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Time-varying bidirectional causality between climate policy uncertainty and renewable energy investments☆,☆☆

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ABSTRACT

Climate change poses a significant systemic risk in the twenty-first century, yet little attention has been paid to its interaction with renewable energy exchange traded funds (ETFs). This study employs the time-varying Granger causality approach to investigate the bidirectional causality between Climate Policy Uncertainty and Renewable ETFs, exploring how this relationship evolves over time. Monthly data spanning from January 2010 to June 2025 from the CPU index and the price of Renewable ETFs were used in this research. The results reveal a dynamic, time-varying, and asymmetric causal relationship between Climate Policy Uncertainty (CPU) and renewable energy ETFs. Strong causal effects are non-linear over time, with the influence of CPU on renewable ETFs intensifying after 2016, while the reverse causality from ETFs to CPU weakens after 2020. These findings emphasize the importance of exploring the relationship between CPU and renewable energy ETF prices. Understanding this interaction not only aids strategic decision-making and risk management for renewable energy investments but also fosters resilience against market fluctuations, driving the advancement of green finance initiatives. This study contributes to both climate change mitigation efforts and the development of sustainable finance strategies.

1. Introduction

Climate change is becoming a significant systemic risk for the world's society in the twenty-first century. For many years, policy actions have been taken to combat climate change, but there is still a great deal of uncertainty about how these initiatives will be implemented (Gavriilidis, 2021). Although the effects of climate change are widely acknowledged, there have not been clear government policies and regulations related to climate change and environmental protection, and thus attempts to reduce emissions are still in their infancy. These regulations, policies, initiatives, and activities result in uncertainties about climate change policies.

Climate Policy Uncertainty (CPU) significantly influences market dynamics, investment decisions, and economic decisions. In the study by Fried et al. (2021), the macroeconomic effects of climate policy were investigated, revealing that uncertainty in climate policy

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Table 1
Variables, sources, and references.

Variable	Source	Reference
Climate Policy Uncertainty Index (CPU)	https://www.policyuncertainty.com/climate_uncertainty.html	Gavriilidis (2021)
Global Climate Policy Uncertainty Index (GCPU)	https://figshare.com/articles/dataset/Global_Climate_Policy_Uncertainty_2000-2023_/24807627?file=49365187	Ma et al. (2024)
Invesco Solar ETF (TAN)	https://www.investing.com	N/A
First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN)	https://www.investing.com	N/A
VanEck Low Carbon Energy ETF (SMOG)	https://www.investing.com	N/A
iShares Global Clean Energy ETF (ICLN)	https://www.investing.com	N/A

Note: N/A means "Not Applicable".

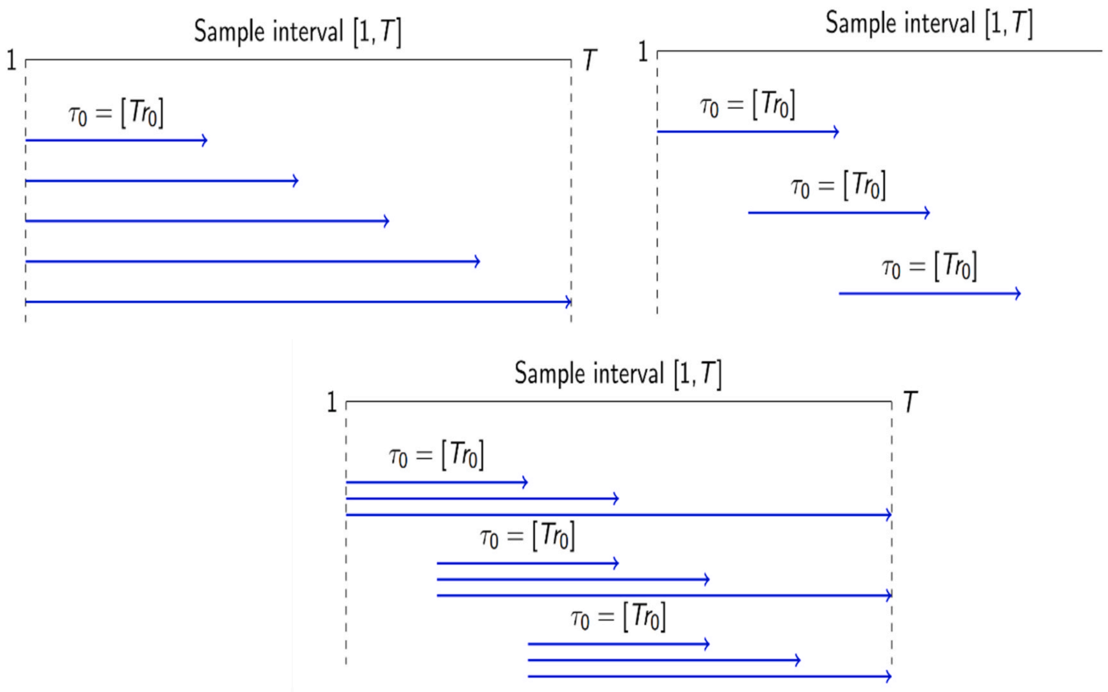

Fig. 1. Window widths and sample sequences. Taken from (Phillips et al., 2015).

decreases carbon emissions as capital stocks transition towards cleaner alternatives. Basaglia et al. (2022) highlighted that CPU impacts stock returns, volatility, research and development, patenting, and employment in firms. Ren, Shi, and Jin (2022) found that CPU negatively affects the mining industry but positively influences the electricity, heat, gas, and water sectors. According to Golub et al. (2020), CPU prompts firms to postpone sustainable climate investments, reduces current carbon pricing, and exposes firms to future risks. In a recent study, Lasisi et al. (2022a) showed that stock market volatility is significantly impacted by CPU. Similarly, Lasisi et al. (2022b) and Liang et al. (2022) studied the impact between renewable energy index volatility and CPU and concluded that CPU has a negative effect on the long-term volatility of the renewable energy index. CPU encourages the use of renewable energy sources while reducing the use of non-renewable energy (Shang et al., 2022). The study by Rodriguez Lopez et al. (2017) demonstrated that, in

Table 2
Summary statistics of the variables used in the research.

Variable	Min	Max	Mean	Median	SD	Skewness	Kurtosis
TAN ETF	2.6609	4.6885	3.6454	3.5579	0.5726	0.1633	−1.3687
QCLN ETF	2.1552	4.3804	3.0923	2.9331	0.5944	0.7131	−0.5998
SMOG ETF	3.3537	5.1734	4.2081	4.1048	0.4426	0.5016	−0.3865
ICLN ETF	1.8421	3.3945	2.4987	2.3716	0.3747	0.4784	−0.9794
CPU	3.6400	6.0193	4.8943	4.8712	0.4771	−0.1026	−0.6105
GCPU	3.342	5.588	5.588	4.612	0.4331	−0.1093	2.5100

Fig. 2. Time series graphs of the variables used in the research.

Table 3
Stationarity Test at level.

Variable	Test Statistic at Level	Test Statistics at First Difference	Outcome
CPU	−4.674**	−13.553**	I (0)
GCPU	−6.36**	−13.429**	I (0)
TAN	−1.721	−9.77**	I (1)
QCLN	−1.693	−10.032**	I (1)
SMOG	−1.891	−9.964**	I (1)
ICLN	−1.858	−9.888**	I (1)

Table 4
Cointegration test results.

Target	Variable	Test Statistic	Cointegrated
CPU	TAN	58.657	No
CPU	QCLN	81.646	No
CPU	SMOG	89.523	No
CPU	ICLN	61.614	No
GCPU	TAN	61.345	No
GCPU	QCLN	143.210	No
GCPU	SMOG	126.681	No
GCPU	ICLN	68.748	No

Table 5
Renewable energy ETFs → CPU, size control/windows = 12.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	12.601**	5.307/7.011/16.515	187.322***	24.027/39.041/82.962	187.322***	19.243/26.922/56.279
QCLN	5.230*	5.089/6.665/10.611	75.882***	20.055/35.605/73.657	75.882***	19.355/27.45/53.448
SMOG	4.266	5.537/8.028/12.021	55.363**	16.855/26.804/60.916	98.966***	18.671/25.863/51.939
ICLN	3.766	5.763/8.277/17.371	49.959**	17.399/29.308/66.377	49.959**	19.721/28.302/58.636

contrast to previous research, CPU may incentivize businesses to invest in reducing their ecological footprint. The body of research clearly demonstrates that CPU does affect stock market volatility.

Managing regular stock market volatility and coping with the uncertainty resulting from climate change legislation are the two difficulties that investors currently face in light of the literature demonstrating that CPU influences stock market volatility (Fuss et al., 2008). To properly manage the associated risks in the stock market, one must comprehend how CPU influences the various sectors of the market. Renewable Exchange-traded funds (ETFs) focused on renewable energy are becoming a popular way for investors to engage in sustainable financing on the stock market. In order to advance sustainable finance and combat climate change, these investments in renewable energy are essential. Investor interest in renewable energy is growing due to its ability to both address climate change and generate returns. According to predictions, renewable energy sources will be able to meet two-thirds of global energy needs by 2050, all the while lowering the emission of greenhouse gases (Gielen et al., 2019).

There has been a paucity of research on the relationship between CPU and renewable exchange-traded funds (renewable energy ETFs), despite the abundance of research on CPU's effects on stock markets. This study aims to fill the gap in the literature by establishing the causal relationships between renewable energy ETFs and climate policy uncertainty. The purpose of this study is to determine whether the price of renewable exchange-traded funds and CPU are causally related to one another through a comprehensive analysis on the bidirectional, time-varying causality between CPU and renewable energy EFT prices. The study will further determine whether there is a long-term stable relationship between the prices of CPU and renewable energy exchange-traded funds (ETFs).

2. Literature review

Much research on the connection between CPU, financial markets, and the economy have provided insights into the ways in which CPU influences and impacts various sectors of our everyday existence from the energy markets to business productivity and sustainable investment. For example, Ren et al. (2023) discovered an interesting dynamic between CPU and energy markets, demonstrating that this relationship is not constant but rather varies over time. According to their analysis, CPU has a more complex influence on energy markets that varies across different energy market sectors. Bouri et al. (2022) examined how CPU affects investor behavior in green and brown energy companies in a prior study. It was discovered, using the CPU index of Gavriilidis (2021), that CPU significantly influences investor preferences in favor of green energy investments during times of crisis. This knowledge is crucial for comprehending the ways in which CPU might affect investment strategy and asset price, particularly in times of market turbulence.

