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Lowering Uncertainty for Sustainable Development: Assessing the Effectiveness of Green Innovation

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ABSTRACT

One of the fundamental challenges on the path to sustainability is the interruption caused by various uncertainties. This study examines how clean energy technology interacts with sustainability uncertainty across different timescales and frequencies, using data from March 2013 to March 2025. Wavelet coherence and partial wavelet coherence analyses are used to explore the dynamic relationships, accounting for the influence of oil futures. The results indicate a dynamic relationship between clean energy technology and sustainability uncertainty. While clean technology and sustainability uncertainty moved in opposite directions between 2014 and 2015, there were positive co-movements from 2017 to 2021. Most changes were driven by clean technology and were evident only in the short term, whereas movements were nearly synchronized in the medium term, with indications of long-term synchronization. Therefore, sustainability uncertainty may be triggered by the market signal effect, which causes most short-term disturbances. However, this relationship is not entirely independent of oil futures, especially in the long term. This suggests that a long-term sustainability path is not independent of oil market dynamics. Consequently, long-term sustainability strategies could be more effective by leveraging attractive clean technology stock indices to improve sustainable finance.

1 | Introduction

The Sustainable Development Goals are intended to address contemporary global challenges more effectively than before. They encompass economic, environmental, and social dimensions, each associated with significant uncertainty. Given the urgent need to accelerate the transition from unsustainable practices to a more sustainable culture, new policies are being developed, and existing regulatory guidelines are being revised, tested, or maintained. Such changes create uncertainty by causing variations in sustainability outcomes. Despite all sustainability plans, global sustainability remains unpredictable due to persistent threats. These include ongoing climate change challenges resulting from rising greenhouse gas emissions and increased environmental vulnerability to economic activities. For example, the IEA (2024) reports that population growth has widened the energy access gap, despite increased access to electricity, resulting in unequal access to clean energy. This highlights the inadequacy of existing sustainability plans. Consequently, sustainable development indicators remain highly uncertain. Diwekar et al. (2021) also identified uncertainty as a major challenge for sustainability efforts. Therefore, uncertainties related to any aspect of sustainable development can delay its achievement. It is essential to adopt more consistent sustainability models to mitigate systemic risks arising from the inability to predict the outcomes of strategies.

Innovation and technology are critical in the journey towards achieving sustainability (Vergragt 2006; Coccia 2024). As reliance on traditional practices declines, countries are increasingly

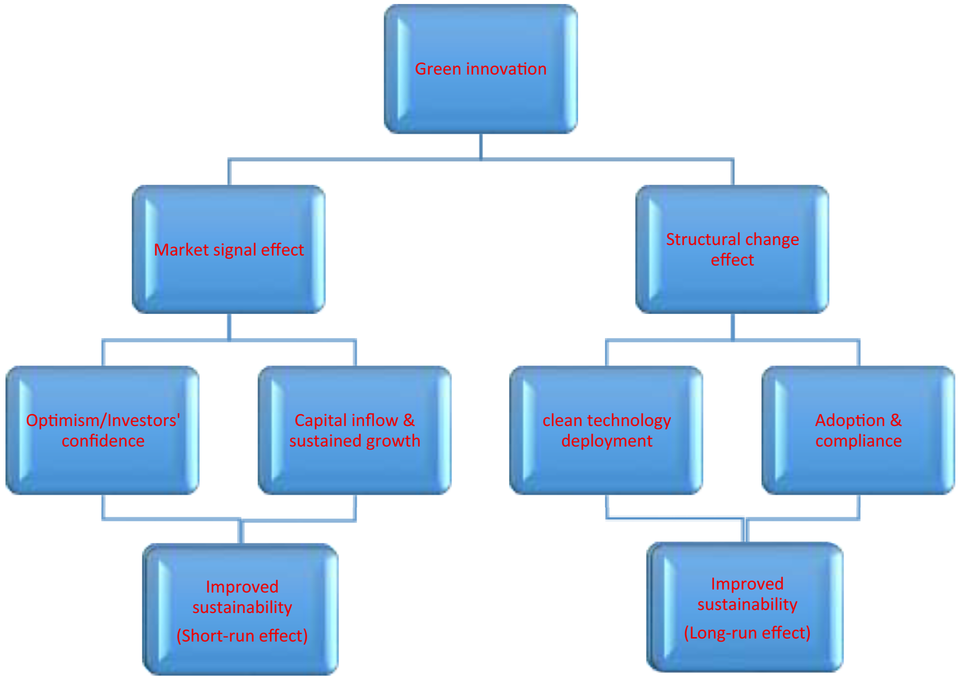

FIGURE 1 | Transmission mechanism of green innovation to sustainability uncertainty.

adopting clean technologies to support sustainability. For example, recognizing that fossil fuel energy consumption is a major source of greenhouse gas emissions, the Paris Agreement is committed to reducing the share of carbon-emitting energy in total energy consumption while increasing the share of clean energy in the global energy mix. Most advanced countries that can afford clean energy technologies have transitioned more rapidly than less advanced countries (Ram et al. 2022). This global shift is expected to reduce reliance on traditional fossil fuels, mitigate environmental degradation, and promote sustainable economic growth. This development has two important transmission mechanisms for sustainability uncertainty: the market signal effect and the structural change effect. This is illustrated in Figure 1.

The first transmission mechanism is the market signal, which shifts investors' perceptions of clean energy equities (Flammer 2021; Van der Auwera et al. 2023; Jiang and Wang 2025). As sustainability policies emerge, investors may perceive profitable opportunities in companies with high sustainability impact. Rising investment valuations and perceived profitability fuel optimism and investor confidence. This signal effect leads to increased capital inflows into the clean technology sector, resulting in sustained growth in this sector (Achuo et al. 2025; Ali et al. 2025). As sustainability policies gain credibility, investors gain a clearer understanding of transition policies and become more willing to accept associated risks (Ali et al. 2025). This alignment helps investment decisions better reflect sustainability policies. It improves sustainability conditions and makes them more predictable, thereby reducing sustainability uncertainty.

However, investors' decisions are based on rational behaviour. Since expectations drive uncertainty, new phases of uncertainty may emerge if optimism becomes excessive and speculative activity increases. Portfolio theory suggests that investors are concerned with the risks and returns of their portfolios. Portfolios may be sufficiently diversified as a risk management strategy for investors (Markowitz 2008). Different expectations regarding future sustainability dynamics can affect the performance of clean technology investments. For example, the relationship between the fossil fuel market and the clean energy technology market determines how investment capacity will influence sustainability uncertainty (Henriques and Sadorsky 2008; Managi and Okimoto 2013; Ozkan et al. 2024, 2025). If increased development of the fossil fuel market promotes fossil fuel consumption, climate risk and transition risk will persist, necessitating policy revision. This positions oil as a mutual determinant of sustainability and clean technology development. This not only generates market volatility but also creates instabilities in sustainability indicators and causes capital misallocation among sectors.

The second channel of transmission is the structural channel, which suggests that sustainability uncertainty decreases with the deployment of clean technology. Financial development directly affects clean technology industries, leading to increased funding for innovation (Shahbaz et al. 2021). Technological progress necessitates structural adjustment, and conventional production methods are phased out as new technologies emerge. This transformation improves sustainability fundamentals, such as energy access, reduced climate risk, and production efficiency, until these factors stabilise in the long term. The effectiveness of clean energy technology ultimately shapes institutional policies and societal norms, resulting in more sustainable structures and reduced uncertainty (Berrone et al. 2013; Schramade 2017; Ao et al. 2023). However, new forms of uncertainty may arise during the transition process through policy reviews, initial coordination challenges, regulatory shocks, and policy risks, particularly during short-term instabilities. Thus, green innovation may initially increase uncertainty before reducing it.

Based on these premises, the role of clean technology in enhancing sustainability performance is widely recognised, but its role in the stability of sustainability indicators remains unclear. Specifically, there is limited empirical evidence on how clean technology investment coordinates with uncertainty related to sustainability. While previous studies, such as Ahmed et al. (2022), Fang (2023), Li et al. (2023), and Cao et al. (2025), have examined the impact of technology on sustainability, they assessed sustainability primarily in terms of carbon emissions reduction. Although environmental issues are critical, this study adopts the view that sustainability improvement extends beyond environmental fundamentals such as energy transition, emissions reduction, climate risk, and resource efficiency. A more policy-relevant approach requires a holistic measure that incorporates the multidimensional underlying conditions determining sustainability. These include production efficiency, investment patterns, policy consistency, regulatory quality, demographic changes, consumption adjustment, and adaptability. The Environmental, Social, and Governance (ESG) index is a measure that captures the comprehensive scope of sustainability. Given the uncertainty in the path to sustainability, the development of a sustainability-related uncertainty index (Ongan et al. 2025) offers a more effective benchmark for assessing sustainability uncertainty. Ongan et al. (2025) measured sustainability potential from the perspective of uncertainty in ESG factors. This index quantifies uncertainty related to sustainability conditions over time so that their changes can be adequately assessed in relation to technology development.

