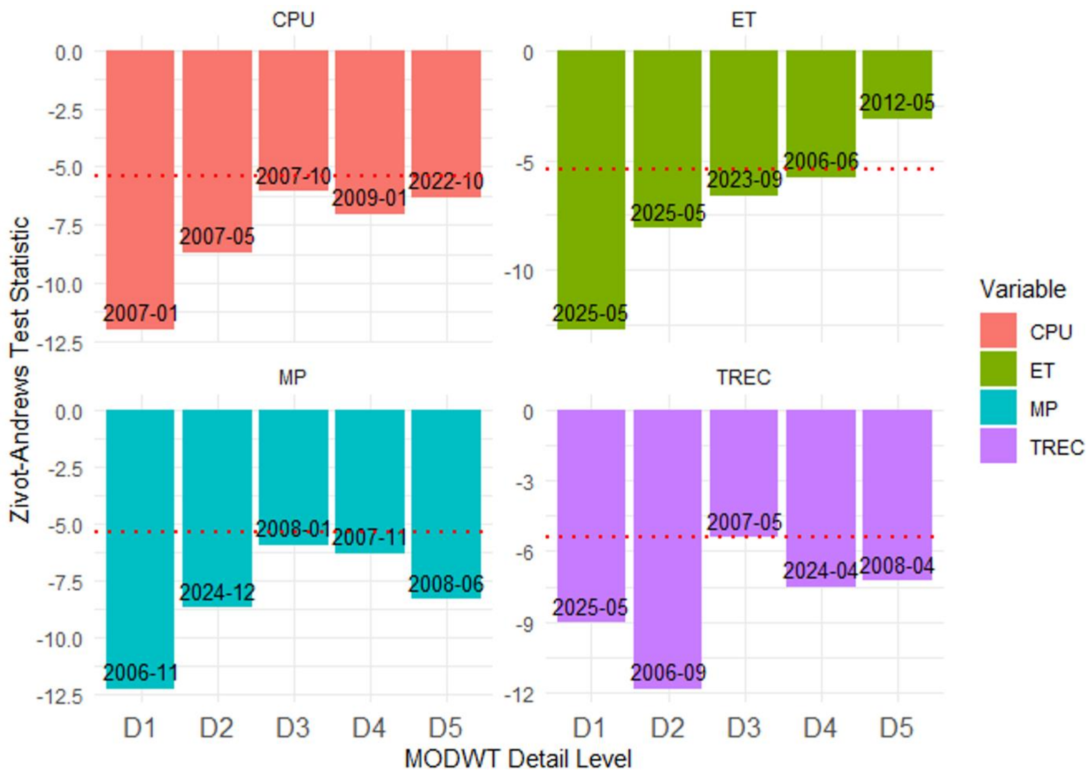

Figure 4.
MODWT Zivot Andrew Test.
Note: Red dotted lines denote 1% level of significance.

4.3. Wavelet Power Spectrum

The study commenced by using the WPS to check the volatility of the variables. For the United States, the wavelet power spectrum shows that volatility is concentrated mainly in the short-frequency band, especially at periods 2 to 8, with some medium-frequency persistence at periods 8 to 16 and weaker long-frequency activity beyond period 16. TREC (see Panel a) records repeated short-run volatility from 2005 to 2024, with stronger bursts around 2007 to 2009, 2014 to 2016, and 2021 to 2024, suggesting that renewable energy consumption reacted strongly to shifts in energy prices, clean-energy incentives, and macroeconomic disruptions rather than following a smooth path. ET (see Panel b) also exhibits clear volatility at short and medium frequencies, particularly during 2006 to 2010, 2018 to 2021, and 2022 to 2024, which is consistent with changing regulatory support, innovation cycles, and investment realignment in the U.S. clean-technology space. This interpretation agrees with studies showing that renewable energy and low-carbon transition variables respond unevenly across time and frequency because policy support, market expectations, and technological adjustments are not constant over time [33-35].

CPU (see Panel c) and MP (see Panel d) display the clearest volatility bursts in the short-run band, especially around periods 2 to 8, indicating that climate-policy and monetary-policy uncertainty in the United States are driven mainly by episodic shocks. CPU is particularly volatile around 2014 to 2017 and 2021 to 2024, with some spillover into medium frequencies, which may reflect major U.S. climate-policy debates, changes in federal environmental priorities, and the recent expansion of green industrial policy [36, 37]. MP shows notable short-frequency volatility around 2005 to 2008, 2010 to 2013, and 2018 to 2022, aligning with the global financial crisis, unconventional monetary policy, inflationary pressures, and Federal Reserve tightening episodes [7]. Overall, the U.S. evidence supports the view that volatility in TREC, ET, CPU, and MP is strongest in the short and medium run, where policy shocks, financial stress, and transition-related reforms are most actively transmitted across the system.