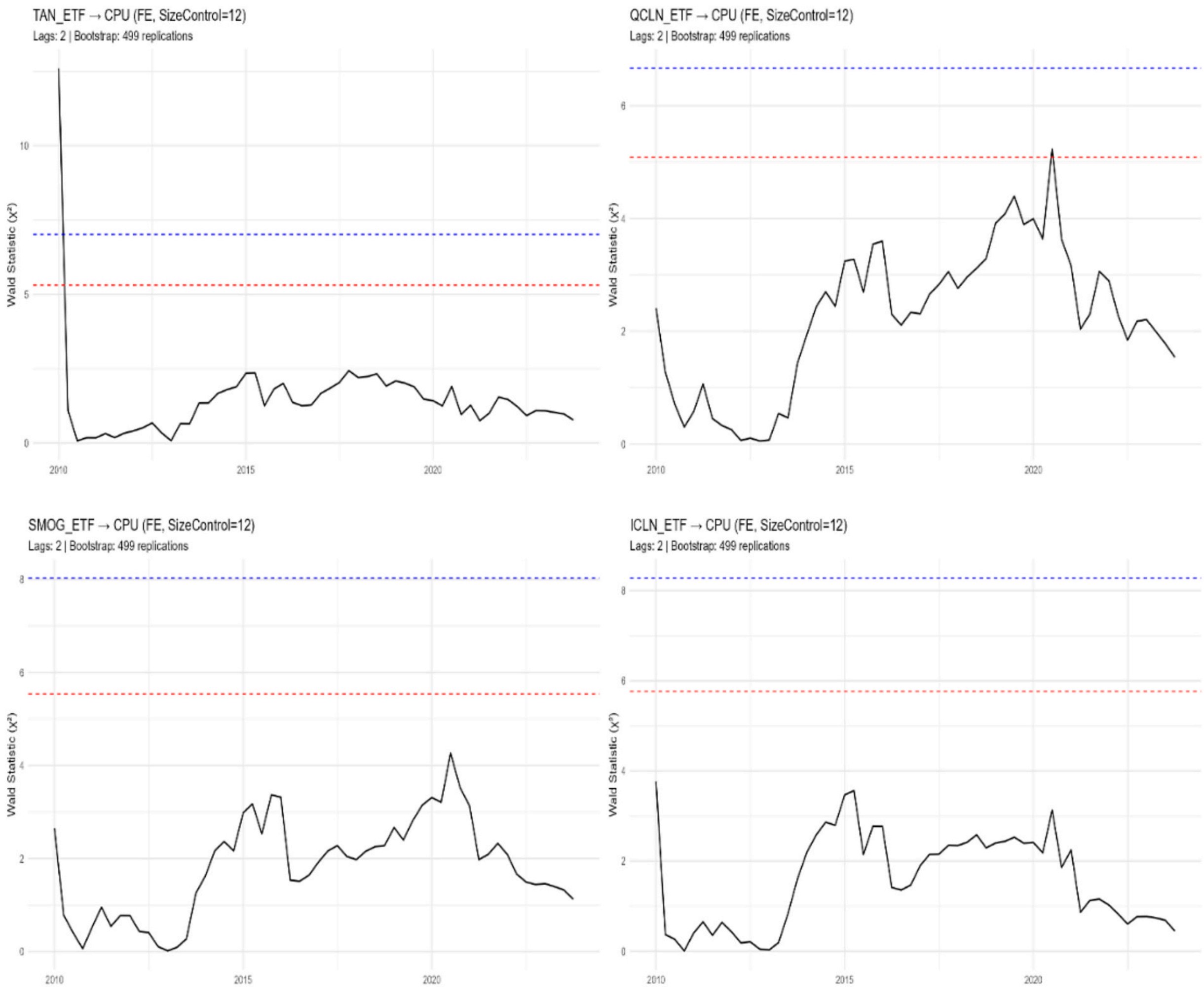

Fig. 3. Forward expanding: Renewable energy ETFs → CPU, size control/windows = 12.

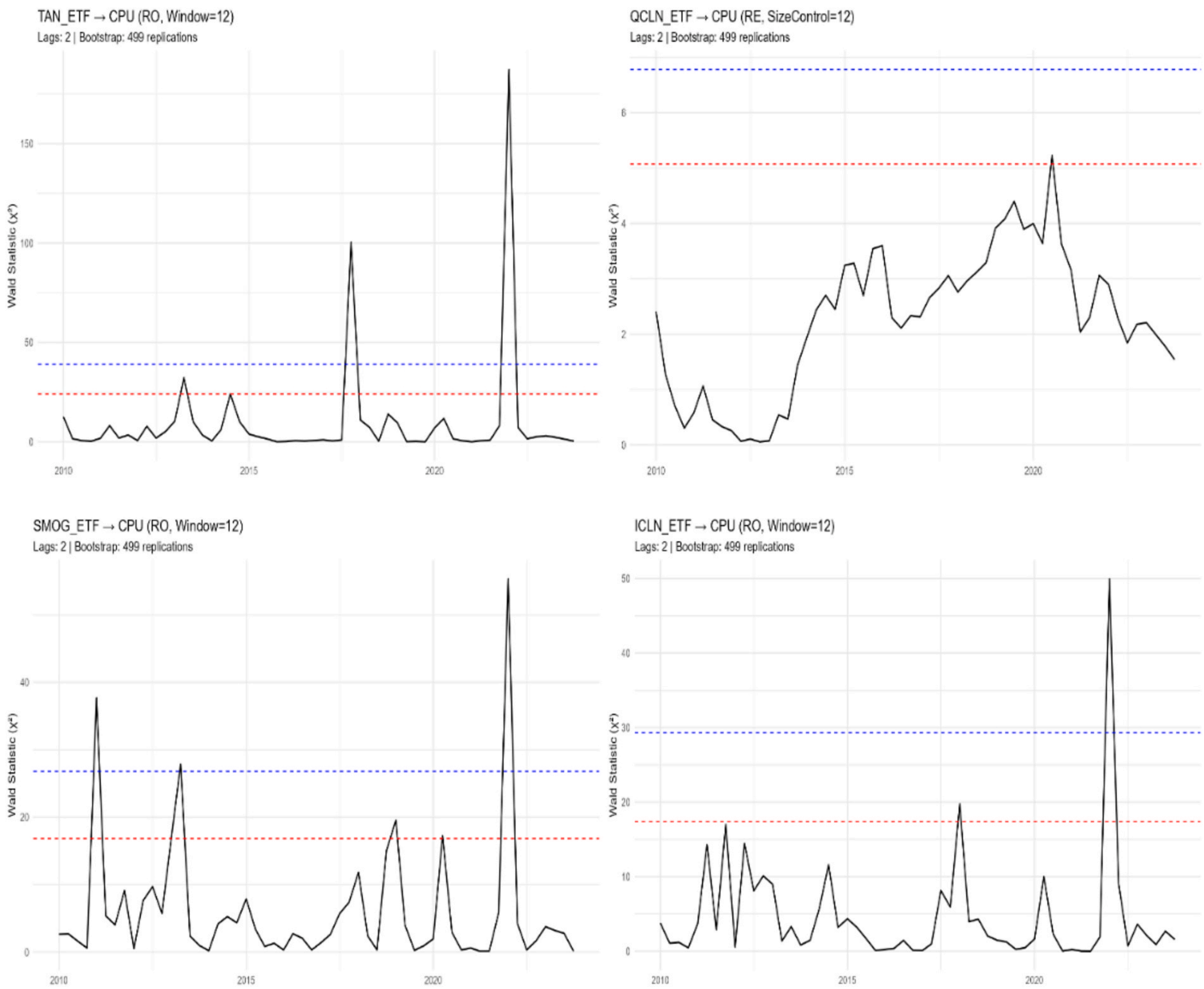

Fig. 4. Rolling window: Renewable energy ETFs → CPU, size control/windows = 12.

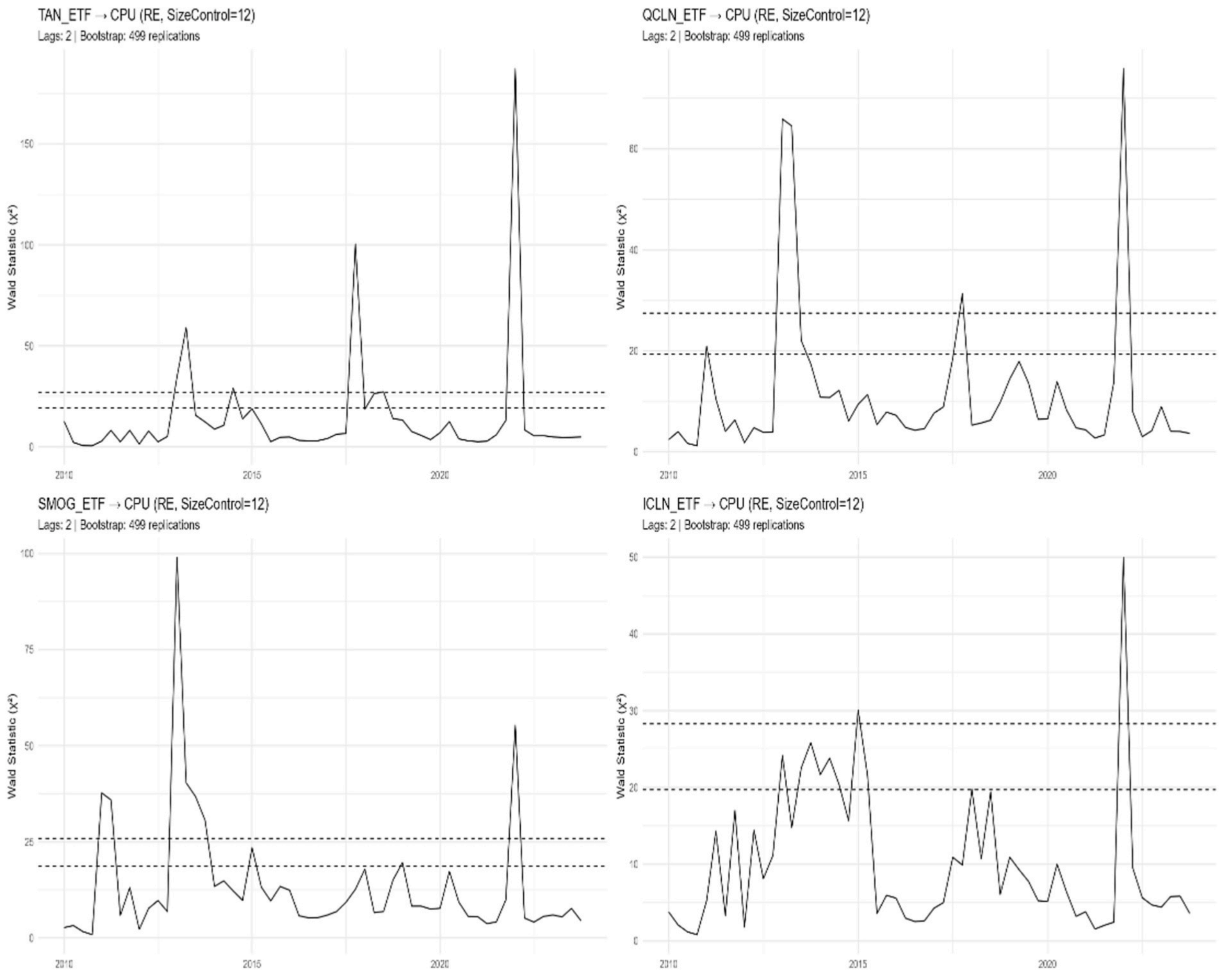

Fig. 5. Recursive expanding: Renewable energy ETFs → CPU, size control/windows = 12.

Table 6
Renewable energy ETFs → GCPU, size control/windows = 12.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	37.311***	5.537/7.972/12.537	37.311**	17.852/35.716/64.544	37.311**	20.359/29.843/67.381
QCLN	29.266***	5.42/7.168/11.265	41.354**	17.05/29.603/72.852	41.354**	19.427/28.296/53.732
SMOG	38.678***	5.653/8.001/12.681	38.678**	16.661/28.742/64.203	38.678**	18.518/26.635/55.913
ICLN	32.594***	5.75/7.775/13.546	32.594**	20.778/31.626/56.118	32.594**	19.711/28.374/55.65

The impact of CPU on productivity in several sectors of Chinese firms was investigated by Ren, Zhang, et al. (2022) at the firm level. According to their research, CPUs, particularly in specific kinds of businesses, can considerably lower total factor productivity. This decline in productivity is the result of tighter cash flows and lower R&D spending, highlighting the significant impact of climate policy uncertainty on innovation and corporate operations.

The study conducted by Guo et al. (2022) demonstrated that the relationship between CPU and energy prices is nonlinear rather than linear. This implies that the way energy prices react to differing CPU levels can also vary, which makes it more difficult for investors to navigate these unpredictable economic times. Sustainable investments are also affected by CPU. With an emphasis on the US market, Olasehinde-Williams et al. (2023) showed how CPU affects the volatility and returns of sustainable investments. The study highlighted the significance of well-defined policy goals and incentives in encouraging sustainable investments and reducing the adverse consequences of regulatory ambiguity. According to Dai and Zhang's (2023), CPU has a conflicting effect on Chinese banks in the banking industry. It seems to lower some risks, but it also raises the danger of insolvency, particularly for listed banks. This hidden effect emphasizes the necessity of carefully crafted climate measures that take financial institutions' unique vulnerabilities into account.