To this end, this study's objective is to investigate how the evolution of sustainability uncertainty is associated with technological change. Specifically, the study examines the dynamic relationship between clean technology investment and sustainability uncertainty across time and frequency. This is important for demonstrating whether clean technology investment aligns with sustainability policies to promote stability. Furthermore, the study evaluates the persistence of this relationship under the influence of the oil market, as clean technology may not have an independent relationship with sustainability uncertainty due to changing market conditions and structural factors over time. Tiwari et al. (2026) established that sustainability-related uncertainties constitute barriers, particularly when unexpected interruptions or policy ambiguity occur. To provide more robust evidence, this relationship is tested using other uncertainty measures, including economic policy uncertainty, climate policy uncertainty, and geopolitical risk. Although these are not adequately sustainability-specific, like the sustainability uncertainty index, which is directly related to green financial markets. This comparison reveals the unique explanatory power of the sustainability uncertainty index in green finance and directs towards less ambiguous policies. The general analysis is anchored in the instabilities in the sustainability system's performance, such as transition shocks, policy shocks, environmental shocks, structural shocks, and volatility in energy markets. This study provides insight into the need for more active sustainability strategies through sustainable finance. It directs policy towards ensuring stability while balancing progress across sustainability systems through an integrated policy approach.

The rest of the study is structured as follows: Section 2 presents the review of theoretical and empirical literature, Section 3 describes the data and methodology, and Section 4 presents results and discussion. The conclusion is presented in Section 5.

2 | Literature Review and Hypotheses Development

The logical relationship that led to associating sustainability uncertainty with technological advancement has also prompted an assessment of their relationships in the literature. The literature highlights various scopes of relationships between sustainability and green technology investment. Hassan et al. (2022) provided long-run and short-run analyses of how green energy investment is significantly correlated with environmental quality in China, using the Markov Switching Equilibrium Correction Model and Kernel-based Regularized Least Squares. Ahmed et al. (2021) also used linear and nonlinear ARDL, but found no sufficient evidence to prove that renewable energy technology investment influences emissions. However, a game-theoretic analysis by Wang et al. (2021) reveals that retailers have a strong motivation to invest in green technology, but high levels of investment in supply chains may have a positive effect on environmental sustainability depending on the sensitivity of environmental impact to green technology. A combination of quantile analyses by Hoque et al. (2025) showed a strong connection between sustainability and innovative assets. Even though stock market volatility and financial stress interfered with this connection, it was strongest during extreme market conditions. Similarly, a TVP-VAR framework by Dogan et al. (2023) showed that the strong interconnection between global carbon markets and renewable energy sources was sensitive to oil shocks and even more sensitive to the COVID-19 pandemic. Although the indifference observed by Ahmed et al. (2021) may have been influenced by the inclusion of economic policy uncertainty, other studies also highlight the importance of global crises and uncertainty in sustainability indicators.

Ahmed et al. (2021) highlighted the negative impact of both positive and negative shocks in economic policy uncertainty on CO_2 emissions in the US, showing that negative shocks in economic policy uncertainty have a dominant effect. Other studies have also evaluated the asymmetric effects of clean technology on sustainability while accounting for uncertainty. Javed et al. (2023) included the effects of green technology and economic policy uncertainty in linear and non-linear ARDL models of carbon emissions determinants in Italy. Positive shocks in green technology reduced CO_2 emissions, while negative shocks significantly increased environmental degradation; however, both positive and negative shocks to economic policy uncertainty increased environmental degradation. Similarly, Ali et al. (2023) examined the role of economic policy uncertainty, green technological innovation, energy consumption, and other factors on CO_2 emissions. They established that economic policy uncertainty and energy consumption increase CO_2 emissions, while green technological innovation reduces CO_2 emissions. These studies demonstrate how clean technology development can influence environmental sustainability in the presence of uncertainty.

Regarding the association between uncertainty and clean technology investment, Husain et al. (2022) demonstrated an asymmetric response of green financial investment to climate policy uncertainty in the US from July 2014 to March 2021 using the cross-quantilogram approach. Giudici et al. (2022) proposed a framework for assessing the influence of climate uncertainty and technological innovation on renewable investments. While climate uncertainty and technological innovation influenced effective investment, the competitiveness of technological innovation may have been affected by the level of investors' risk aversion. Peng et al. (2025) also provided robust evidence that digital transformation improves investment efficiency, but this effect weakens under high environmental uncertainty. This line of research suggests that the strength of green investment can vary with environment-related uncertainty.

Other key factors determine the relationship between green innovation and uncertainty. Li et al. (2021) found a positive association between environmental regulation and green innovation in China, but the negative impact of economic policy uncertainty on green innovation limits the strength of this relationship. Similarly, Hassan et al. (2022) reported that natural resources and uncertainty decrease environmental quality in China, while highlighting these as key factors in green energy investment. Dou et al. (2025) used a two-way fixed effects model to show that the World Uncertainty Index (WUI) negatively affects green technology innovation, with a stronger effect in high-income countries than in low-income countries. However, environmental regulation mediates this negative effect. While uncertainty appears to delay green innovation by increasing the inconsistency of environmental regulation and reducing financial support, environmental challenges may decrease through efficiency and conservation or increase through pollution and resource depletion as technology advances (Meijer and Hekkert 2013).

2.1 | Research Gap

The most notable trend in the literature is the assessment of the relationship among environmental sustainability, economic policy uncertainty, and technology. Although studies remain limited, the uncertainty associated with sustainability policies has been overlooked. For more stable sustainability policies, these research gaps raise questions that need to be addressed. First, the focus of previous related studies can be divided into two categories. Some have mainly examined the association between sustainability and clean technology investment, while others have focused on the association between uncertainty and clean technology investment. This study differs by investigating the link between uncertainty associated with sustainability and investment in clean technology. Second, while most studies have explored how sustainability and uncertainty shape clean energy markets, this study takes a different approach. It focuses on how clean energy investment influences sustainability uncertainty over time. The question posed here is whether clean technology investment can shape the uncertainty associated with sustainability. This study seeks to determine if the level of uncertainty encountered in sustainability can diminish as investment in clean energy technology increases. Third, the literature is silent on the effects of market interference that may influence the relationship between investment in clean technology and sustainability uncertainty. This study examines whether the observed relationship is independent of other market influences. To this end, it employs time-varying wavelet analysis and partial wavelet analysis to address these questions. The following null hypotheses are tested:

i. H_0: There is no significant co-movement between clean energy technology equities and sustainability uncertainty across time and frequency.

ii. H_0: There is no evidence of significant anti-phase (negative) co-movement between clean technology equities and sustainability uncertainty within specific frequency bands.

iii. H_0: The association weakens when conditioning on oil across the specific frequency bands.

The measures of sustainability may differ, but they show similar patterns of evolution, as they are all sensitive to events and changing policies over time (Šević et al. 2024). This indicates interconnectedness among the measures of uncertainty related to sustainability; thus, their common driver could be the rationale for sustainability transition. Based on this, the study offers robust evidence on the effectiveness of green innovation in promoting sustainability. Separate tests assess the co-movement of clean energy technology with economic policy uncertainty, climate policy uncertainty, and geopolitical risk, both with and without the influence of oil futures. While the economic policy uncertainty index, climate policy uncertainty, and geopolitical risk index primarily capture economic stability, climate regulations, and external or geopolitical shocks, respectively, they do not adequately reflect the dynamics related to sustainability transition. This hinders the development of sustainability-specific policies. The study provides direct insight into the dynamics of clean technology finance in relation to sustainability investment.

3 | Theoretical Framework, Data, and Methodology

3.1 | Theoretical Framework

Economic activities raise concerns for climate change at an early stage of development. The excessive reliance on traditional sources of energy at this stage is to increase production, so the economy grows at the expense of the environment (Grossman and Krueger 1995). The resultant impact of production scale on sustainability is known as the scale effect. At the latter stage of economic growth, structural changes occur, and preferences shift toward adopting better production techniques, especially as they now have the capacity to afford more sophisticated, efficient technologies. This, known as the technique effect, can reduce unsustainable practices (Cole and Elliott 2003; Ahmed et al. 2021). It, however, depends on other factors, including the stringency of environmental regulations and resource endowments. The technique effect drives investment in clean energy technology and the development of new energy firms. This will, in turn, increase access to cleaner production technologies and the adoption of more efficient technology. Thus, if sustainability can be promoted through investment in clean technologies (Koçak and

Ulucak 2019; Ahmed et al. 2021), then uncertainty associated with sustainability can decrease.

This framework highlights distinct time–frequency patterns in the relationship between clean-energy market equities and sustainability uncertainty. As discussed earlier, the market signal and increased investment flows into clean technology sectors drive the scale effect. Early-stage growth in this sector reflects rapid market responses to clean technology developments arising from optimism. The expansion of cleaner production techniques may initially introduce high volatility and adjustment pressures in sustainability indicators. This is expected to generate a short-run, in-phase relationship and high-frequency coherence between sustainability uncertainty and clean technology equities. In contrast, the technique effect operates through the structural channel, where the maturity of investment and sustained growth in the clean technology sector lead to technological transformation and greater stability in sustainability indicators over time. This should generate persistent long-run coherence at low frequency, but the dynamics are anti-phase. Therefore, while clean technology equities may reduce sustainability uncertainty in the long run, they may cause short-term increases in sustainability uncertainty during the initial periods.

Oil prices are strongly linked to clean technology stock indices (Salisu et al. 2024; Umar et al. 2024). On this basis, the role of clean energy technology investment in mitigating sustainability uncertainty is examined, while accounting for oil price expectations. Oil serves as a substitute for clean energy (Henriques and Sadorsky 2008), and the attractiveness of investment in the non-renewable energy sector can encourage unsustainable practices. This positions oil prices as a common driver of both sustainability and clean technology equities. This market-related factor is included to assess the net effect of clean energy technology on sustainability uncertainty. It evaluates the strength of the relationship between clean energy technology and sustainability uncertainty as market options change. Given the mutual influence of oil markets on sustainability dynamics and clean technology markets, reduced coherence is expected when the influence of the oil market is excluded.