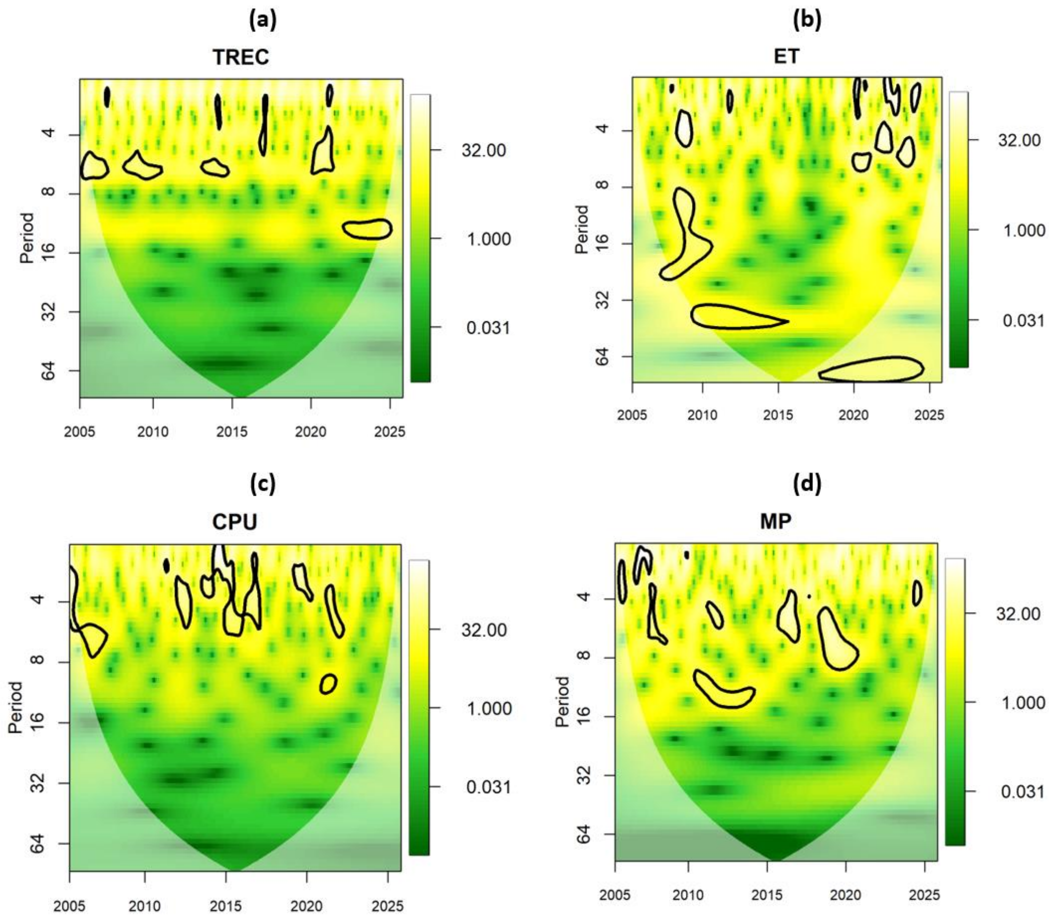

Figure 5.
Wavelet Power Spectrum Results.

4.4. Wavelet Coherence Result

To further examine the time–frequency interaction between TREC, ET, MP, and CPU, we employ wavelet coherence in Figure 6. Warmer shades indicate stronger coherence, the thick black contour marks statistically significant regions, and the grey cone of influence highlights edge areas that should be interpreted cautiously. The arrows capture phase dynamics, with rightward arrows showing positive co-movement, leftward arrows showing negative co-movement, and upward or downward tilts indicating lead–lag relationships across time horizons.

Panel (a) shows that the coherence between TREC and CPU is concentrated mainly in the short- and medium-run bands, especially around periods 2 to 8 and 8 to 16, with notable clusters during 2005 to 2010, 2011 to 2016, and again around 2019 to 2024. The arrows change direction across significant regions, which suggests that the lead–lag relationship between renewable energy consumption and climate policy uncertainty is not stable over time. In several short-run episodes, the association appears strong but temporary, while some medium-run islands indicate delayed adjustment between the two series. This implies that U.S. renewable energy consumption responds unevenly to climate-policy-related shocks, which is plausible in a setting where federal policy reversals, regulatory uncertainty, and clean-energy legislation can alter investment timing and energy deployment. This shows that climate

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ISSN: 2576-8484
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policy uncertainty can hinder or reshape renewable energy activity and that the effect is time-varying rather than constant across periods and energy components, thus validating the claim of Fu et al. [38]; Huo et al. [24] and Khan et al. [39].