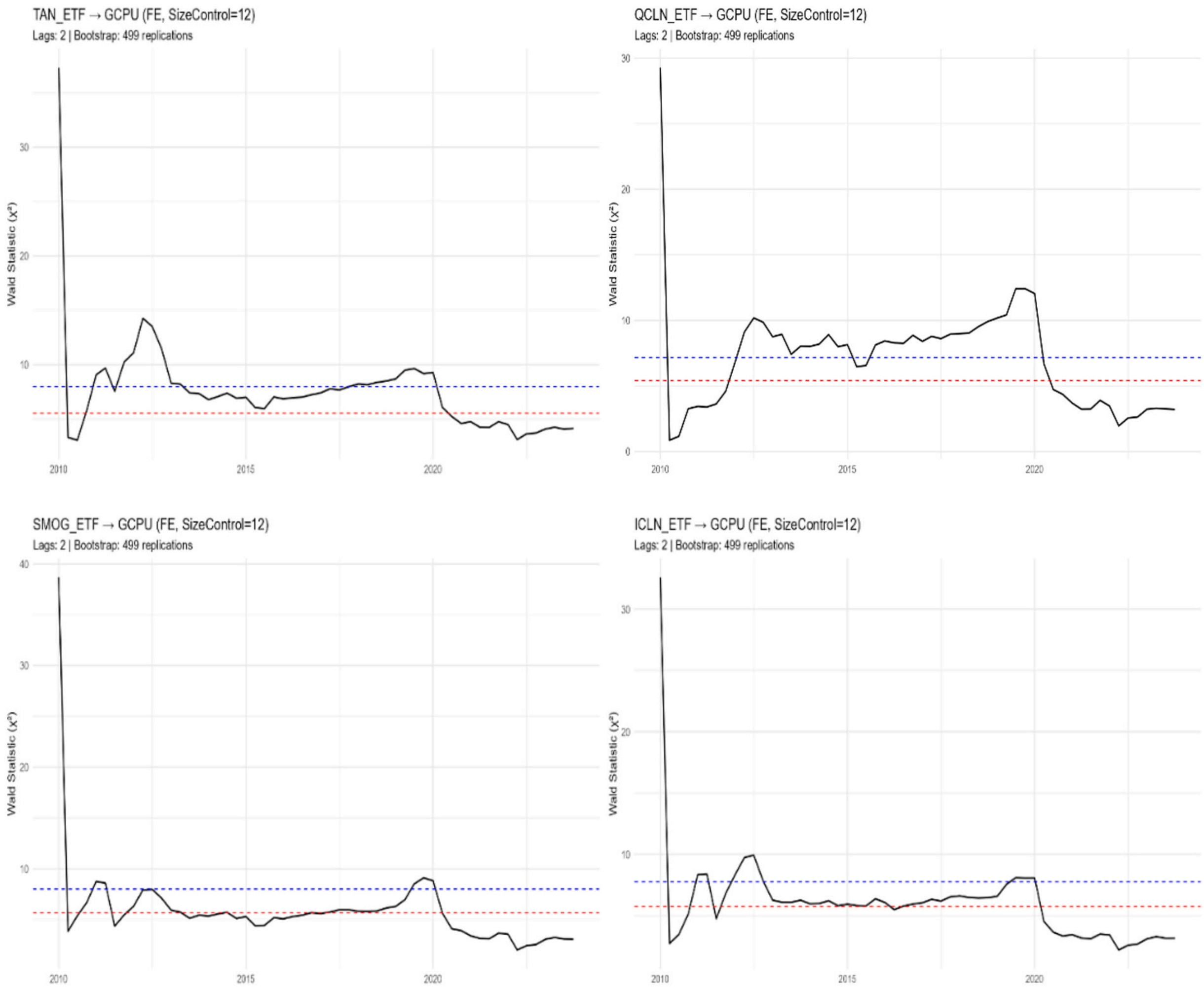

Fig. 6. Forward expanding: Renewable energy ETFs → GCPU, size control/windows = 12.

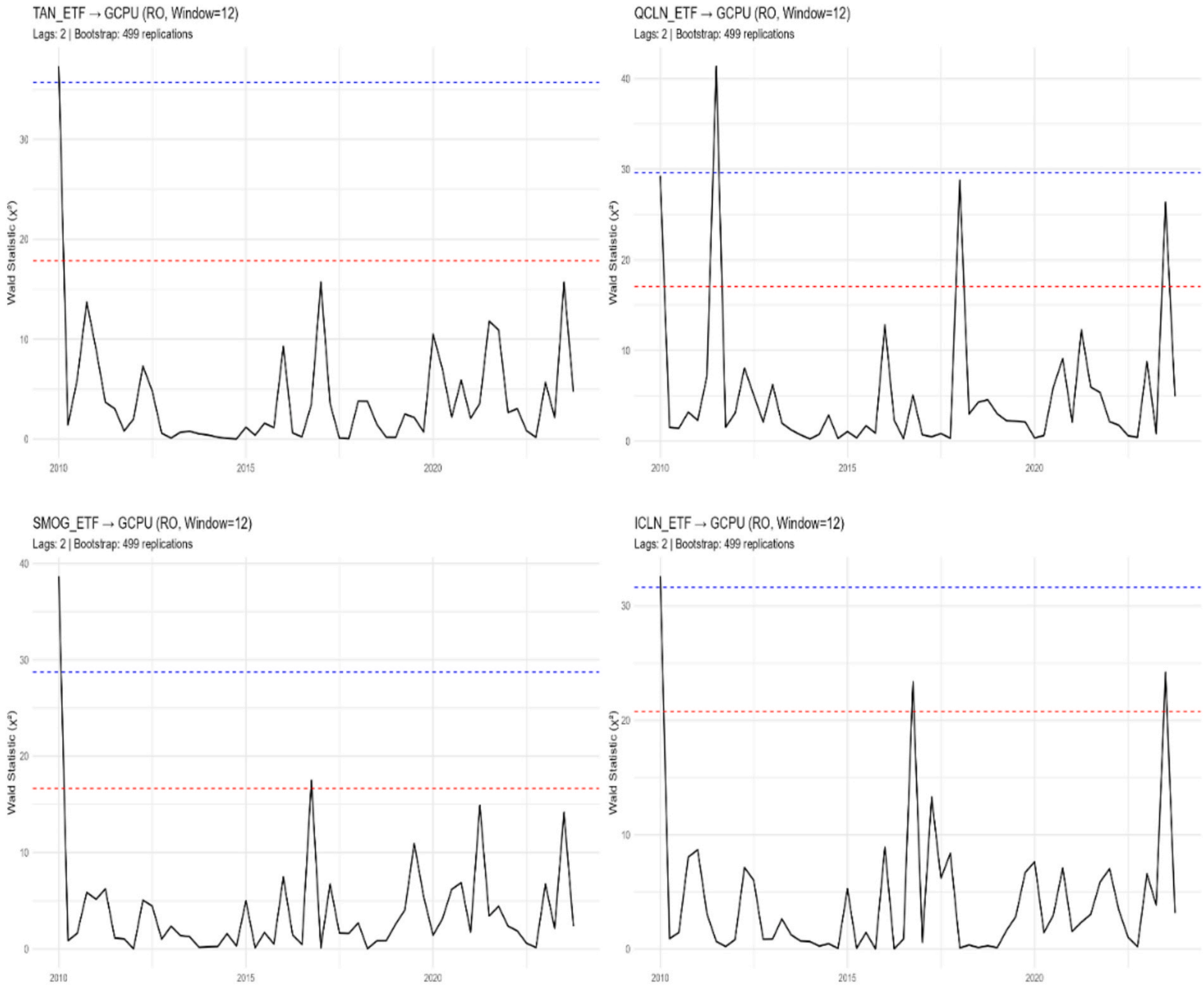

Fig. 7. Rolling window: Renewable energy ETFs → GCPU, size control/windows = 12.

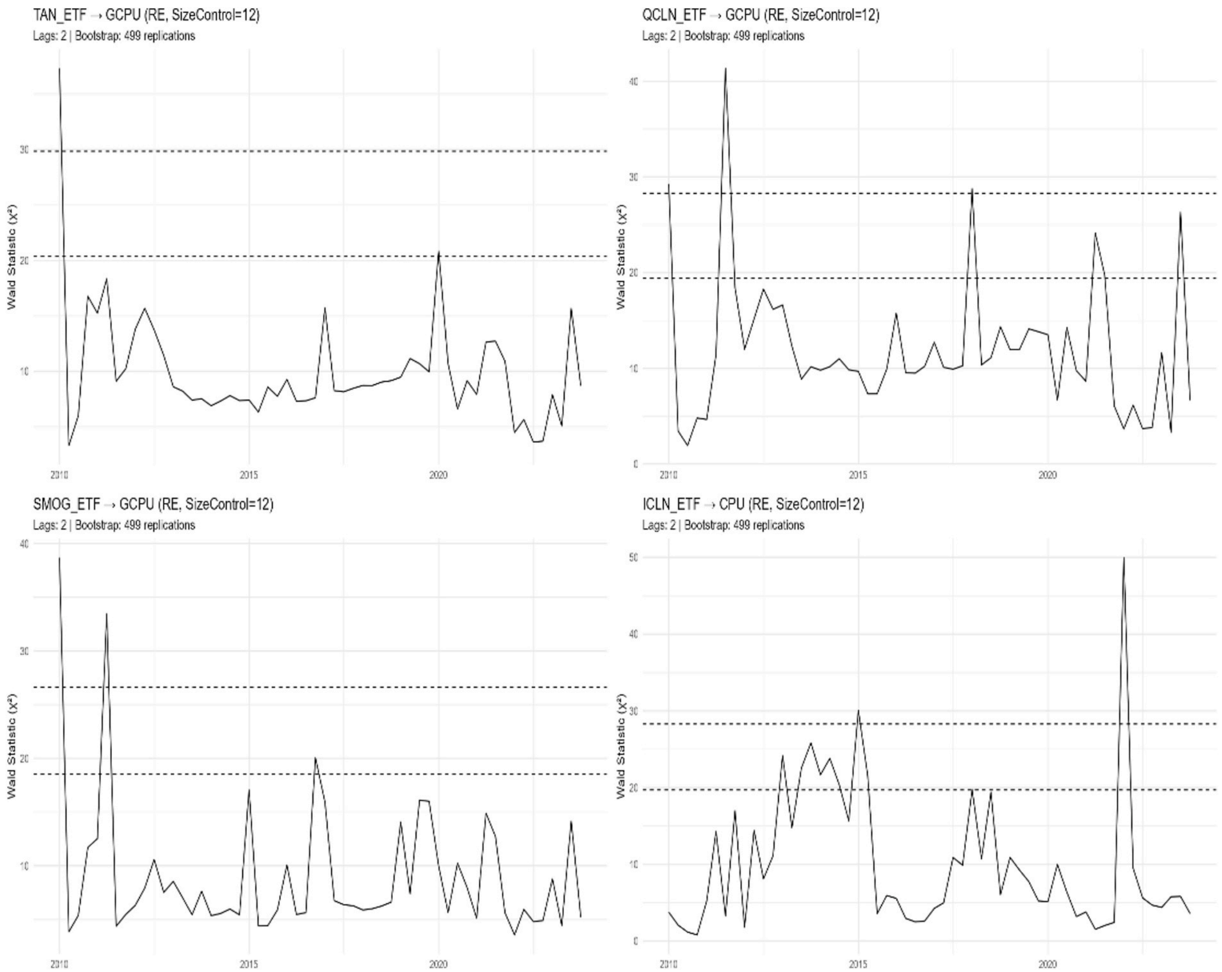

Fig. 8. Recursive expanding: Renewable energy ETFs → GCPU, size control/windows = 12.

Table 7
Renewable energy ETFs → CPU, size control/windows = 36.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	2.432	4.858/6.388/9.955	7.150*	6.402/8.888/14.784	9.372	9.731/12.464/19.16
QCLN	5.230*	4.633/6.158/10.2	14.420***	6.227/8.554/14.295	14.420**	9.938/12.863/20.169
SMOG	4.266	5.05/6.736/10.557	12.489**	6.46/8.836/15.007	15.096**	10.202/13.141/20.96
ICLN	3.563	5.212/7.062/10.715	18.264***	6.703/9.333/15.879	24.979***	10.603/13.545/21.253

The literature demonstrates the diverse effects of CPU on various economic environments. CPU is becoming increasingly important in our changing economic landscape, having an impact on everything from the stability of the banking sector to the dynamics of the energy market and investor behavior. All the evidence points to the need for consistent, transparent climate policies that promote sustainable development and economic stability. It also highlights how crucial it is to take CPU into account when making investment and asset allocation decisions. Understanding and tackling the difficulties brought on by the uncertainties surrounding climate policy will be essential as we manage the shift to a low-carbon economy in order to reduce economic disruptions and promote a resilient, sustainable future.