3.2 | Data

To assess the role of technology investment in mitigating sustainability uncertainty, this study analyses monthly data from March 2013 to March 2025. The proxy for sustainability uncertainty (ESGUI) is the composite global GDP-weighted ESG-based sustainability uncertainty index by Ongan et al. (2025), sourced from www.policyuncertainty.com. The index represents the monthly average values of the environmental (E), social (S), and governance (G) sub-indices, as well as the uncertainty sub-index, scaled from 0 (minimum) to 100 (maximum). According to Ongan et al. (2025), the monthly global index is constructed from the country-level ESGUI indices of 25 sampled countries, aggregated into a global ESGUI index based on the relative GDP weights of individual countries. This index adequately captures systemic sustainability uncertainty at the global level. To capture market-based clean technology development, clean energy technology equities with a substantial technology-oriented composition are used as a proxy for clean technology (CTECH) development from a financial market perspective. This is represented by the monthly average stock price of the NASDAQ Clean Edge Green Energy Index (CELS), expressed in US dollars and sourced from www.investing.com. The index tracks the market valuation of a basket of publicly traded clean-technology companies, thereby capturing investors' sentiment towards innovative clean energy firms. Oil futures (OIL) refer to Crude Oil WTI Futures, which serve as a continuous front-month proxy for the WTI futures contract. The quote is expressed in US dollars per barrel and sourced from www.investing.com. Although there is no explicit roll methodology, the series follows standard market practice by rolling to the nearest contract before expiration. Oil futures and clean technology stock prices are pure financial variables. So, they are transformed into their logarithms to stabilize variance and reduce non-normality in their statistical properties. The uncertainty index is an index construction and is therefore retained in level form. Wavelet coherence focuses on time-frequency co-movement, unlike other regression methods that estimate parameter magnitudes, so mixed transformation does not affect estimation results. However, to address any concerns, Appendix provides supplementary results in which all variables are subjected to the same transformation.

This analysis is extended to test the coherence between clean technology prices and other uncertainty indices. This allows us to validate the consistency of clean technology development under different forms of uncertainty and to compare the performance of the ESGUI index with other uncertainty measures. These include global economic policy uncertainty (GEPU), climate policy uncertainty (CPU), and geopolitical risk (GPR). According to Gavriilidis (2021), climate policy uncertainty measures uncertainty related to global climate change, climate policy, and the introduction of new emissions legislation. The averaged monthly indices are normalised to a mean value of 100. Global economic policy uncertainty is a GDP-weighted average of national EPU indices, normalised to a mean of 100 (Davis 2016). It reflects the frequency of the terms economy (E), policy (P), and uncertainty (U) in newspaper articles each month. The geopolitical risk index is the share of news articles related to tensions or adverse geopolitical events in the total number of news articles (Iacoviello and Caldara 2020). All indices were obtained from www.policyuncertainty.com.

Figure 2 provides a pictorial representation of the variables. The sustainability uncertainty index fluctuated around its mean until early 2025, when there was a sharp rise in sustainability uncertainty. The prominent spikes observed between late 2024 and early 2025 in the uncertainty indices indicate divergence in transition strategies, geopolitical tensions, increased economic uncertainty, and climate policy shifts resulting from major climate impacts. For example, 2024 was declared the world's warmest year on record by the World Meteorological Organization (WMO). Geopolitical risk subsided after a significant spike in early 2022, which is linked to the Russian–Ukrainian war. There was a slight increase in clean energy technology stock prices in 2014 and mid-2015, but the most notable increase occurred in 2020. The rise in 2020 is associated with the global shift towards technology due to the health crisis, after which stock prices fluctuated steadily in a downward trend. Oil futures recorded a marked decline in 2020, which is also attributed to the global health crisis. The sharp increase in clean technology prices and

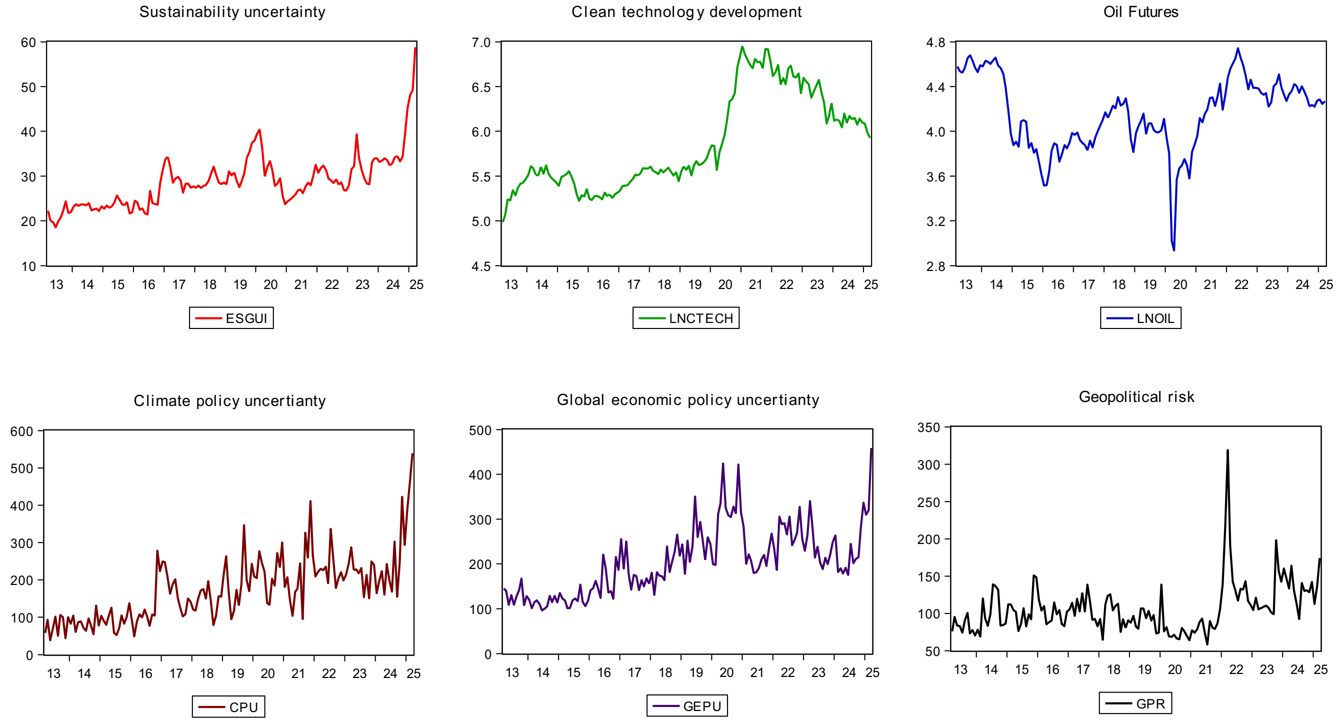

FIGURE 2 | Plots of data series.

TABLE 1 | Descriptive statistics.

	ESG	LNCTECH	LNOIL	GEPU	CPU	GPR
Mean	28.715	5.863	4.158	204.781	173.175	105.822
Median	28.262	5.606	4.192	195.582	163.967	101.140
Maximum	58.801	6.951	4.742	458.715	539.370	318.950
Minimum	18.548	4.985	2.936	96.495	38.092	58.420
Std. Dev.	5.921	0.533	0.328	74.585	87.681	33.239
Skewness	1.559	0.562	−0.617	0.721	1.094	2.411
Kurtosis	7.822	1.919	3.804	3.307	4.966	14.094
Jarque-Bera	199.196***	14.694***	13.107***	13.126***	52.271***	884.093***
Prob.	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Observations	145	145	145	145	145	145

Note: ***Significance of the Jarque-Bera Statistics at 1%. Jarque-Bera *p*-values are in parentheses.

the sharp fall in oil futures during the same period support the theoretical explanation of the substitution relationship between the two (Henriques and Sadorsky 2008). Overall, there is no consistent trend across all variables.

The descriptive statistics of the variables are shown in Table 1. The standard deviation values indicate that clean energy technology exhibits greater volatility than oil futures. The sustainability uncertainty index displays the lowest variation among all the uncertainty indices. Additionally, while the log of oil futures is negatively skewed, the other variables have positive skewness within an acceptable range. However, the uncertainty indices and the log of oil futures exhibit excess kurtosis, indicating that the data distribution is highly peaked. Transforming clean technology prices and oil futures into their logarithmic forms reduced their variance and the abnormalities typical of financial price series. Overall, the significance of all Jarque-Bera statistics indicates that the variables remain characterised by non-normality.

3.3 | Methodology

The estimation follows the procedure of wavelet analysis and partial wavelet analysis as demonstrated in Wu et al. (2020). The wavelet transform is generally suitable for analysing the interrelationships between nonstationary time series. This method provides information about the co-movement between two economic variables across different times and frequencies (Kirikkaleli and Athari 2020). Thus, it accounts for structural changes in the data series and is efficient when dealing with nonnormality, nonlinearity, volatility clustering, and trends (Ramsey 2002). The time-varying and frequency dynamics of the wavelet coherence between two time series, X and Y, are presented in a visual plot. The model of a cross-wavelet transform (XWT) of two time series X_n and Y_n can be written as follows:

$$W^{XY} = W^{X} W^{Y*} \tag{1}$$

where * represents complex conjugation (Grinsted et al. 2004).