Panel (b) indicates that the coherence between TREC and ET is more visible in the medium- and long-run bands, especially around periods 16 to 32 and 32 to 64, with strongly significant regions around 2005 to 2013 and again from about 2019 to 2025. The arrows in several of these longer-horizon regions lean leftward, pointing to an inverse co-movement in some episodes, while other patches suggest that the interaction changes across time. This pattern implies that environmental technology and renewable energy consumption are linked more strongly over longer adjustment horizons than in the immediate short run, which is reasonable because technological innovation, patenting, diffusion, and infrastructure adoption usually take time before they materially affect aggregate renewable energy use. This reading agrees with studies showing that environmental technologies improve energy efficiency and can support renewable energy consumption through gradual innovation and diffusion channels rather than instant transmission [3, 16, 18].

Panel (c) reveals that the coherence between TREC and MP is also concentrated in the short- and medium-run frequencies, especially around periods 2 to 8, 8 to 16, and selected long-run bands near 32 to 64. Strong, significant islands appear from 2007 to 2015 and re-emerge around 2020 to 2025. The arrows vary across these regions, showing that the direction of influence is not uniform, although several medium- and long-run areas suggest persistent interdependence. This means that monetary policy conditions matter for renewable energy consumption in the United States, but their effects differ by horizon and episode, likely because interest rates, credit conditions, inflation control, and policy uncertainty shape financing costs for renewable projects differently across time. This interpretation aligns with U.S. evidence that monetary conditions affect renewable energy consumption and with broader evidence showing that monetary shocks can alter renewable energy production through investment and financing channels [7, 40].

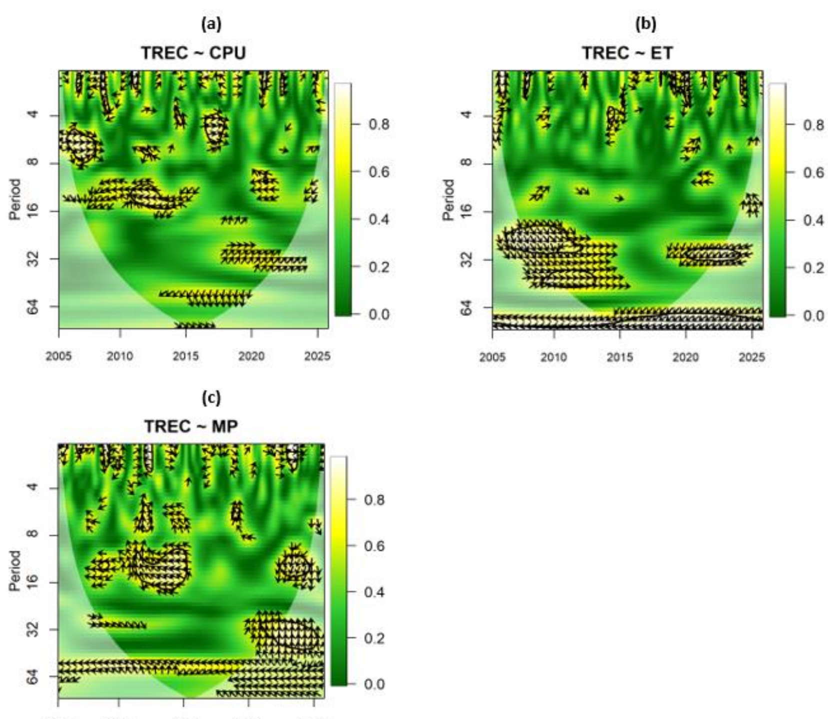

Figure 6.
Wavelet Coherence Results.

4.5. Partial Wavelet Coherence Result

To extend the baseline wavelet coherence analysis, Figure 7 reports partial wavelet coherence, capturing the time–frequency association between two variables once the effect of a third variable has been accounted for.

Panels (a) and (b) report the conditional coherence between TREC and CPU after accounting for ET and MP, respectively. In panel (a), once ET is controlled for, statistically significant coherence between TREC and CPU is concentrated mainly in the short-run band, especially around 4 to 8 periods, with visible clusters in the early years of the sample and again around the mid-2010s to late-2010s. This suggests that the TREC–CPU nexus is not solely driven by technological conditions, since climate-policy-related uncertainty continues to align with renewable energy consumption even after netting out ET. Panel (b) shows a similar pattern when MP is controlled for, with significant coherence remaining mostly in the short-run horizon and only a few scattered pockets in the medium band. This indicates that climate policy uncertainty retains an independent association with renewable energy consumption beyond monetary-policy-related disturbances. Across both panels, the most dependable evidence lies away from the cone edges and is strongest in the short-frequency range, implying that climate-policy shocks influence renewable energy consumption more through temporary and adjustment-related channels than through persistent long-run channels.