3. Data and methodology

In this study, the time-varying Granger causality will be employed in order to examine the case of bidirectional time-varying causality between Renewable Energy Exchange-Traded Funds and Climate Policy Uncertainty. The methodology is based on econometric time series modeling, in particular, the concept of predictability in determining causality as introduced by Granger in 1988

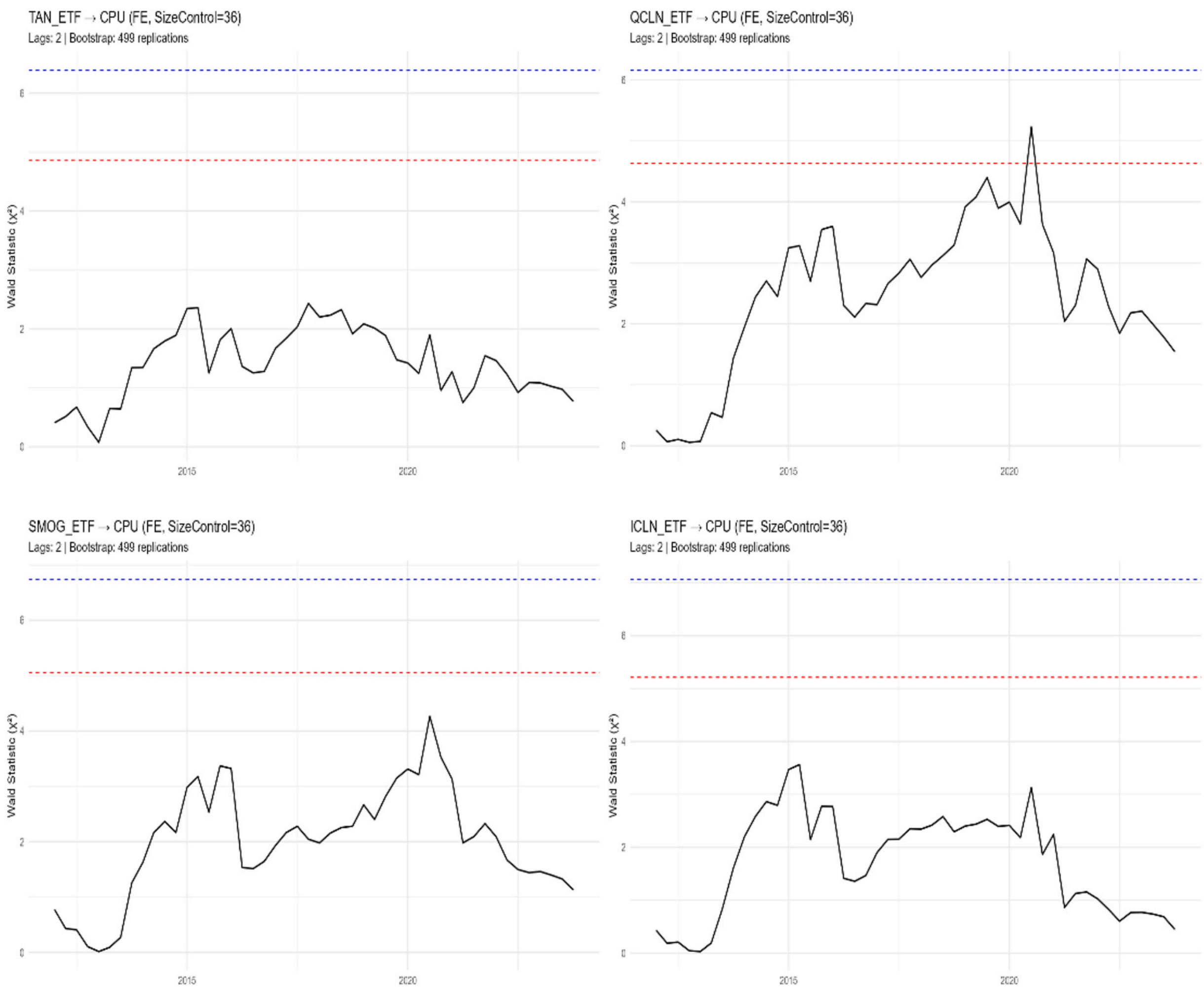

Fig. 9. Forward expanding: Renewable energy ETFs → CPU, size control/windows = 36.

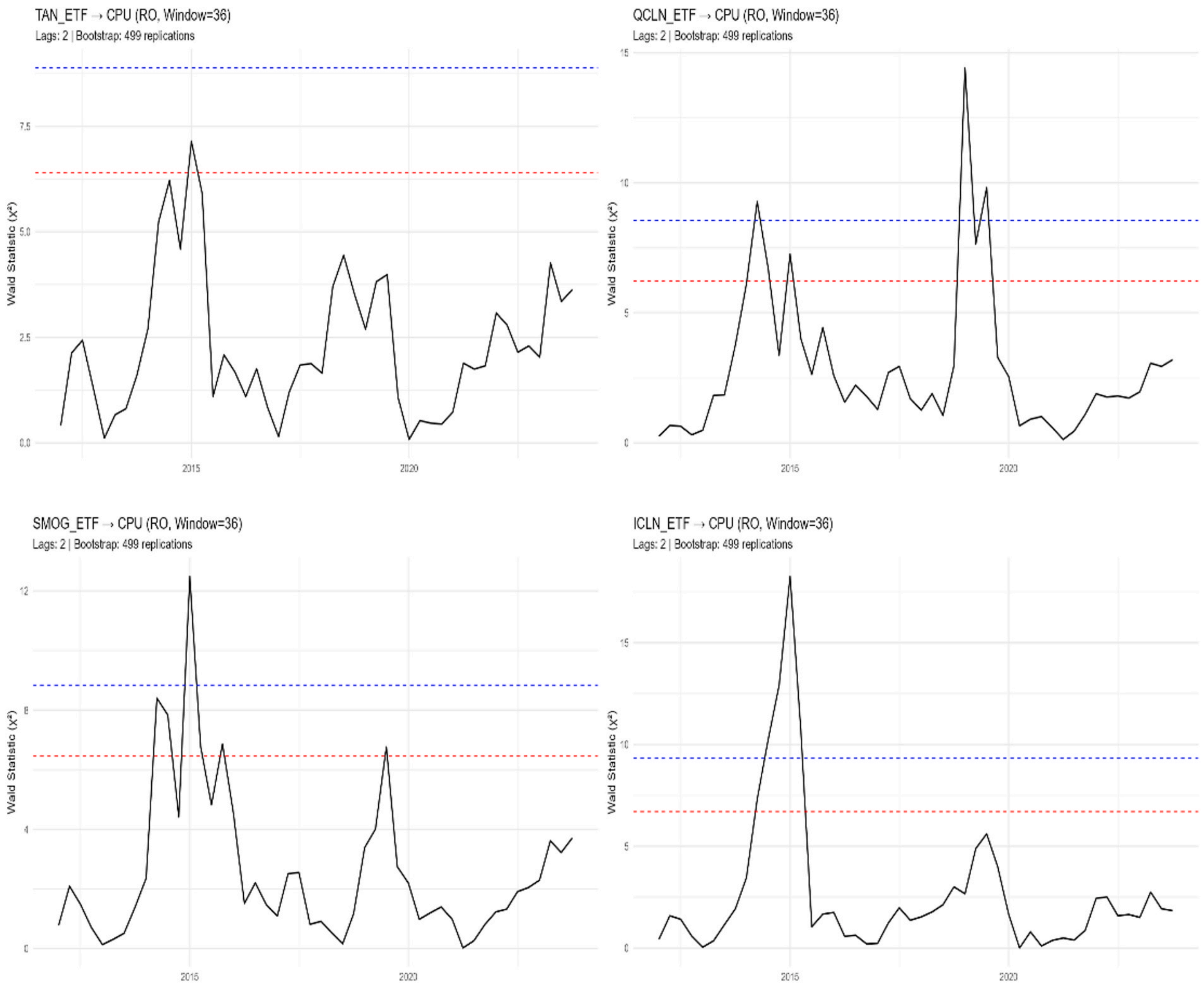

Fig. 10. Rolling window: Renewable energy ETFs → CPU, size control/windows = 36.

(Granger, 1988).

3.1. Data

The empirical analysis draws secondary data at a monthly frequency spanning January 2009 to June 2025. The sample period from January 2010 to June 2025 was chosen to ensure reliable data coverage for all ETFs and CPU, capture both long-term structural trends and short-term fluctuations in uncertainty and reflect key episodes such as the post-financial crisis recovery, the COVID-19 crisis, and the 2021–2022 policy tightening cycle. To measure climate policy uncertainty, we utilize the Climate Policy Uncertainty (CPU) Index developed by Gavriilidis (2021), retrieved from the Policy Uncertainty Project website (https://www.policyuncertainty.com/climate_uncertainty.html). This index has gained wide recognition in literature and is constructed using established text-mining methodologies. To complement this measure, we also employ the Global Climate Policy Uncertainty (GCPU) Index developed by Ji et al. (2024), obtained from Figshare (https://figshare.com/articles/dataset/Global_Climate_Policy_Uncertainty_2000-2023_/24807627?file=49365187), which captures cross-country climate policy uncertainty and thus allows us to compare national and global perspectives. GCPU spans January 2010 to December 2023. Renewable energy investments are proxied by four widely tracked ETFs: the Invesco Solar ETF (TAN), First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), VanEck Low Carbon Energy ETF (SMOG), and iShares Global Clean Energy ETF (ICLN). The price data for these ETFs were obtained from Investing.com, a widely used and publicly accessible financial data platform. To ensure accuracy, sample checks were cross validated against Yahoo Finance and Morningstar, with no material discrepancies detected. While subscription-based datasets such as Bloomberg or Refinitiv could serve as additional sources in future research, the use of Investing.com facilitates replication and transparency. A detailed summary of all variables, definitions, and sources is presented in Table 1.

Following the suggestions from Lütkepohl and Xu (2012), a logarithmic transformation is applied to the original data series as a pre-processing technique to enhance better stationarity and to reduce estimation errors. This enhances data stability and is also a good

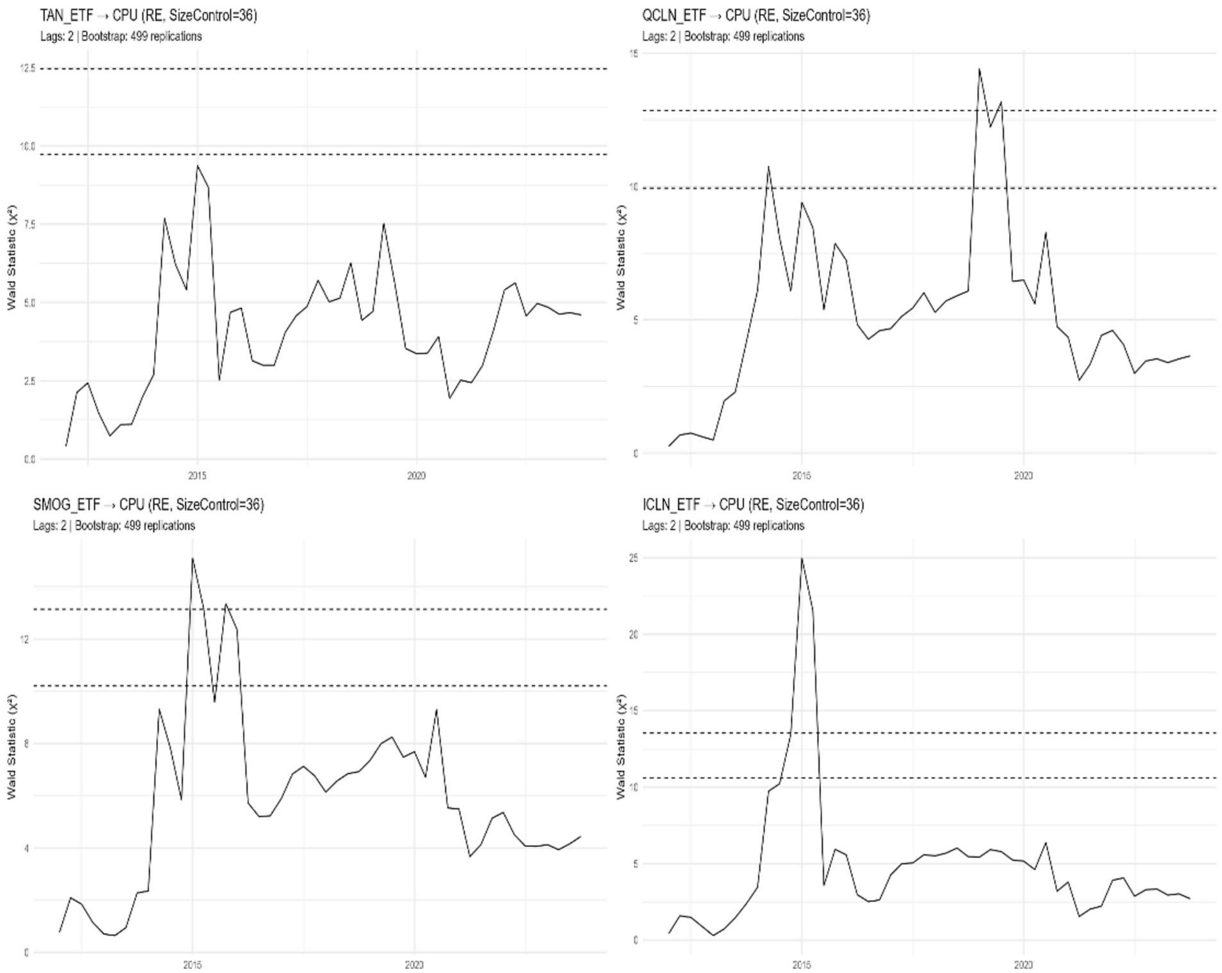

Fig. 11. Recursive expanding: Renewable energy ETFs → CPU, size control/windows = 36.