Following Torrence and Compo (1998) and Grinsted et al. (2004), the squared absolute value of normalising a wavelet cross-spectrum to a single wavelet power spectrum can be obtained from the squared wavelet coherence equation as follows:

$$R_n^2(s) = \frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^{X}(s)\right|^2\right)\cdot S\left(s^{-1}\left|W_n^{Y}(s)\right|^2\right)} \tag{2}$$

In Equation (2), S denotes the smoothing parameter in scale and time frequency, and it is expressed as follows:

$$S(W) = S_{\text{scale}}\left(S_{\text{time}}\left(W_n(s)\right)\right) \tag{3}$$

The estimated wavelet coherence value is denoted as $R_n^2(s)$ for which $0 \le R_n^2(s) \le 1$ (Torrence and Compo 1998), whereby correlation between two series ranges between 0 (no correlation) and 1 (strongest correlation) (Kirikkaleli 2021). The degrees of correlation between the data series are indicated by shades of colour ranging from blue (zero values or no relationship) to red (strong correlation). The closer the colour is to red, the stronger the correlation, and vice versa. Statistical significance is indicated by a black line surrounding an area.

The phase difference distinguishes a positive relationship from a negative one (Torrence and Compo 1998; Pal and Mitra 2019). This allows the type of relationship between the variables to be determined. Equation (2) is further specified as:

$$\o_{XY}(s) = \tan^{-1}\left(\frac{L\left\{S\left(s^{-1}W_{XY}(s)\right)\right\}}{O\left\{S\left(s^{-1}W_{XY}(s)\right)\right\}}\right) \tag{4}$$

where $\o_{XY}(s)$ refers to the estimated wavelet coherence value through the phase difference between the two series at time and scale, while L and O respectively refer to the imaginary and real part operators. The wavelet coherence phase difference estimates are portrayed by the black arrows in a bi-dimensional plot. Where there is a positive correlation between two series, the arrows point towards the right. The evolution of wavelet coherence phase difference is zero, and the two series move together for that particular scale (Pal and Mitra 2019). Where the arrows point towards the left, the evolution of wavelet coherence phase difference is $-180°$. There is a negative correlation between the series; this indicates an anti-phase, that is, the two series move in opposite directions on that particular scale. Where the arrow points downward, the evolution of wavelet coherence phase difference is $-90°$. It indicates that the first series leads the second series in the relationship. Where the arrow points upward, the evolution of wavelet coherence phase difference is $+90°$. This indicates that the second series leads the first series in the relationship. A direction of the arrow towards the bottom-right or top-left indicates the lead role on the first variable, while an arrow that points towards top-right or bottom-left indicates the lead role of the second variable (Lee et al. 2024).

The study further examines the time-frequency dependence of the relationships between uncertainty and technology, taking into account the influence of mutually associated factors. This is done through partial wavelet coherence analysis, which assesses co-movement between two series, X and Y, by controlling for the influence of a third series, Z (Mihanović et al. 2009). In accordance with Mihanović et al. (2009), the partial wavelet coherence (PWC) equation is expressed as:

$$RP_n^2(x,y,z) = \frac{\left|R_n^{xy} - R_n^{xz}\cdot R_n^{(zy)*}\right|^2}{\left(1-\left(R_n^{xz}\right)^2\right)\left(1-\left(R_n^{zy}\right)^2\right)} \tag{5}$$

In Equation (4), $RP_n^2(x,y,z)$ refers to the estimated partial wavelet coherence for which $0 \le RP_n^2 \le 1$. It shows the dominance level of the y series in the x variance. If higher values are observed in the regions of high wavelet coherence squared, R^2, this implies an important covariance between y and x at that time and scale, and y has a more independent influence on x than z. Otherwise, lower values imply that time series y has less or no independent influence on x at that time and frequency space; instead, the effects of time series z dominate the variance in the x series (Ng and Chan 2012). According to Mihanović et al. (2009), x can be influenced by both y and z if both partial coherences have significant bands (but not necessarily very high). In this study, x denotes the uncertainty indices (ESGUI, GEPU, CPU, and GPR), y denotes clean energy technology (CTECH), and z represents oil futures (Oil). Therefore, we examine the co-movement between clean energy technology and uncertainty after controlling for the influence of oil futures.

4 | Empirical Results

4.1 | Correlation Analysis

The relationships under examination are first contextualised in a correlation matrix presented in Table 2. This indicates that clean energy technology investment may have a positive relationship with the uncertainty indices. There is no significant evidence that oil futures have a negative correlation with sustainability uncertainty. As expected, increases in climate policy uncertainty, geopolitical risk, and economic policy uncertainty may raise sustainability uncertainty. The formal investigation of these relationships is conducted using wavelet analysis. Before this, the stationarity properties of the variables were verified using multiple unit root tests, including the conventional ADF and PP tests, the modern DF-GLS test, and the Zivot–Andrews test, which accounts for structural breaks. The results are presented in Tables A1–A3 in Appendices A–C. Although the wavelet procedures conveniently handle non-stationarity, the base estimation preserves long-run information by estimating the variables in levels, while the stability of the main findings is corroborated by first difference estimations.

TABLE 2 | Correlation matrix.

Probability	ESGUI	LNCTECH	LNOIL	GEPU	CPU	GPR
ESG	1.000					
	—					
LNCTECH	0.311***	1.000				
	(0.000)	—				
LNOIL	−0.041	0.271***	1.000			
	(0.626)	(0.001)	—			
GEPU	0.631***	0.542***	−0.171**	1.000		
	(0.000)	(0.000)	(0.039)	—		
CPU	0.759***	0.541***	−0.006	0.704***	1.000	
	(0.000)	(0.000)	(0.941)	(0.000)	—	
GPR	0.321***	0.199**	0.284***	0.116	0.233***	1.000
	(0.000)	(0.016)	(0.001)	(0.164)	(0.005)	—

Note: *** and *** indicate the significance of correlation coefficients at 1% and 5% levels of significance. *p*-values are in parentheses.

Following the approach of Wu et al. (2020), the first step involves considering the wavelet coherence between clean energy technology stock prices and sustainability uncertainty as a benchmark, before assessing the influence of oil futures. Using the same procedure, this analysis was compared to the performance of other measures of uncertainty. The uncertainty indices were estimated in index form; however, for more robust evidence, their estimations after conversion to their natural logarithm forms are provided in Figures A1–A8 in Appendices D–K, respectively.

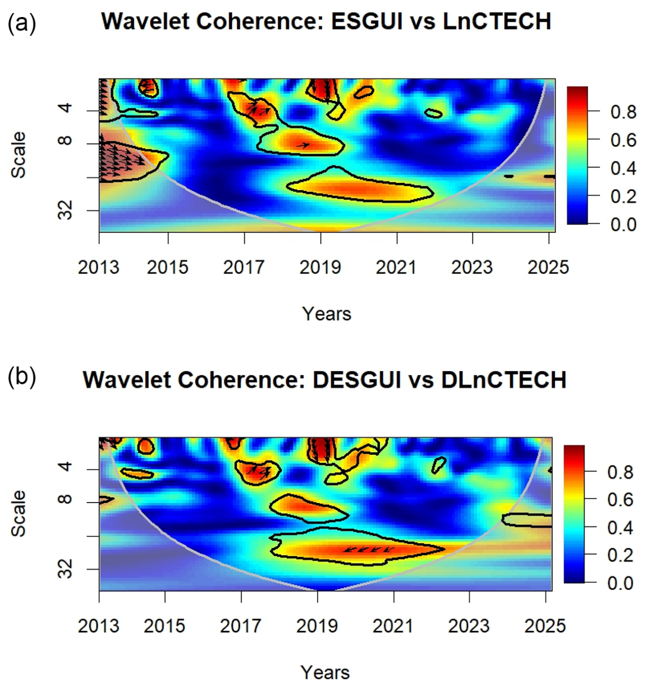

FIGURE 3 | (a) Wavelet coherence plot between the sustainability uncertainty index and clean technology price. (b) Wavelet coherence plot between the differenced sustainability uncertainty index and clean technology price.

4.2 | Co-Movements Between the Sustainability Uncertainty and Clean Energy Technology

The wavelet coherence map in Figure 3a shows the wavelet coherence between clean energy technology stock prices and sustainability uncertainty. The correlation varies over time and frequency. Strong and significant co-movement is concentrated at higher and medium frequencies, indicating more short- and medium-term co-movements during the period examined. These are evident around 2013–2015 and 2017–2020, with a weak but significant coherence around 2022. These short-run dynamics can be attributed to the signal effect from increased climate change concerns, greater global awareness of climate change, oil price decline, and major actions to promote green growth, which signalled optimism and growth in sustainable finance. A strong and significant long-term co-movement between sustainability uncertainty and clean energy technology is observed from 2018 to 2022. This reflects the policy and structural shifts towards sustainable system adoption that led to alignment between sustainability uncertainty and clean technology. The pattern of co-movement indicates an initial anti-phase movement, that is, a negative relationship in the earlier period, around 2015. However, the later years show an in-phase movement, indicating a positive relationship between the two variables. At high frequencies, changes in clean energy technology slightly led the negative and positive relationships with sustainability uncertainty around 2014–2015 and 2017–2019, respectively. However, by 2019, changes in sustainability uncertainty took a more significant lead, as the arrows pointed completely downwards in the short-term. Rather than relying on visual inspection, the average phase differences over key regions were extracted and are presented in Table 3. This analysis is corroborated by the first-difference estimation shown in Figure 3b, which confirms the stability of the main findings. In general, there is a strong relationship between sustainability uncertainty and investment in clean energy technology during the identified periods.