Panels (c) and (d) focus on the conditional coherence between TREC and ET after controlling for CPU and MP. In panel (c), after removing the effect of CPU, strong and statistically significant coherence appears in the medium- to long-run bands, especially around 16 to 32 periods in the late 2000s and early 2010s, with another clear long-run pocket toward the end of the sample. This pattern implies that the TREC–ET relationship is more persistent and structurally embedded than the TREC–CPU linkage, suggesting that technological development shapes renewable energy use through deeper transition and innovation channels. Panel (d) reveals a broadly similar result when MP is controlled for, as significant coherence remains pronounced in the medium and lower-frequency ranges, particularly from the mid-2000s to the mid-2010s. This means that the association between renewable energy consumption and environmental technologies is not merely reflecting monetary policy conditions but rather points to an independent technological channel supporting renewable energy uptake over longer horizons.

Panels (e) and (f) assess the conditional coherence between TREC and MP after controlling for CPU and ET. In panel (e), once CPU is accounted for, the remaining significant coherence is mainly clustered in the short- to medium-run bands, with noticeable pockets around 8 to 16 periods during the 2010s and early 2020s. This suggests that monetary-policy uncertainty influences renewable energy consumption through cyclical financing, borrowing costs, and investment sentiment channels that operate more clearly over short and intermediate horizons than over the long term. Panel (f) shows that controlling for ET still leaves meaningful coherence between TREC and MP, again concentrated mainly in the short- and medium-frequency bands, with only weak evidence at longer horizons. Overall, the partial wavelet coherence plots indicate that ET has the most persistent medium- and long-run linkage with TREC, whereas CPU and MP are more relevant in the short and medium run. This suggests that renewable energy consumption in the United States responds more durably to technological progress but remains sensitive to policy-related uncertainty over shorter adjustment horizons.

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Vol. 10, No. 4: 512-531, 2026
DOI: 10.55214/2576-8484.v10i4.12717