Table 8
Renewable energy ETFs → GCPU, size control/windows = 36.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	14.267***	5.303/7.012/11.09	11.323**	6.486/8.924/15.041	14.267**	10.269/12.914/19.241
QCLN	12.415***	4.71/6.267/9.785	13.028**	6.286/8.624/14.925	14.129**	9.738/12.286/18.807
SMOG	9.107**	4.941/6.546/10.429	7.323*	6.203/8.469/13.733	12.208**	9.68/12.067/17.412
ICLN	9.935**	5.274/7.052/10.965	8.349*	6.699/9.432/16.03	9.935	10.431/13.204/19.712

econometric practice in the analysis of time series. It does so on a dataset spanning over a decade and measuring both the CPU and the renewable energy investment vehicles. On this basic empirical foundation, this study will push forward to more precisely define the causal relationship between CPU and renewable ETFs, using a time-varying Granger Causality approach. This will empirically show the interaction of climate policy development and performance of renewable energy ETFs.

3.2. Granger Causality

The classic Granger causality test is often used in econometrics because it can accommodate randomness in variables and has flexible model settings (Shi et al., 2018). However, according to Psaradakis et al. (2003), it has drawbacks including sensitivity to sample periods and a limited ability to capture causal links over time. We use time-varying Granger causality to get around this restriction and accomplish the study's goal.

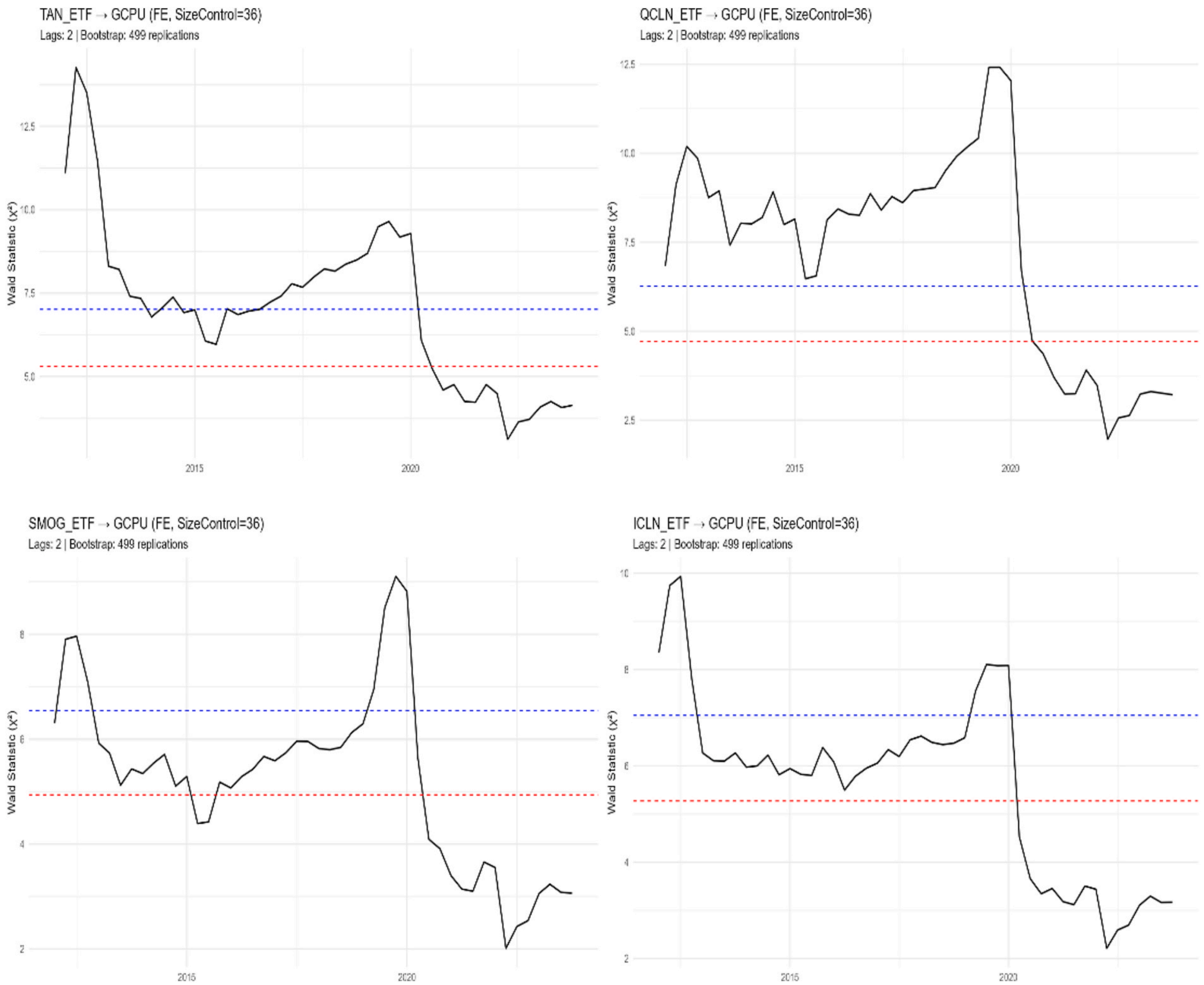

Fig. 12. Forward expanding: Renewable energy ETFs → GCPU, size control/windows = 36.

3.2.1. Time-varying granger causality

This study uses the time-varying Granger causality approach created by Shi et al. (2018, 2020) to overcome these constraints. To examine causal links between variables across time, this approach makes use of three algorithms: forward expanding, rolling, and recursive evolving windows, along with a lag-augmented Vector Autoregressive (VAR) specification. In contrast to the traditional method, the time-varying methodology uses historical data to identify causal linkages in real time. Among its benefits are its data-driven nature, ability to show variations in causality over time, resilience to data trends, and precision in determining the exact moment of causal shifts.

3.2.2. Model specifications

The bivariate vector autoregressive model of order m (i.e., VAR(m)) is given by:

$$y_{1_t} = \alpha_0{}^{(1)} + \sum^{k=1m} \alpha_{1k}{}^{(1)}\, y_{1,t-k} + \sum^{k=1m} \alpha_{2k}{}^{(1)}\, y_{2,t-k} + \varepsilon_{1t} \tag{1}$$

$$y_{2_t} = \alpha_0{}^{(2)} + \sum^{k=1m} \alpha_{1k}{}^{(2)}\, y_{1,t-k} + \sum^{k=1m} \alpha_{2k}{}^{(2)}\, y_{2,t-k} + \varepsilon_{2t} \tag{2}$$

where y_{1_t} and y_{2_t} represent Renewable Energy ETFs and Climate Policy Uncertainty, respectively. Variable y_1 is said to Granger cause variable y_2 if the previous values of y_1 can predict the current value of y_2, conditional on the past values of y_2.

To test for the null hypotheses of no Granger causality from y_1 to y_2, the joint significance of $\alpha_{1k}{}^{(2)}$ $(k = 1, \ldots, m)$ must be assessed by means of a Wald test.

The matrix notation of the bivariate VAR(m) is given by:

$$y_t = \Pi x_t + \varepsilon_t \tag{3}$$

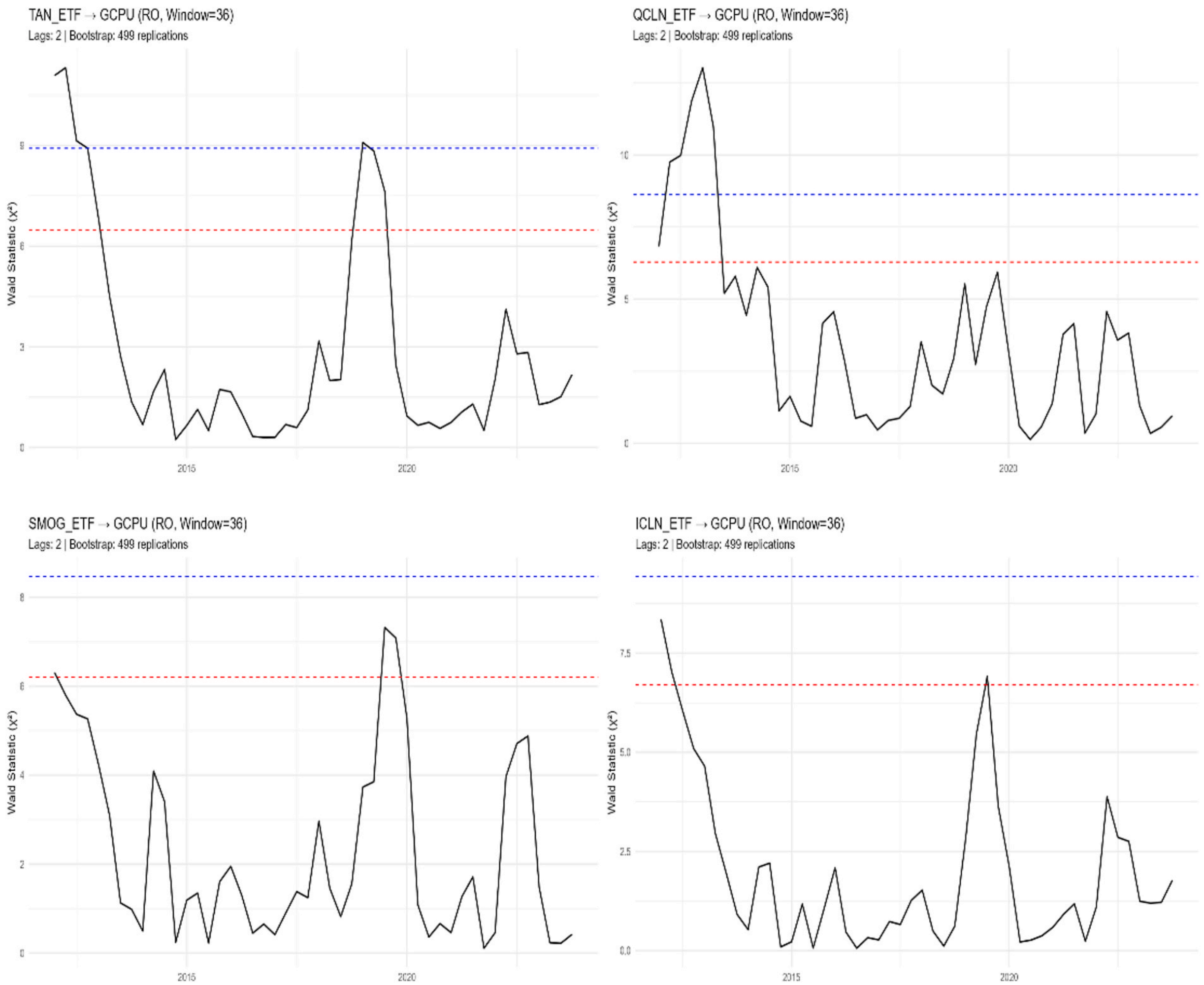

Fig. 13. Rolling window: Renewable energy ETFs → GCPU, size control/windows = 36.