This empirical analysis rejects the earlier hypothesis that there is no significant co-movement between clean energy technology equities and sustainability uncertainty across time and

TABLE 3 | Summary of the lead–lag relationship between sustainability uncertainty and clean technology.

Region	Time window	Scale band	Avg phase (°)	Interpretation
1	2014–2015	Short (2–8)	−1.800662	Anti-phase relationship; the clean technology leads.
2	2017–2018	Short (2–8)	0.87101	Positive co-movement; clean technology leads.
3	2019–2019	Short (2–8)	−1.094269	In-phase relationship, and the sustainability uncertainty leads. The pictograph reveals downward-facing arrows over this region; this suggests that the dynamics of their relationships over this region are mixed, but a positive co-movement is dominant.
4	2017–2021	Medium (8–16)	0.2567954	Positive and nearly synchronized co-movement, clean technology leads slightly.

Note: Decision rule: $-\frac{\pi}{2} < \varnothing < 0 \rightarrow$ in-phase, first variable leads; $\frac{\pi}{2} > \varnothing > 0 \rightarrow$ in-phase, second variable leads; $-\pi < \varnothing < -\frac{\pi}{2} \rightarrow$ anti-phase, second variable leads; $\pi > \varnothing > \frac{\pi}{2}$ $\rightarrow$ anti-phase, first variable leads.

frequency. The relationship is highly dynamic, varying over time from the short-term to the medium-term and long-term. The negative relationship observed in earlier periods indicates that rapid investment in clean technology could be associated with low levels of uncertainty in sustainability indicators during that time. Although this effect was short-lived, it can be linked to expectations arising from policy announcements and increased climate change awareness, which created a short-term adjustment. This confirms the expectation that investment in clean technologies leads to improved sustainability outcomes, as seen in previous empirical studies such as Wang et al. (2021), Hassan et al. (2022), and Hoque et al. (2025). However, the positive co-movement observed between sustainability uncertainty and clean technology stock prices from 2017 to 2019 suggests that sustainability uncertainty did not decrease as investment in clean technology increased during that period. This may be due to policy instability, a mismatch between supply and demand, and unpredictable environmental impacts of policies. Before that period, there was a significant shift in global energy policy, which shaped market expectations and may have caused market volatility. As sustainability requires long-term finance, the patterns of co-movement reflect market volatilities that could delay the long-term achievement of sustainability goals, despite increased investment in clean technology.

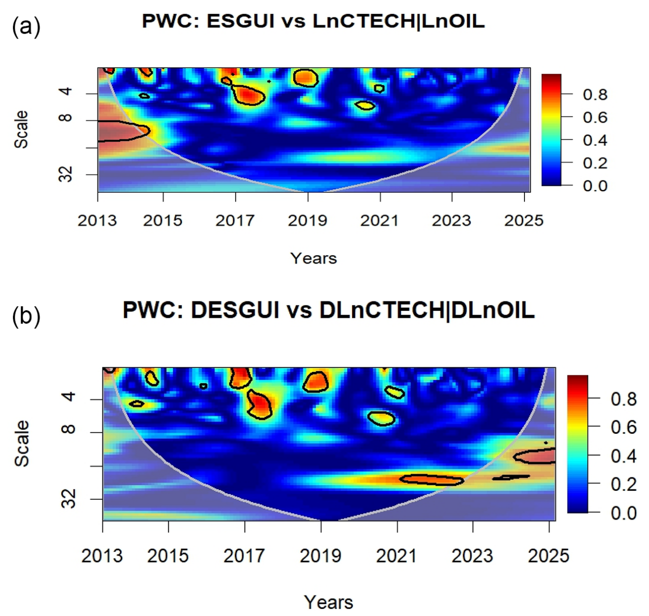

FIGURE 4 | (a) Partial wavelet coherence plot between the sustainability uncertainty index and clean technology price/oil futures. (b) Partial wavelet coherence plot between the differenced sustainability uncertainty index and clean technology price/oil futures.

4.3 | Partial Wavelet Coherence Between the Sustainability Uncertainty, Clean Energy Technology, and Oil Futures

This section examines the significance of the co-movement between sustainability uncertainty and clean energy technology when the effects of a confounding factor are eliminated. This requires holding oil futures constant to reveal the partial correlation between sustainability uncertainty and clean technology investment. The partial wavelet coherence after removing the influence of oil futures is shown in Figure 4a. Compared to Figure 3a, the relatively cool colours indicate a decline in the strength of coherence across time and frequencies. The significant regions have also decreased. While there is no significant region at lower frequencies, there are fewer significant regions at higher frequencies, particularly around late 2016–2017, 2018–2019, and late 2020–2021. This suggests the transmission of shocks between the oil and clean technology markets during those periods. Oil futures and clean technology equities both share explanatory power across the time and frequency domains; therefore, the coherence previously observed in the medium- and long-term dynamics of the relationship may have been driven by the influence of oil futures. This can also be associated with the shared transition dynamics that characterise these two factors. This indicates that technological progress matters more for sustainability only in the short term, but the relationship is not independent of the oil market in the medium term and long term. The partial wavelet coherence plot for the differenced variables is presented in Figure 4b.

4.4 | Co-Movements Between Climate Policy Uncertainty and Clean Energy Technology

Figure 5a shows the co-movement between climate policy uncertainty and clean technology indices. Significant strong coherence appears only at lower and medium scales. There is no evidence of a long-term relationship between climate policy uncertainty and clean technology prices. The co-movement pattern indicates a positive relationship, particularly from 2021 to 2024. During this period, climate policy uncertainty led the short-run movement between 2021 and 2022, while clean technology led the other movements. These co-movements are also confirmed by the calculated average phase differences presented in Table 4. Figure 5b shows the co-movement for the differenced variables.

4.5 | Partial Wavelet Coherence Between the Climate Policy Uncertainty, Clean Energy Technology, and Oil Futures

Figure 6a presents the time–frequency correlation between climate policy uncertainty and clean technology stock prices, controlling for the influence of oil futures. Coherence remains nearly the same across the lower and medium scales despite the influence of oil futures. This analysis demonstrates that oil has less explanatory power in the relationship between climate policy uncertainty and clean technology development than between clean technology and sustainability uncertainty. This is also corroborated in Figure 6b.

4.6 | Co-Movements Between Global Economic Policy Uncertainty and Clean Energy Technology

Figure 7a corroborated by Figure 7b, shows the wavelet coherence between the global economic policy uncertainty index and clean technology stock prices. The co-movement of these two variables is sparse in the short-term but concentrated in the medium- and long-term domains. High-frequency coherence is observed between 2019 and 2022, while medium- and low-frequency coherence is steadier, spanning 2017 to 2022. There are mixed directions of co-movement in the short-term, but the calculated average phase differences over key regions presented in Table 5 indicate a dominant positive co-movement led

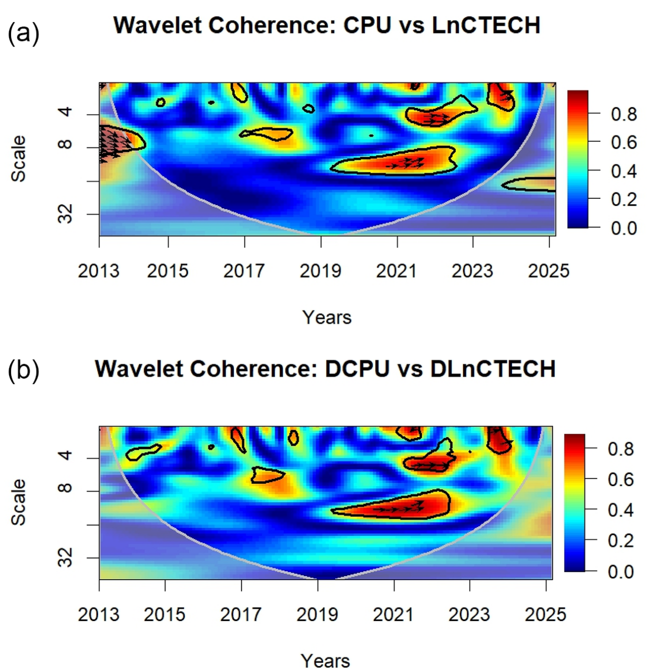

FIGURE 5 | (a) Wavelet coherence plot between the climate policy uncertainty index and clean technology price. (b) Wavelet coherence plot between the differenced climate policy uncertainty index and clean technology price.

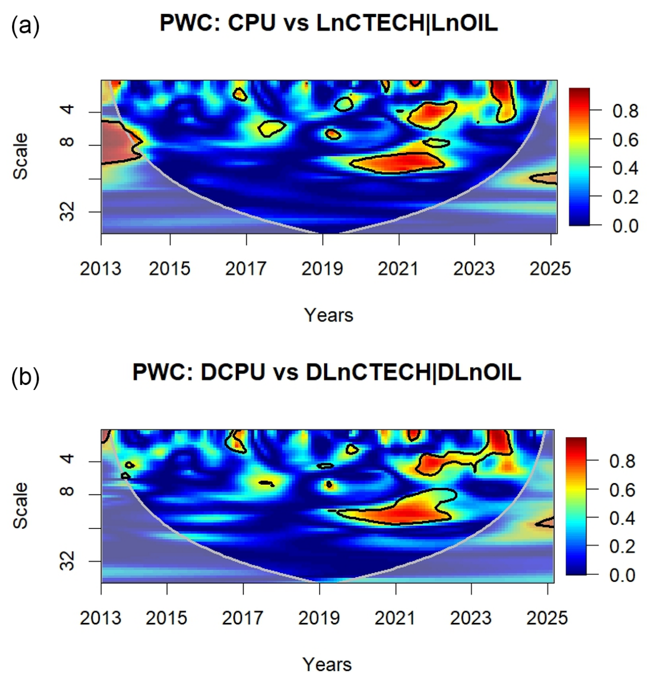

FIGURE 6 | (a) Partial wavelet coherence plot between the climate policy uncertainty index and clean technology price/oil futures. (b) Partial wavelet coherence plot between the differenced climate policy uncertainty index and clean technology price/oil futures.