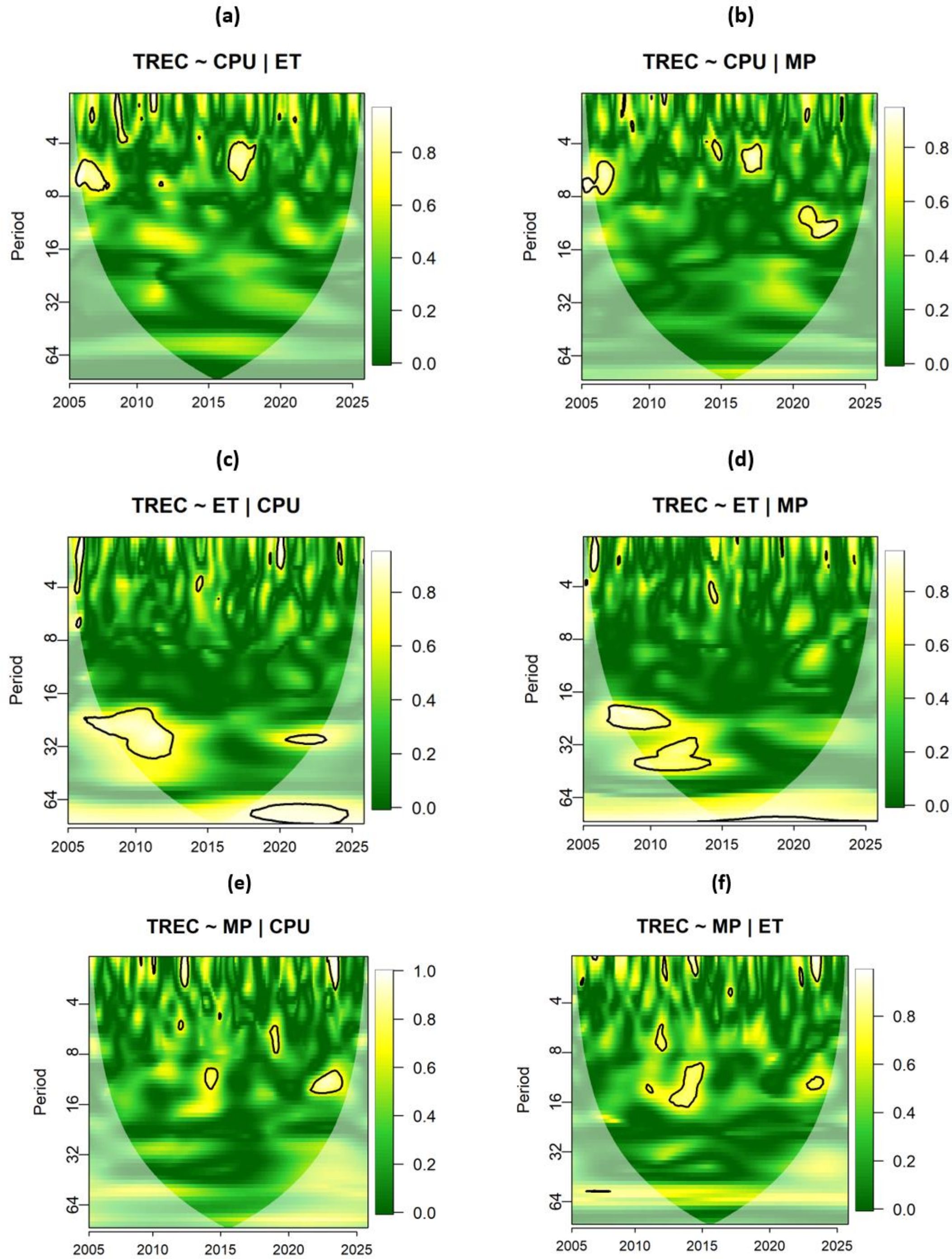

Figure 7.
Partial Wavelet Coherence.

4.6. Multivariate Wavelet Coherence Result

To further confirm the robustness of the partial wavelet coherence findings, we employ a multiple wavelet coherence (see Figure 8) framework. In this setting, the method examines how TREC evolves jointly with pairs of drivers across time and different frequency horizons.

Panel (a) links TREC with CPU and MP jointly, revealing sizeable statistically significant regions from the mid-2000s through the 2020s, with the strongest clusters mainly around 4 to 16 periods and some extension into longer horizons. This pattern suggests that climate policy uncertainty and monetary policy uncertainty jointly shape the cyclical behavior of renewable energy consumption in the United States. The persistence of coherence within these short- and medium-run bands implies that fluctuations in policy uncertainty can influence renewable energy demand, investment timing, and adjustment decisions over horizons typically associated with policy reactions, financing conditions, and market expectations.

Panel (b) relates TREC with ET and CPU jointly and shows broad, significant areas stretching from the mid-2000s into the 2020s, with especially clear coherence around 8 to 32 periods and additional pockets at shorter horizons. This indicates that environmental technologies and climate policy uncertainty jointly matter for the time-varying dynamics of renewable energy consumption. The wider coherence regions suggest that technological progress in the environmental sector, when combined with climate-policy-related instability, shapes renewable energy use through both short-run adjustment channels and more persistent medium-run transition mechanisms.

Panel (c) examines TREC with ET and MP jointly and also displays strong coherence from the mid-2000s onward, concentrated mainly around 8 to 32 periods, with some evidence extending into longer cycles near the lower part of the spectrum. This finding implies that environmental technologies and monetary policy uncertainty jointly influence renewable energy consumption in the United States. The concentration of significance in the medium-run band is consistent with adjustment processes that are not immediate, such as technology adoption, investment reallocation, credit-cost transmission, and the gradual scaling of renewable energy systems. Overall, the multivariate wavelet coherence results suggest that renewable energy consumption in the United States is shaped not only by technological conditions but also by the combined uncertainty environment surrounding climate and monetary policy.