where,

$$y_t = \left[y_{1_t}, y_{2_t}\right]' \tag{4}$$

$$x_t = \left[1, y'_{t-1}, y'_{t-2}, \ldots, y'_{t-k}\right]' \tag{5}$$

$$\Pi_{2\times(2m+1)} = [\ \Phi_0\ \Phi_1\ \ldots\ \Phi_m\ ] \tag{6}$$

with,

$$\Phi_0 = \left[\alpha_0{}^{(1)}\ \alpha_0{}^{(2)}\right]' \tag{7}$$

and

$$\Phi_k = \begin{bmatrix} \alpha_{1k}{}^{(1))} & \alpha_{2k}{}^{(1)} \\ \alpha_{1k}{}^{(2)} & \alpha_{2k}{}^{(2)} \end{bmatrix} \text{ for k} = 1, \ldots, \text{m}$$

The null of the Granger causality from the variable y_1 to y_2 is $R_1{\rightarrow}_2\pi = 0$ where $R_{1\to2}$ is the coefficient restriction matrix and $\pi = vec(\Pi)$ using row vectorization. The heteroskedastic-consistent Wald statistics of the null hypothesis is denoted by $W_1{\rightarrow}_2$ and is defined as:

$$W_{1\to2} = T\left(R_1{\rightarrow}_2\widehat{\pi}\right)'\left(R_1{\rightarrow}_2\widehat{V}R_{1\to2'}\right)^{-1}R_1{\rightarrow}_2\widehat{\pi} \tag{8}$$

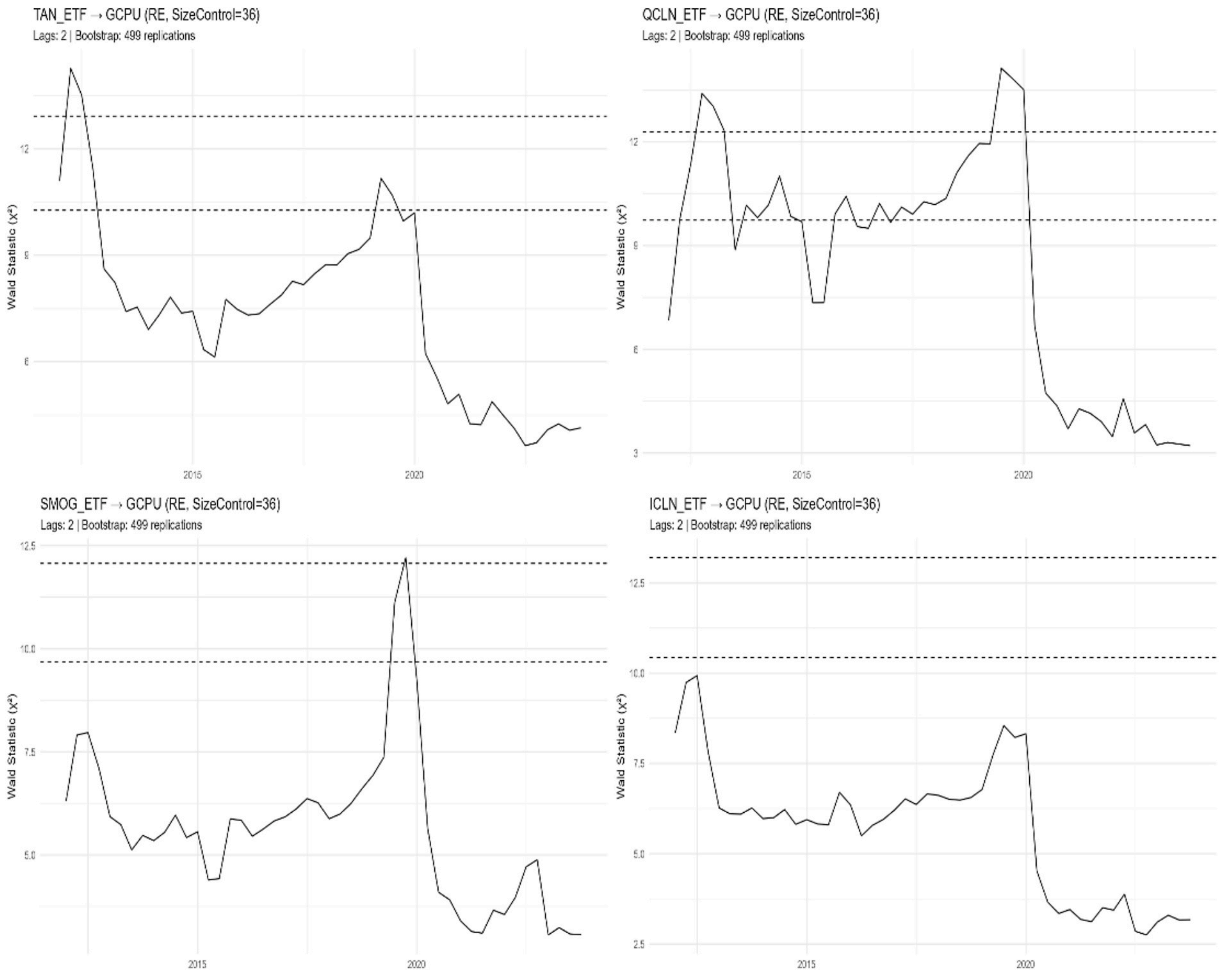

Fig. 14. Recursive expanding: Renewable energy ETFs → GCPU, size control/windows = 36.

Table 9
CPU → renewable energy ETFs, size control/windows = 12.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	4.173	6.027/8.01/12.609	213.789***	23.098/38.253/60.382	213.789***	20.373/29.003/55.022
QCLN	5.359	5.534/7.292/11.787	72.525***	14.341/27.417/53.548	72.525***	17.747/24.955/49.031
SMOG	4.537	5.855/8.053/12.877	110.523***	17.038/34.485/61.941	279.479***	19.188/26.797/50.388
ICLN	3.498	5.619/7.898/12.572	87.805***	16.888/24.816/48.497	87.805***	18.997/26.541/51.556

where $\widehat{V} = I_n \otimes \widehat{Q}$ and $\widehat{Q} = T^{-1}\sum_t x_t x_t'$ and $\widehat{\sum} = T^{-1}\sum_t \widehat{\xi}_t \widehat{\xi}_t'$ with $\widehat{\xi}_t = \widehat{\varepsilon}_t \otimes x_t$ and $\widehat{\varepsilon}_t = y_t - \widehat{\Pi} x_t$

3.2.3. Recursive estimation methods

Recursive estimation methods are employed to account for time variation in Granger causal orderings and for date stamping the timing of the changes. For each period of interest, a sequence of Granger Causality Test Statistics must be computed, and this information is then used for inference. The sequence of test statistics can be produced by three different algorithms: the recursive evolving (RE) window, the rolling (RO) window, and the forward expanding (FE) window techniques. Consider a subset of $T+1$ observations $\{y_0, y_1, \ldots, y_T\}$ along with a number r so that $0 < r < 1$. Also let $[Tr]$ represent the floor value of the product. Then $T_{r_1,r}$ will be taken to denote a Wald test statistic computed over a subsample starting at $y_{[T_{r1}]}$ and ending at $y_{[T_r]}$.

The Forward Expanding (FE) algorithm works by first calculating the Wald test statistic for a minimum window length, $\tau_0 = [Tr_0] > 0$, where $[Tr_0]$ means taking the integer part of Tr_0. It then grows this window by adding one new observation at a time, recomputing the Wald statistic each time until it has used the entire dataset. The first window always starts with the first data point. By the end, the FE algorithm produces a sequence of Wald statistics, Tr_1, r with $r_1 = 0$ and $r \in [r_0, 1]$.

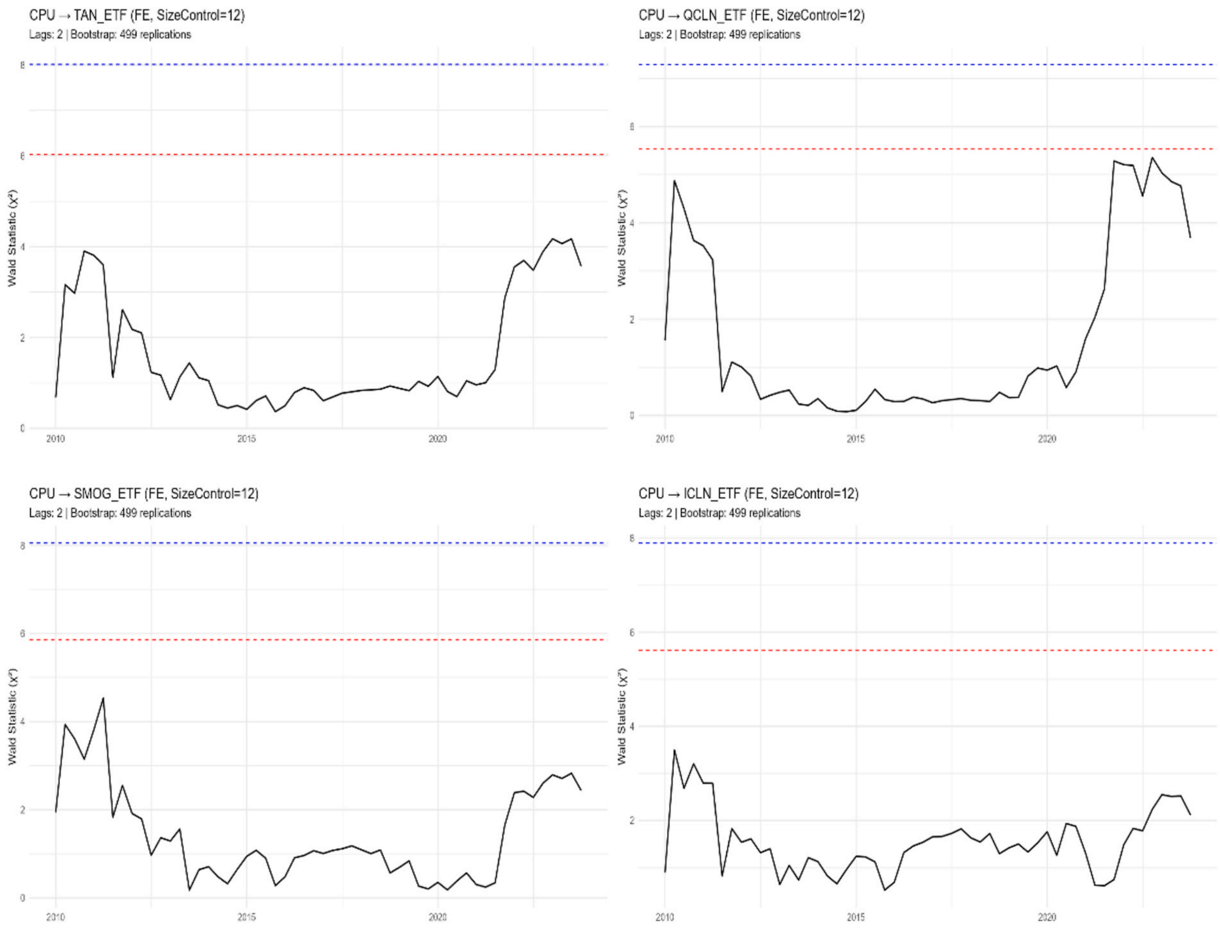

Fig. 15. Forward expanding: CPU → renewable energy ETFs, size control/windows = 12.

The Rolling Window (RO) algorithm takes a window of fixed size $[Tw]$ and rolls it through the data, moving ahead one observation at a time. It computes a new Wald statistic for each position of the window. This produces a sequence of Wald statistics, Tr_1, r with $r_1 = r - w$ and $r \in [r_0, 1]$, where each Wald statistic is calculated on a subsample of the same window size $[Tw]$, with $0 < w < 1$.

For the Recursive Evolving (RE) algorithm, pick any observation of interest, say the $[T_{r1}]$ *th* observation. The algorithm will compute a Wald statistic for that observation using all possible subsamples that include that point and are at least the minimum window size r_0. It repeats this for every observation in the data after the first one. So each observation beyond the first is associated with a set of Wald statistics computed over different subsample windows that all end at that point. Phillips et al. (2015) propose taking the maximum or supremum value from each of these sets as the test statistic of interest. Mathematically, the RE algorithm produces a sequence of test statistics Tr_1, r with $r_1 \in [0, r - r_0]$ and $r \in [r_0, 1]$ which are the supremum norms of the Wald statistics at each observation window.