TABLE 4 | Summary of the lead–lag relationship between climate policy uncertainty and clean technology.

Region	Time window	Frequency band	Avg phase (°)	Interpretation
1	2021–2022	Short (2–8)	−0.2720797	Nearly synchronized positive co-movement; climate policy uncertainty slightly leads.
2	2023–2024	Short (2–8)	0.4034545	Positive co-movement; clean technology leads.
3	2020–2022	Medium (8–16)	0.2626023	Nearly synchronized positive co-movement; clean technology slightly leads.

Note: Decision rule: $-\frac{\pi}{2} < ø < 0 \rightarrow$ in-phase, first variable leads; $\frac{\pi}{2} > ø > 0 \rightarrow$ in-phase, second variable leads; $-\pi < ø < -\frac{\pi}{2} \rightarrow$ anti-phase, second variable leads; $\pi > ø > \frac{\pi}{2}$ $\rightarrow$ anti-phase, first variable leads.

by clean technology. Similarly, clean technology led a nearly synchronous medium-term co-movement.

4.7 | Partial Wavelet Coherence Between the Global Economic Policy Uncertainty, Clean Energy Technology, and Oil Futures

When accounting for the effect of oil futures on the relationship between global economic policy uncertainty and clean technology, Figure 8a shows less coherence across time and frequency domains compared to Figure 7a. This indicates that the strong relationship between the two variables is significantly influenced by oil futures, especially in the short-term, while a medium- and long-term relationship is sustained between 2017 and late 2022. The result of the differenced variables in Figure 8b is quite similar. This suggests a direct long-term relationship between clean technology and economic policy uncertainty.

4.8 | Co-Movements Between Geopolitical Risk and Clean Energy Technology

Figure 9a,b shows relatively weak coherence between geopolitical risk and clean technology compared to other uncertainty indices. The high-frequency movement is relatively small, but there is more low-frequency co-movement. This demonstrates that geopolitical risk has a long-term relationship with clean technology.

4.9 | Partial Wavelet Coherence Between the Geopolitical Risk, Clean Energy Technology, and Oil Futures

Figure 10a,b shows that the coherence between geopolitical risk and clean technology is slightly reduced after accounting for the effects of oil futures. As with other uncertainty indices, oil futures may have driven the previously observed relationship.

4.10 | Implications of Findings

These results address the questions posed in this study. First, the study establishes a dynamic relationship between sustainability uncertainty and clean technology development from a financial market perspective. The two variables moved in opposite directions only between 2014 and 2015, a period that coincided with major sustainability commitments leading to the signing of the Paris Agreement; however, this relationship was

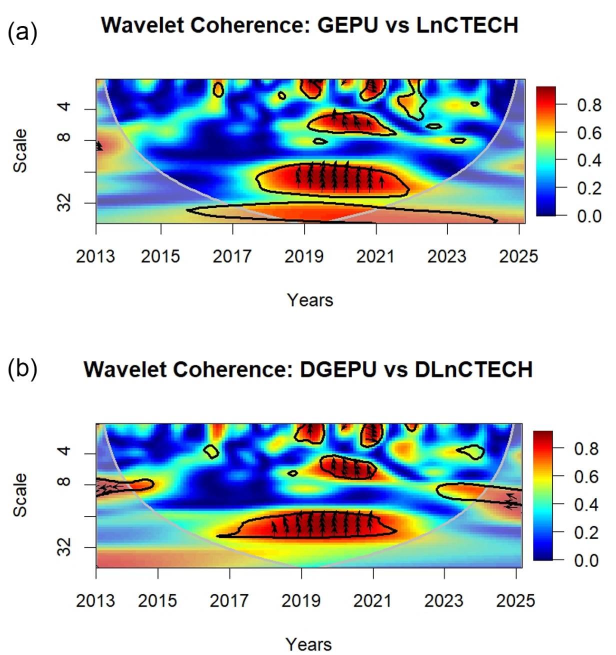

FIGURE 7 | (a) Wavelet coherence plot between the global economic policy uncertainty index and clean technology price. (b) Wavelet coherence plot between the differenced global economic policy uncertainty index and clean technology price.

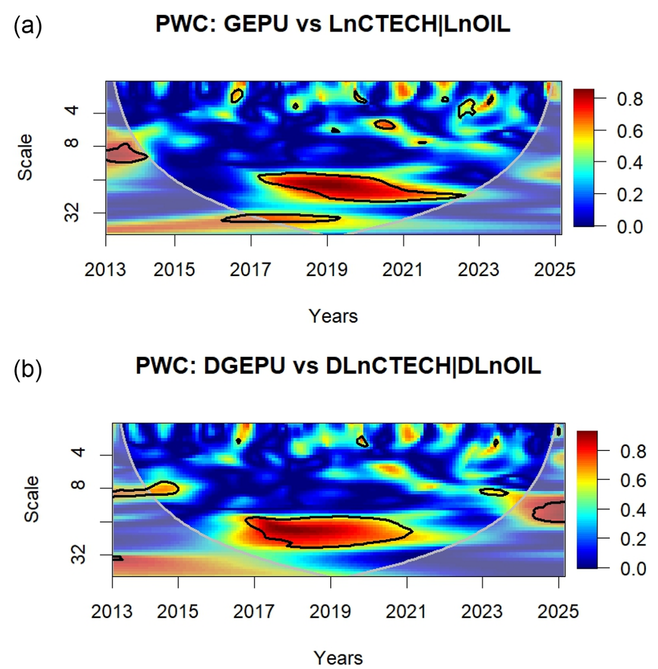

FIGURE 8 | (a) Partial wavelet coherence plot between the global economic policy uncertainty index and clean technology price/oil futures. (b) Partial wavelet coherence plot between the differenced global economic policy uncertainty index and clean technology price/oil futures.

TABLE 5 | Summary of the lead–lag relationship between global economic policy uncertainty and clean technology.

Region	Time window	Frequency band	Avg phase (°)	Conclusion
1	2019–2021	Short (2–8)	0.9505932	Positive co-movement; clean technology leads.
2	2018–2022	Medium (8–16)	1.543389	Positive co-movement; clean technology strongly leads.

Note: Decision rule: $-\frac{\pi}{2} < \o < 0 \rightarrow$ in-phase, first variable leads; $\frac{\pi}{2} > \o > 0 \rightarrow$ in-phase, second variable leads; $-\pi < \o < -\frac{\pi}{2} \rightarrow$ anti-phase, second variable leads; $\pi > \o > \frac{\pi}{2}$ $\rightarrow$ anti-phase, first variable leads.

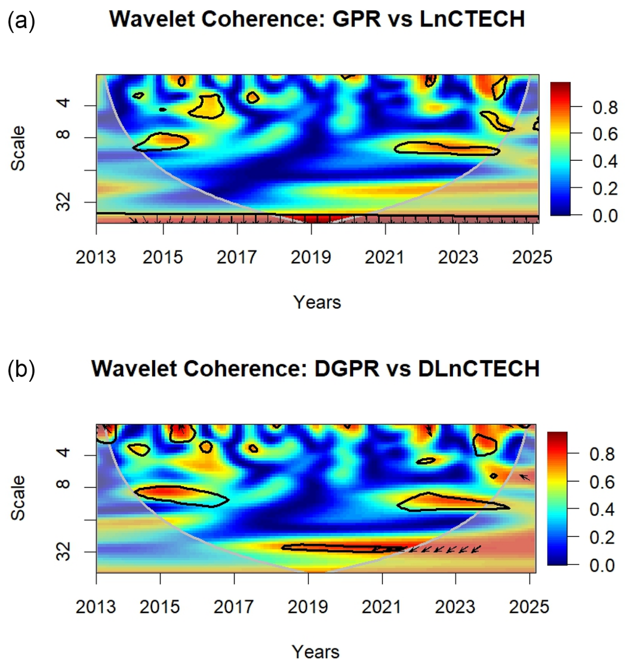

FIGURE 9 | (a) Wavelet coherence plot between the geopolitical risk index and clean technology price. (b) Wavelet coherence plot between the differenced geopolitical risk index and clean technology price.