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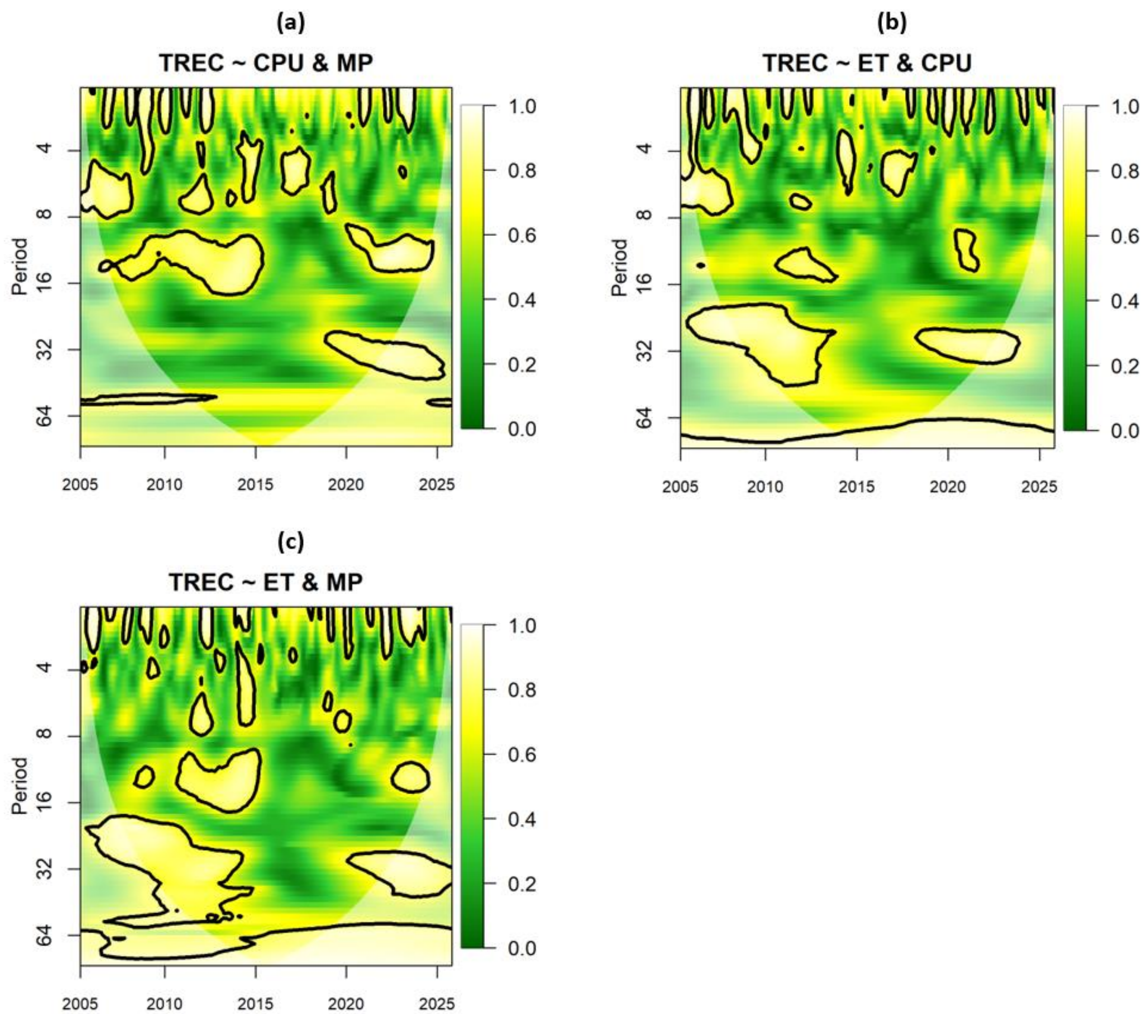

Figure 8.
Multivariate Wavelet Coherence.

4.7. Wavelet Granger Causality Result

Finally, predictability among TREC and the explanatory variables is evaluated through a wavelet Granger causality network. Figure 9 and Table 2 summarize the causal pattern from D1 to D5, with nodes representing variables and arrows indicating predictive effects.

The causality network reveals that the direction and strength of interactions among TREC, MP, CPU, and ET vary substantially across frequency bands in the United States. In D1, the only visible linkage is a bidirectional causal relationship between MP and CPU, showing that at the highest frequency or shortest horizon, monetary policy uncertainty and climate policy uncertainty respond to one another directly, while TREC and ET remain disconnected. In D2, the network becomes denser. TREC and ET exhibit bidirectional causality, suggesting mutual feedback between renewable energy consumption and environmental technologies at this horizon. At the same time, MP and CPU also remain bidirectionally linked, while MP additionally causes TREC unidirectionally, indicating that monetary policy-related uncertainty begins to influence renewable energy dynamics more clearly in this band. In D3, the structure shifts to mostly unidirectional effects, with arrows running from ET to MP, MP to TREC, and CPU to TREC. This pattern suggests that, in the medium-term band, renewable

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 10, No. 4: 512-531, 2026
DOI: 10.55214/2576-8484.v10i4.12717

energy consumption is more of a receiving variable, responding to impulses coming from environmental technologies and both policy-uncertainty channels.

The lower-frequency results in D4, D5, and the original series further clarify the long-horizon dynamics. In D4, MP causes both TREC and CPU, while TREC causes ET, implying that at this horizon, monetary-policy uncertainty plays a central transmitting role, whereas renewable energy consumption also feeds into environmental technologies, possibly reflecting induced innovation or adaptation effects. In D5, the network becomes much simpler, with only TREC causing MP, which indicates that in the very long run, renewable energy consumption may itself shape monetary-policy conditions or expectations rather than merely responding to them. For the original series, the dominant pattern is that ET causes MP and MP causes TREC, while CPU shows no direct link, implying that when all frequencies are combined, the main transmission channel runs from environmental technologies through monetary policy uncertainty to renewable energy consumption. Overall, the figure suggests that MP is the most central node across scales, CPU matters mainly in the short and medium term, ET becomes important through indirect and medium-run channels, and TREC alternates between being a receiver of shocks in some bands and a transmitter in others.