For each of the three algorithms for time varying methods, calculate the maximum values of each bootstrapped test statistic sequence as:

$$\text{Forward}: M^b_{1,t} = \underset{t\in[\tau_0,\tau_0+\tau_b-1]}{\text{argmax}} \left\{T^b_{1,t}\right\}$$

$$\text{RO}: M^b_{t-\tau_0+1,t} = \underset{t\in[\tau_0,\tau_0+\tau_b-1]}{\text{argmax}} \left\{T^b_{t-\tau_0+1,t}\right\}$$

$$\text{RE}: \overline{M^b_t}(\tau_0) = \underset{t\in[\tau_0,\tau_0+\tau_b-1]}{\text{argmax}} \left\{\overline{T^b_t}(\tau_0)\right\}$$

where the notation $\overline{M^b_t}(\tau_0)$ is used to denote the supremum norm of a sequence of supremum norm Wald tests.

Fig. 1 provides a graphic representation of the three distinct algorithms, with each arrow symbolizing a potential subset over which the required test statistic is calculated. The forward expanding window is shown graphically in the top-left diagram, and the rolling

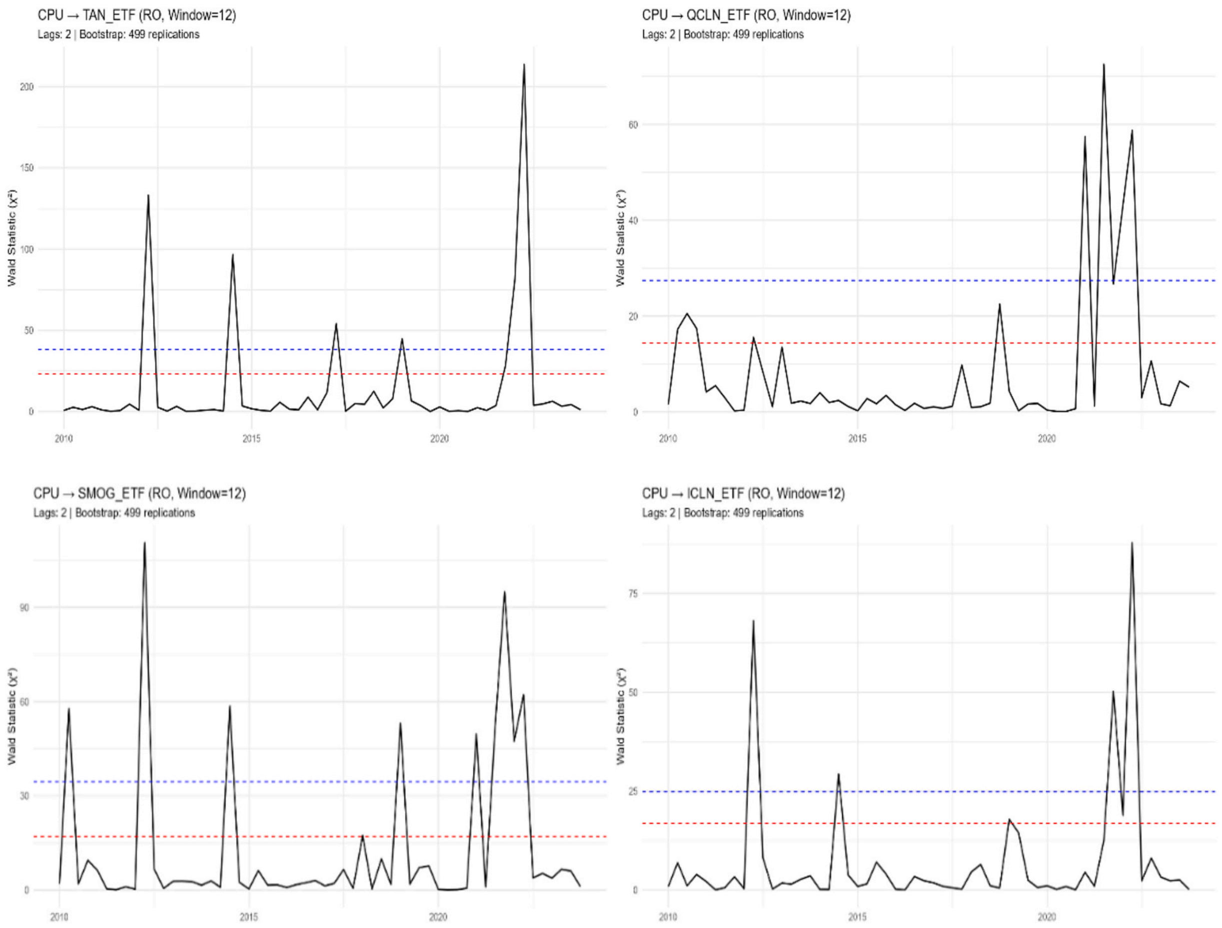

Fig. 16. Rolling window: CPU → renewable energy ETFs, size control/windows = 12.

window is shown in the top-right diagram. The process of calculating the statistic for the recursive evolving window is shown in the diagram in the bottom row.

Inference for the time-varying Granger causality tests was conducted using a wild bootstrap procedure with 499 replications. Resampling was performed with block lengths equal to the respective window sizes (12, 36 months) to preserve temporal dependence. For each bootstrap sample, Wald statistics were computed, and empirical critical values were derived from the 90th, 95th, and 99th percentiles of the simulated distributions. This bootstrap-based approach, following Shi et al. (2020) and Baum et al. (2021), provides robust size control for the non-standard distribution of the maximal test statistics across rolling, forward-expanding, and recursive evolving windows.

A key strength of TVGC is its ability to uncover temporal instability and regime-specific predictability. Traditional methods give one summary while TVGC sees how the relationship evolves over time. However, the method also has limitations. First, it identifies predictive rather than structural causality, and thus common shocks or omitted variables may influence results. Second, outcomes can be sensitive to the choice of window length and algorithm, with rolling windows capturing short-lived bursts but sometimes noisy, while expanding windows emphasize longer-term persistence. Third, edge effects and data endpoints can reduce power, particularly when series terminate at different times.

The robustness of the time-varying Granger Causality (TVGC) analysis was addressed through a comprehensive methodological framework. This was achieved by employing three distinct algorithms - Rolling Windows (RO), Forward Expanding (FE), and Recursive Expanding (RE) - each configured with two different window/control sizes of 12 and 36 months. The 12-month parameter was selected to capture short-to medium-term fluctuations, while the 36-month parameter was used to isolate longer-term dynamics.

The consistency of the bidirectional results ("Uncertainty to Renewable ETFs" and "Renewable ETFs to Uncertainty") across these varied algorithmic designs strengthens confidence in the main findings. It is acknowledged that all tests involving the GCPU index (ending December 2023) are restricted to this sample period, while ETF-CPU pairs extend to June 2025. Statistical significance for all tests was rigorously assessed against the 90th, 95th, and 99th percentile critical values specific to each window configuration, with the noted limitations being factored into the final interpretation.

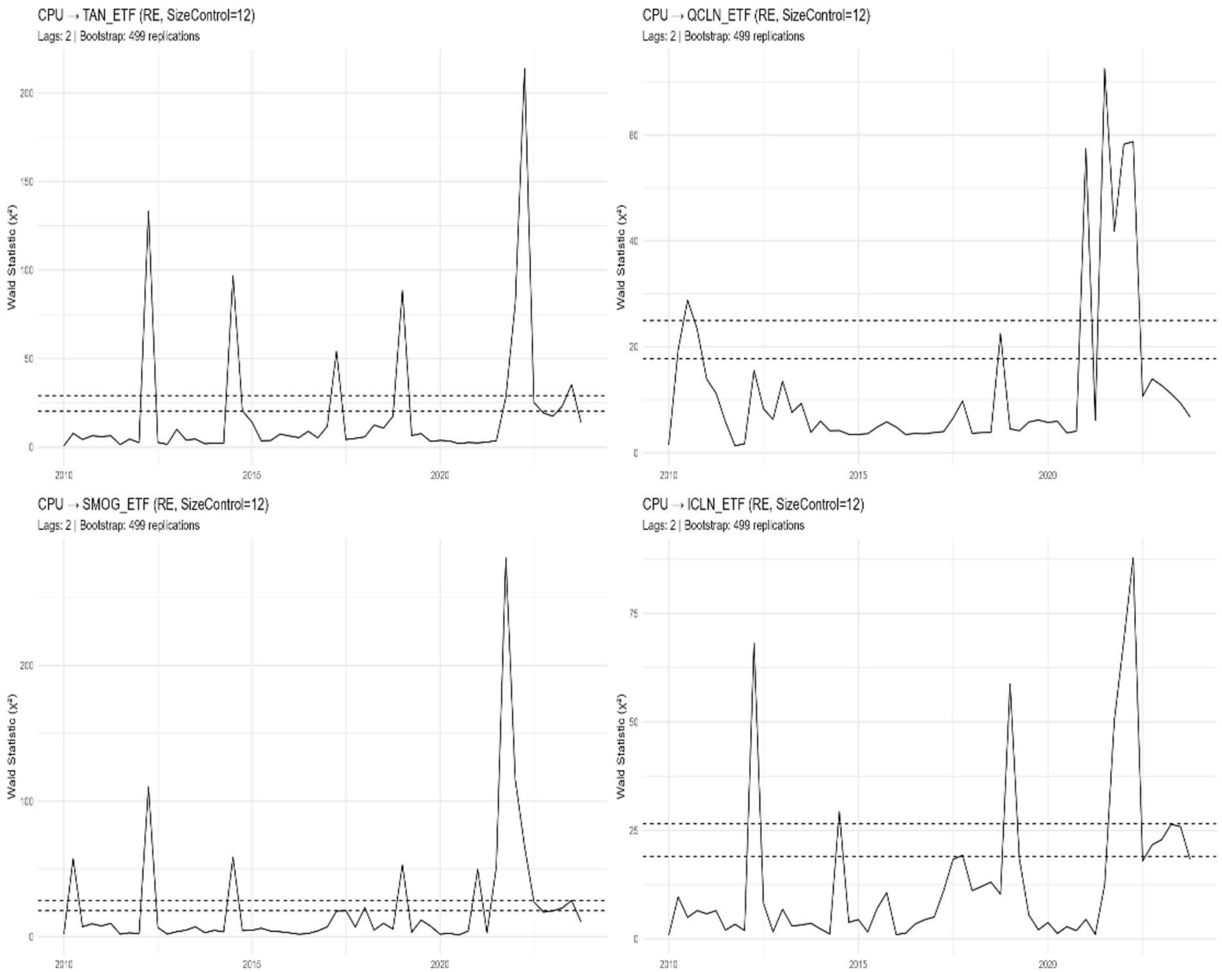

Fig. 17. Recursive expanding: CPU → renewable energy ETFs, size control/windows = 12.

Table 10
GCPU → renewable energy ETFs, size control/windows = 12.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	3.83	5.144/6.839/10.757	32.153*	19.183/34.348/73.676	34.084**	19.776/28.45/55.03
QCLN	4.486	4.969/6.527/10.421	44.107**	15.602/26.014/50.597	53.467***	18.516/26.222/51.947
SMOG	3.318	4.924/6.403/9.907	47.995**	17.265/32.521/69.417	47.995**	19.564/27.173/52.762
ICLN	1.901	4.898/6.372/9.785	417.582***	15.358/35.392/86.461	563.716***	18.904/26.767/56.765

4. Results and discussion

4.1. Results

The summary statistics of the logged variables for renewable energy ETFs (TAN, QCLN, SMOG, ICLN) and the climate policy uncertainty indices (CPU and GCPU), presented in Table 2, provide important insights into their distributions and variability, which are central to our investigation of bidirectional causality.

The mean values indicate that the SMOG ETF has the highest average price (4.2081) among the ETFs, while the ICLN ETF records the lowest (2.4987). In contrast, the CPU and GCPU indices report higher average values of 4.8943 and 5.588, respectively, relative to the ETFs. The median values closely align with the means across all variables, suggesting limited skewness—this is confirmed by the skewness statistics. For instance, QCLN ETF and SMOG ETF display moderate positive skewness (0.7131 and 0.5016, respectively), pointing to longer right tails, whereas CPU (−0.1026) and GCPU (−0.1093) exhibit slight negative skewness.