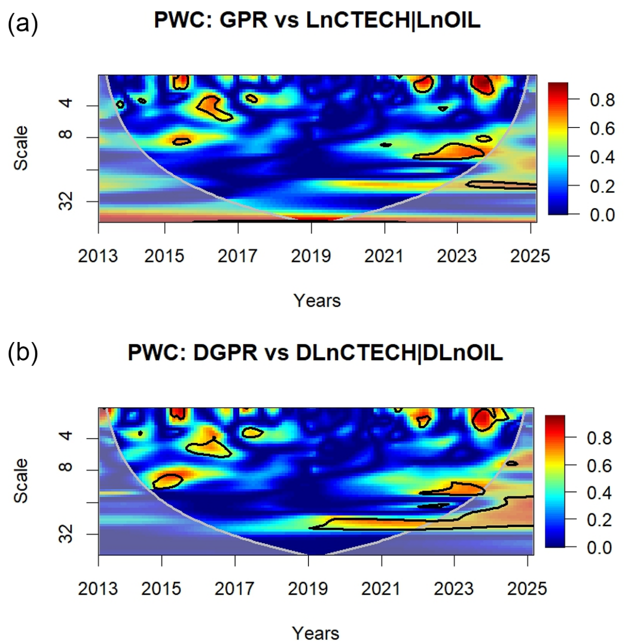

FIGURE 10 | (a) Partial wavelet coherence plot between the geopolitical risk index and clean technology price/oil futures. (b) Partial wavelet coherence plot between the differenced geopolitical risk index and clean technology price/oil futures.

short-lived at high frequency. After this period, sustainability uncertainty and clean technology have reinforced each other, with clean technology predominantly leading the relationship. Second, the results suggest that the evolution of sustainability uncertainty over time is driven by the leading influence of clean technology. The development of the clean technology sector was typically followed by increased sustainability uncertainty until after 2019, when both tended to synchronize and move almost simultaneously. Although there is no definitive lead–lag relationship in the long-term, the significant coherence observed between 2018 and 2022 suggests meaningful long-term synchronization between sustainability uncertainty and clean technology. Third, the relationship between sustainability uncertainty and technological progress may be dynamic, but it is partly driven by oil futures. This is reflected in the disappearance of some observed regions of relationship between clean technology and sustainability uncertainty after accounting for oil futures, especially in the medium- and long-term. Based on this, clean technology has an independent relationship with sustainability uncertainty only in the short-term.

The sustainability uncertainty index shows greater dynamism across time and frequency domains compared to the most commonly used uncertainty measures: climate policy uncertainty, economic policy uncertainty, and geopolitical risk. The results suggest that improvements in clean technology predominantly lead, while global economic policy uncertainty and climate policy uncertainty lag in their positive relationships throughout the periods. The relationship between geopolitical risk and clean technology is relatively weak, with no defined average phase for the significant regions. Unlike other indices, the relationship of climate policy uncertainty with clean technology is in the short- and medium-term. Similar to sustainability uncertainty, oil futures partly contribute to these relationships.

This result has implications for sustainability policy and investment. Market-based evidence suggests that clean technology stock growth can introduce temporary shocks to sustainability uncertainty, and vice versa. For policymakers, the dominant lead of clean technology stock prices observed in most results serves as a market indicator of a forward-looking market. The dominance of short-term and medium-term co-movement implies high investor sentiment and sensitivity to sustainability-related news. Investors may anticipate policy changes and make decisions before actual changes in uncertainty occur. Therefore, persistent uncertainty introduced by policy reforms could cause short-term shocks or an initial coordination challenge, creating short-run disturbances. Higher sustainability uncertainty is thus preceded by positive changes in clean technology stock prices. However, there are indicators that the positive lead relationship between clean technology development and sustainability uncertainty does not persist over time, and the effects dissipate. Sustainability uncertainty is therefore only transitory, induced mainly by the market signal effect; the system eventually adjusts to prevent a permanent long-run co-movement. However, the need for short-run stabilization policies cannot be overemphasized because short-term fluctuations remain significant. If the market is stable and attractive, clean technology stock indices can serve as a lever for efficient resource allocation, which in turn supports and strengthens sustainability plans. As this draws capital to the clean technology sector, growth in innovation can provide sustainable infrastructure and more stable solutions to recurring sustainability challenges that contribute to sustainability uncertainty. Therefore, uncertainty can be reduced by limiting the inconsistencies associated with policy reviews, as policy choices are capable of sending market signals that change investors' perspectives on sustainability. However, the shared influence of oil futures in this relationship suggests that unconventional energy markets still play a key role in sustainability outcomes, despite the widely acknowledged importance of clean energy technology sector development in sustainability plans.

For investors, while the clean technology sector signals high profitability due to policy support, they may not be completely protected from oil market shocks. However, the absence of persistent coherence offers diversification potential between clean technology and oil markets against transition shocks, oil price volatility, climate-related risks, and resulting policy changes.

5 | Conclusion

Uncertainties arising from environmental, social, and economic factors may delay the achievement of sustainable development goals, as they tend to undermine the stability of sustainability indicators. However, as innovation grows, sustainability strategies may improve, making sustainability outcomes more predictable. The novelty of this study lies in examining how the development of the clean technology sector shapes the trajectories of sustainability uncertainty, using data from March 2013 to March 2025. Wavelet coherence analysis was used to demonstrate the time-varying relationship between the sustainability uncertainty index (ESGUI) developed by Ongan et al. (2025) and clean energy technology stock indices. The effect of oil futures on this relationship was assessed using partial wavelet coherence analysis. The study also compares this relationship by representing uncertainty with other measures, including climate policy uncertainty, global economic policy uncertainty, and geopolitical risk. The results show that the relevance of clean technology stock prices to all uncertainty indices ranges from the short term to the long term, and oil futures partly explain all these relationships.

Specifically, the relationship between sustainability uncertainty and the clean technology stock index is highly dynamic, showing negative co-movement between 2014 and 2015, but positive co-movement thereafter. The prevailing time-lagged positive association indicates that market changes precede the emergence of uncertainty. This market-based evidence suggests that increased clean technology development can help predict higher sustainability uncertainty, particularly in the short-run. As market expectations naturally drive uncertainty, short-run coherence signals optimism and speculative activity. However, a significant portion of long-term relationships is explained by oil market expectations. Thus, the oil market continues to serve as the transmission channel for this dynamic relationship, influencing both investor expectations regarding energy market alternatives and sustainability.

Market stability is therefore crucial for managing sustainability uncertainty. Stability can be achieved by reducing shocks that impact new technology markets, such as regulatory shocks, oil market shocks, policy uncertainty shocks, and innovation shocks. Policy changes and regulations shape investors' commitment to allocating resources to sustainability-related firms, as their decisions are subjective and influenced by market sentiment. Signals of higher probability of profitability and stability will enhance sustainability finance.

Although this study offers new insights by examining the lead–lag relationship between innovation and sustainability from an uncertainty perspective, it has certain limitations. It provides only a financial market-based assessment of innovation development. Therefore, future research should extend the evaluation of clean technology effectiveness to other proxies for green innovation, which this study could not capture. In addition to oil futures, multiple factors can influence both investors' decisions and the effectiveness of clean technology, including interest rates, the equity risk premium, and economic policy uncertainty. These factors should be investigated in future studies to broaden the literature. Sustainability uncertainty may also be further predicted using other predictors, such as causality and impulse response analyses.

Author Contributions

Ifedolapo Olabisi Olanipekun: conceptualization, investigation, writing – original draft, methodology, visualization, writing – review and editing, formal analysis, data curation, resources, project administration.

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Appendix A

TABLE A1 | PP and ADF unit root test results.

	Level		First difference		
	Constant	**Constant and trend**	**Constant**	**Constant and trend**	**Conclusion**
PP test					
ESGUI	0.495	−1.154	−9.311***	−9.405***	I (1)
	(0.986)	(0.915)	(0.000)	(0.000)	
LNCTECH	−1.693	−1.072	−12.621***	−12.714***	I (1)
	(0.433)	(0.929)	(0.000)	(0.000)	
LNOIL	−2.461	−2.482	−10.119***	−10.239***	I (1)
	(0.127)	(0.337)	(0.000)	(0.000)	
CPU	−3.537***	−7.069***	—	—	I (0)
	(0.008)	(0.000)			
GEPU	−2.595	−5.134***	−17.670***	−17.668***	I (1)
	(0.096)	(0.000)	(0.000)	(0.000)	
GPR	−5.064	−5.523	−23.752***	−24.113***	I (0)
	(0.000)	(0.000)	(0.000)	(0.000)	
ADF test					
ESGUI	0.869	−0.448	−9.318***	−9.424***	I (1)
	(0.995)	(0.985)	(0.000)	(0.000)	
LNCTECH	−1.692	−1.061	−12.638***	−12.732***	I (1)
	(0.433)	(0.931)	(0.000)	(0.000)	
LNOIL	−2.833*	−2.893	−10.124***	−9.267***	I (1)
	(0.056)	(0.168)	(0.000)	(0.000)	
CPU	−1.828	−6.794***	−12.014***	—	I (1)
	(0.366)	(0.000)	(0.000)		
GEPU	−1.902	−3.537**	−16.354***	−16.335***	I (1)
	(0.331)	(0.039)	(0.000)	(0.000)	
GPR	−5.064***	−5.523***	—	—	I (0)
	(0.000)	(0.000)			

Note: ***, **, and * indicate the significance levels of the t-statistics at 1%, 5%, and 10%, respectively. *p*-values are in parentheses.

Appendix B

TABLE A2 | DF-GLS unit root test.

	Level		First difference		
Variable	**Constant**	**Constant and trend**	**Constant**	**Constant and trend**	**Conclusion**
ESGUI	−2.115	−2.115	−3.074**	−3.074**	I (1)
LNCTECH	−1.246	−1.246	−3.676 ***	−3.676 ***	I (1)
LNOIL	−1.588	−1.588	−6.358***	−6.358***	I (1)
CPU	−3.327**	−3.327**	—	—	I (0)
GEPU	−2.829*	−2.829*	−3.881***	−3.881***	I (1)
GPR	−3.761***	−3.761***	—	—	I (0)

Note: Critical values are −3.53 (1%), −2.93 (5%), and −2.65 (10%) for the model with constant and the model with constant and trend. ***, **, and * indicate a rejection of the null hypothesis of no stationarity at 1%, 5%, and 10%, respectively.