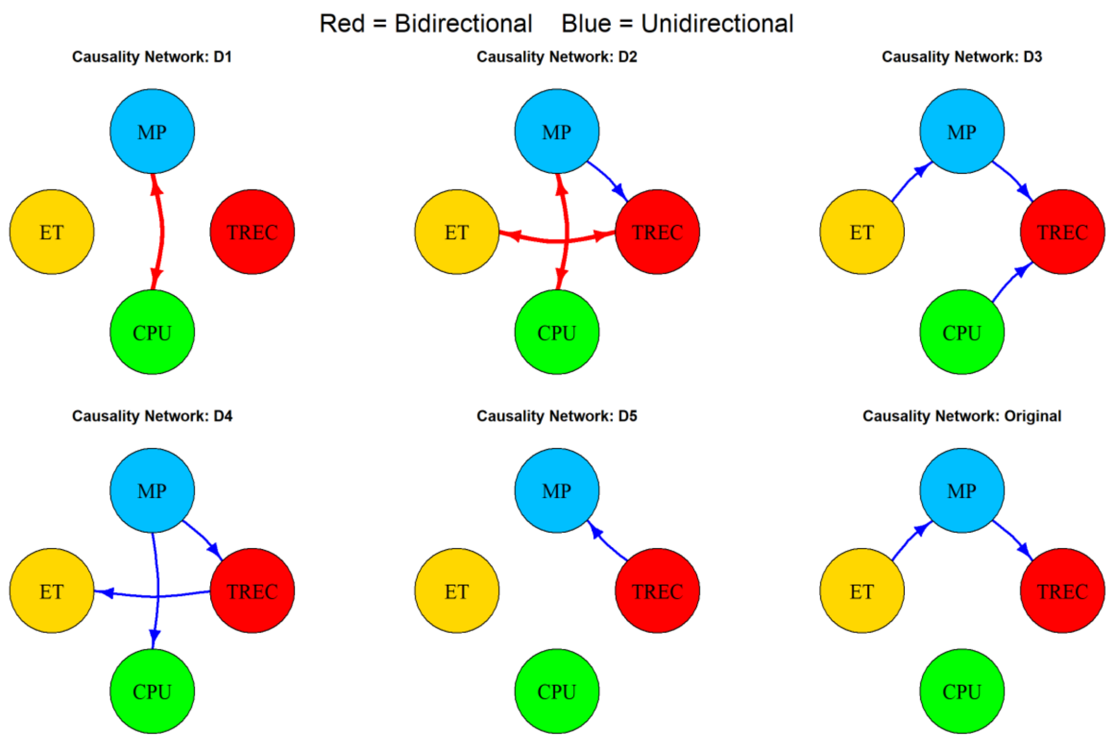

Figure 9.
Wavelet Granger Causality Results.

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Table 2.
MODWT Granger causality outcomes.

Scales	**Dependent Variable**	**TREC**	**MP**	**ET**	**CPU**
D1	TREC	-	0.4878	0.8263	1.7402
	MP	1.0379	-	1.6049	10.6987***
	ET	0.1111	0.3783	-	1.9763
	CPU	0.8742	4.4080**	0.7426	-
D2	TREC	-	5.9568***	3.3172**	2.4191*
	MP	2.2663	-	0.8236	18.5451***
	ET	3.2231**	0.3543	-	1.4547
	CPU	2.2095	4.4180**	0.0314	-
D3	TREC	-	5.1643***	0.1796	4.8072***
	MP	0.8125	-	3.7375**	0.2675
	ET	1.1191	1.4658	-	0.1413
	CPU	2.9980*	1.1473	0.6553	-
D4	TREC	-	9.2481***	2.0681	1.8303
	MP	0.5262	-	0.6734	0.0209
	ET	9.0125***	2.8896*	-	0.3974
	CPU	0.5615	3.3266**	2.9434*	-
D5	TREC	-	1.5349	2.8134*	0.2443
	MP	5.3079***	-	0.9201	0.7102
	ET	0.1389	0.2467	-	2.7200*
	CPU	0.7974	1.0900	1.9890	-
Original	TREC	-	5.5349***	0.5559	0.4174
	MP	1.7235	-	3.0400**	2.3781*
	ET	0.2816	0.1427	-	1.0963
	CPU	0.5970	1.1794	0.5740	-

Note: ***p ≤ 0.01, **p ≤ 0.05, and *p ≤ 0.10. The values shown are Granger-causality F-statistics accompanied by significance stars. The F-test reflects whether the null hypothesis of no causality can be rejected. D1 to D5 capture the wavelet detail levels, and original stands for the original series.