Appendix C

TABLE A3 | Zivot–Andrews test (one structural break).

Variable	Level		First difference		Conclusion
	Constant	Constant and trend	Constant	Constant and trend	
ESGUI	−2.098	−2.787	−9.747***	−10.288***	I (1)
	[2020M03]	[2023M05]	[2017M03]	[2023M04]	
LNCTECH	−3.555	−5.486**	−13.469***	−13.629***	I (1)
	[2020M04]	[2020M07]	[2021M02]	[2020M04]	
LNOIL	−3.832	−3.600	−8.045***	−8.276***	I (1)
	[2020M01]	[2015M07]	[2020M05]	[2020M05]	
CPU	−4.418	−5.140**	−12.239***	−12.698***	I (1)
	[2021M01]	[2023M05]	[2017M02]	[2023M04]	
GEPU	−4.646*	−4.283	−9.566***	−2.098***	I (1)
	[2021M01]	[2021M02]	[2020M06]	[2023M05]	
GPR	−7.020***	−7.051***			I (0)
	[2021M12]	[2021M12]			

Note: ***, **, and * indicate a rejection of the null hypothesis of no stationarity at 1%, 5%, and 10%, respectively. Break dates are in square brackets [ ]. Critical values are −5.34 (1%), −4.93 (5%), and −4.58 (10%) for the model with intercept only, and −5.57 (1%), −5.08 (5%), and −4.82 (10%) for the model with intercept and trend.

Appendix D

Co-movements between the sustainability uncertainty and clean energy technology after taking the log of the sustainability uncertainty index.

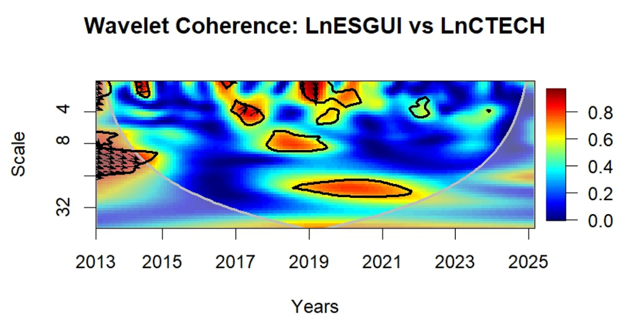

FIGURE A1 | Wavelet coherence plot between the sustainability uncertainty index and clean technology price (wavelet coherence: LnESGUI vs. LnCTECH).

Appendix E

Partial wavelet coherence between the sustainability uncertainty, clean energy technology, and oil futures after taking the log of the sustainability uncertainty index.

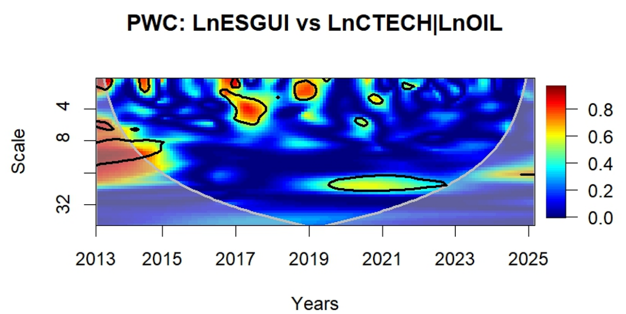

FIGURE A2 | Partial wavelet coherence plot between the sustainability uncertainty index and clean technology price/oil futures (PWC: LnESGUI vs. LnCTECH|LnOIL).

Appendix F

Co-movements between the climate policy uncertainty and clean energy technology after taking the log of the climate policy uncertainty index.

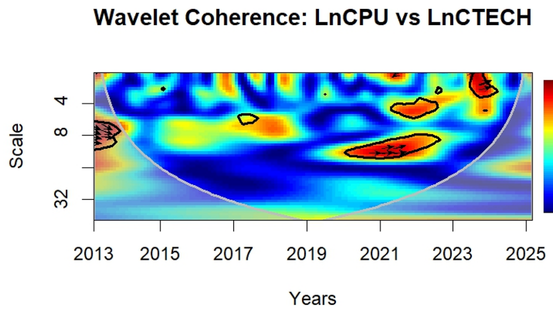

FIGURE A3 | Wavelet coherence plot between the climate policy uncertainty index and clean technology price (wavelet coherence: LnCPU vs. LnCTECH).

Appendix G

Partial wavelet coherence between the climate policy uncertainty, clean energy technology, and oil futures after taking the log of the climate policy uncertainty index.

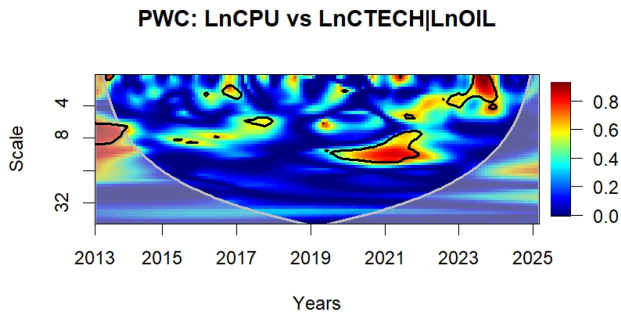

FIGURE A4 | Partial wavelet coherence plot between the climate policy uncertainty index and clean technology price/oil futures (PWC: LnCPU vs. LnCTECH|LnOIL).

Appendix H

Co-movements between the global economic policy uncertainty and clean energy technology after taking the log of the global economic policy uncertainty index.

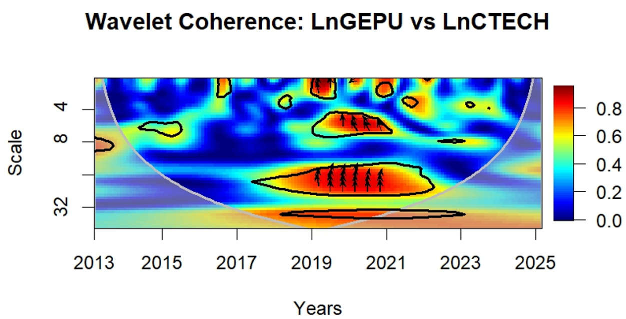

FIGURE A5 | Wavelet coherence plot between the global economic policy uncertainty index and clean technology price (wavelet coherence: LnGEPU vs. LnCTECH).

Appendix I

Partial wavelet coherence between the global economic policy uncertainty, clean energy technology, and oil futures after taking the log of the global policy uncertainty index.

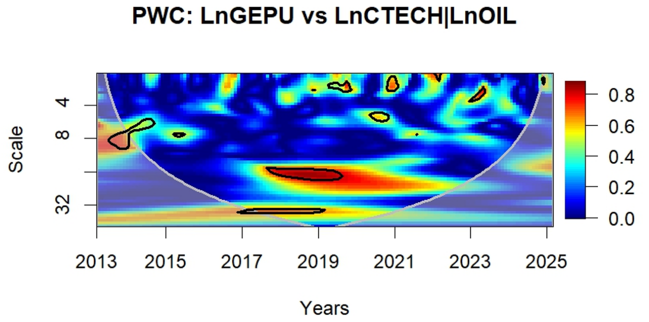

FIGURE A6 | Partial wavelet coherence plot between the global economic policy uncertainty index and clean technology price/oil futures (PWC: LnGEPU vs. LnCTECH|LnOIL).

Appendix J

Co-movements between the geopolitical risk and clean energy technology after taking the log of the geopolitical risk index.

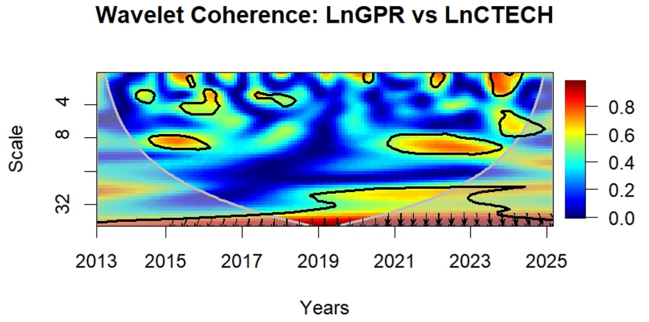

FIGURE A7 | Wavelet coherence plot between the global economic policy uncertainty index and clean technology price (wavelet coherence: LnGPR vs. LnCTECH).

Appendix K

Partial wavelet coherence between the geopolitical risk, clean energy technology, and oil futures after taking the log of the geopolitical risk index.

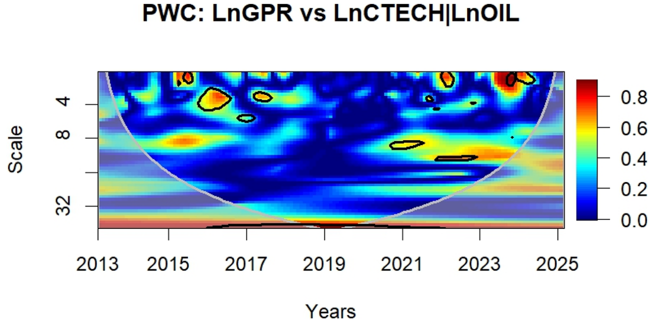

FIGURE A8 | Partial wavelet coherence plot between the geopolitical risk index and clean technology price/oil futures (PWC: LnGPR vs. LnCTECH|LnOIL).