5. Conclusion and Policy Implications

5.1. Conclusion

Using monthly U.S. data spanning 01/05/2005 to 01/11/2025, the study employs advanced time–frequency approaches, including wavelet coherence, partial wavelet coherence, and multiple wavelet coherence, to examine the coherence between total renewable energy consumption (TREC) and its key drivers, namely climate policy uncertainty (CPU), monetary policy uncertainty (MP), and environmental technologies (ET). The wavelet-based findings show that the relationship between TREC and its key drivers in the United States is strongly time- and frequency-dependent. The baseline wavelet coherence results indicate that CPU and MP are linked with TREC mainly over the short and medium run, whereas ET shows a stronger connection with TREC over the medium and long run. The partial wavelet coherence results reinforce this interpretation by showing that the TREC–CPU nexus remains largely short-run even after controlling for ET and MP, while the TREC–ET relationship remains persistent across medium- and long-run horizons after accounting for CPU and MP. The multivariate wavelet coherence analysis further confirms that TREC is shaped not only by individual drivers but also by the joint influence of uncertainty and technology, especially across medium frequencies. Finally, the wavelet Granger causality network reveals that causal linkages vary across scales, with MP emerging as the most central transmitting variable, CPU mattering mainly in the short and medium term, ET exerting influence through indirect and medium-run channels, and TREC alternating between acting as a receiver and a transmitter of shocks depending on the decomposition level.

5.2. Policy Implications

The findings imply that U.S. policymakers should place greater emphasis on policy consistency and credibility in climate governance. Since renewable energy consumption responds unevenly to climate policy uncertainty across short- and medium-term horizons, frequent policy reversals, unclear regulatory signals, and unstable clean-energy incentives can delay investment and weaken deployment. This means that federal and state authorities should reduce uncertainty by maintaining predictable renewable energy targets, stable subsidy frameworks, and transparent implementation timelines. A more credible climate-policy environment would help investors, utilities, and producers make long-term decisions with greater confidence and reduce the stop-and-go pattern that often slows the energy transition.

The results also suggest that environmental technologies should be treated as a long-term strategic pillar of renewable energy expansion rather than as a source of immediate gains. Because the ET–TREC relationship is stronger in the medium and long run, policy should focus on sustained support for green innovation, research and development, clean-energy patents, grid modernization, storage systems, and technology diffusion. This requires patient public investment, stronger university–industry collaboration, and industrial policies that encourage the commercialization of environmental innovations. In practical terms, the transition to renewable energy is likely to be more durable when governments invest not only in energy deployment itself but also in the technological ecosystem that supports it over time.

Another important implication is that monetary and financial conditions matter for renewable energy uptake, especially over short- and medium-term horizons. Since monetary policy uncertainty can alter financing costs, borrowing conditions, and investment timing, macroeconomic authorities should recognize that renewable energy development is sensitive to credit-market disruptions and policy instability. This points to the need for better coordination between climate and macroeconomic policy, including measures that improve access to affordable green finance during periods of tightening or uncertainty. Lower financing barriers, targeted green credit facilities, and stable financial conditions can help shield renewable energy projects from policy-driven volatility and make the transition more resilient across changing economic episodes.

5.3. Limitation and Future Directions

One limitation of this study is that it focuses on the United States and on a specific set of drivers of renewable energy consumption, namely environmental technologies, monetary policy uncertainty, and climate policy uncertainty, which may omit other relevant influences such as fiscal policy, energy prices, financial development, political polarization, or structural changes in the energy market. In addition, although the wavelet-based framework is well-suited for uncovering time- and frequency-varying relationships, it is primarily informative about dependence and predictability across horizons rather than fully identifying deeper structural mechanisms. Future research can extend this analysis by incorporating additional macroeconomic, institutional, and financial variables, comparing the U.S. case with other advanced and emerging economies, and applying complementary approaches that allow for stronger structural interpretation. It would also be useful to examine sector-specific renewable energy dynamics and to distinguish among different renewable sources, since solar, wind, hydro, and bioenergy may respond differently to technological progress and policy-related uncertainty.

Use of Generative AI:

The study uses Grammarly exclusively for proofreading and copy-editing to correct grammar, spelling, punctuation, and minor clarity issues, while keeping the meaning, structure, tone, and length unchanged.

Institutional Review Board Statement:

All authors listed in the manuscript have agreed to authorship, have read and approved the final version of the manuscript, and have given their consent for its submission and subsequent publication.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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