The standard deviations highlight differences in volatility: QCLN ETF has the highest variability (0.5944), while ICLN ETF shows

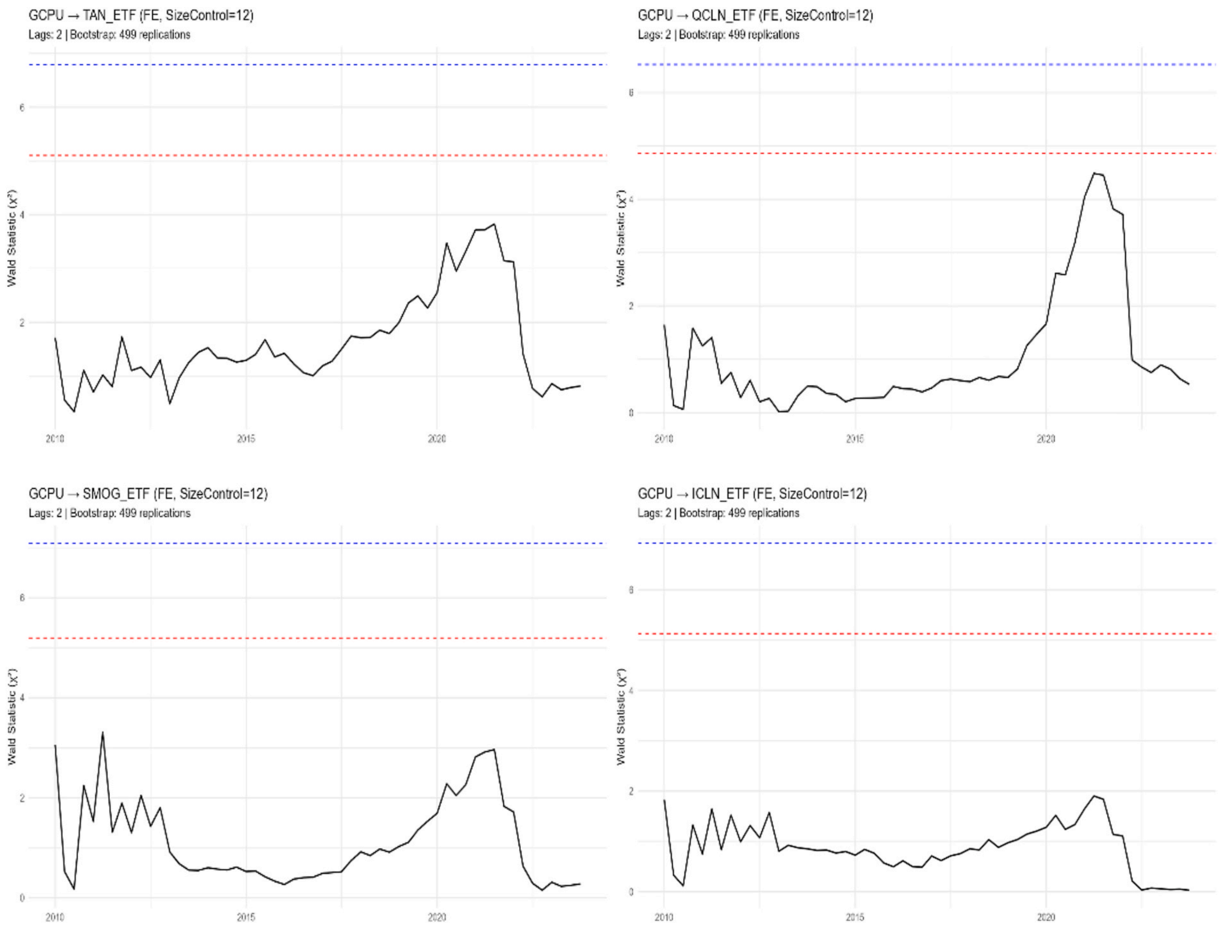

Fig. 18. Forward expanding: GCPU → renewable energy ETFs, size control/windows = 12.

the lowest (0.3747), suggesting that QCLN ETF prices fluctuate more widely compared to ICLN ETF. Both CPU (0.4771) and GCPU (0.4331) fall within the mid-range of volatility levels. The kurtosis values reveal that most ETFs and the CPU index exhibit negative kurtosis, indicating flatter-than-normal distributions with fewer extreme values or outliers. In contrast, the GCPU index shows strongly positive kurtosis (2.5100), pointing to a more peaked distribution with heavier tails.

The time series plots in Fig. 2 further illustrate the historical dynamics of the four renewable energy ETFs alongside the CPU index. The ETFs, representing distinct segments of the renewable energy sector, generally display upward trends over the years, marked by substantial growth around 2020 followed by notable declines. TAN and SMOG, in particular, exhibit sharp surges before subsequent downturns. By contrast, the CPU index demonstrates pronounced and frequent fluctuations, reflecting the varying levels of climate policy uncertainty over time. These fluctuations are more abrupt and irregular compared to the relatively smoother and gradual long-term trends observed in the renewable energy ETFs.

4.1.1. *Stationarity test*

We employed the Dickey-Fuller (ADF, 1979) test to check for the stationarity of the variables used in this research. The optimal lags for the Dickey Fuller test were determined for all the variables and the variables were tested for stationarity. As shown in Table 3, all the variables are non-stationary at level. Upon analyzing the first difference of the variables, we discovered that all the variables are stationary at first difference as shown in the table below.

4.1.2. *Cointegration test*

To determine whether the variables are cointegrated, we used the Engle-Granger two-Step Method (Engle & Granger, 1987). As shown in Table 4 below, we see that Invesco Solar ETF(TAN) and CPU/GCPU are not cointegrated. This means that, aside from Invesco Solar ETF, there is a long-term relationship between all the renewable energy ETFs considered in this research.

4.1.3. *Time varying granger causality test*

Renewable Energy ETFs to Climate Policy Uncertainty.

For the ETF to CPU direction from Table 5 and Figs. 3–5, the 12-month specification provides some evidence of short-run causality.

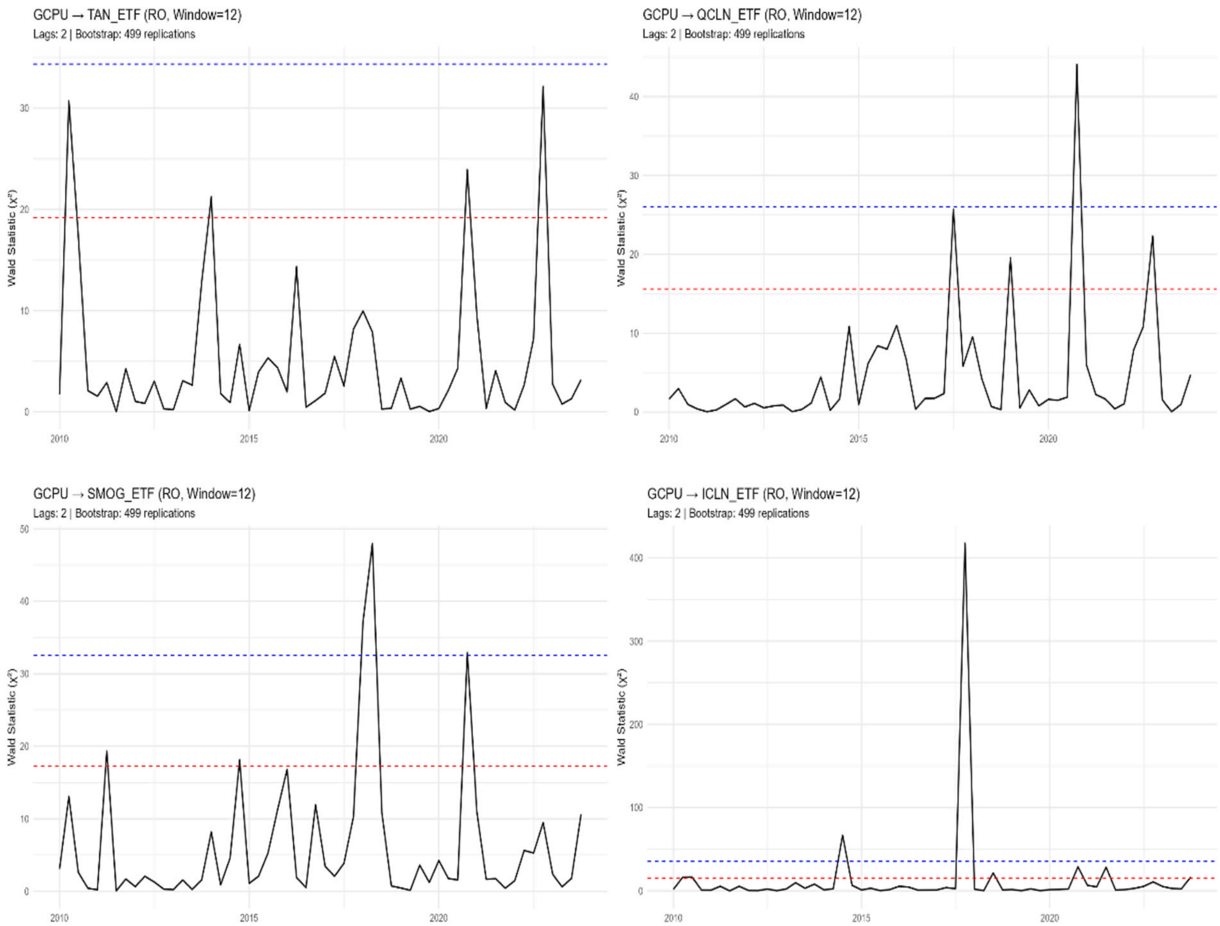

Fig. 19. Rolling window: GCPU → renewable energy ETFs, size control/windows = 12.

Under the Forward and Recursive frameworks, most test statistics fall below critical thresholds, indicating weak or insignificant predictive power of ETFs over domestic policy uncertainty. However, Invesco Solar ETF (TAN) and First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN) have statistical significance under all three algorithms: Forward, Recursive and Rolling Window Algorithm, suggesting some short-lived influence. VanEck Low Carbon Energy ETF (SMOG) and iShares Global Clean Energy ETF (ICLN) are statistically significant under the Recursive and Rolling Windows algorithms but not significant under the forward expanding algorithm. We see some spiky behaviours in the graphs which are due to the fewer data points (12 observations) used for windows length of 12, capturing short-term impacts of some events. These spikes indicate that around 2013–2014 and 2019–2020, domestic policy uncertainty was more strongly anticipated by renewable ETF investments, though the effect is episodic rather than persistent. We also see that, there is a general increase in the predictive power from 2012 to around 2020 and then the predictive power starts to decrease.

In the ETF to GCPU direction from Table 6 and Figs. 6–8, the 12-month horizon reveals much stronger and more consistent causal patterns as compared to the ETF to CPU test at window length of 12. Across all three frameworks (Forward, Rolling, Recursive), the Wald statistics for all four ETFs are well above the 1 % critical threshold. Invesco Solar ETF (TAN), First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), VanEck Low Carbon Energy ETF (SMOG), and iShares Global Clean Energy ETF (ICLN) display highly significant results, indicating robust short-run predictive power for global climate policy uncertainty. When we compare these findings to ETF to CPU (window length 12) relationship, we see that renewable ETFs are more closely tied to global policy debates than domestic uncertainty in the short run, reflecting their international investor base and sensitivity to cross-border regulatory signals. Like ETF to CPU at window length of 12, we see that the relationship starts to drop after 2020.

Table 7 and Figs. 9–11 help us understand ETF to CPU direction at 36-month horizon. At the 36-month horizon, the ETF to CPU direction demonstrates stronger and more systematic evidence of causality, particularly under the Rolling-Window framework. First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN) has a statistically significant relationship across all three algorithms. Except for the Forward Expanding Algorithm, we see a significant relationship between renewable energy ETS and CPU. We see a pattern where the relationship between ETF and CPU increase in the early years and then start to decrease after about 2020. These outcomes suggest that domestic policy uncertainty is influenced by renewable ETFs primarily during periods of heightened volatility, captured most effectively by the rolling specification. But for the rolling window algorithm, after the decrease in the relationship

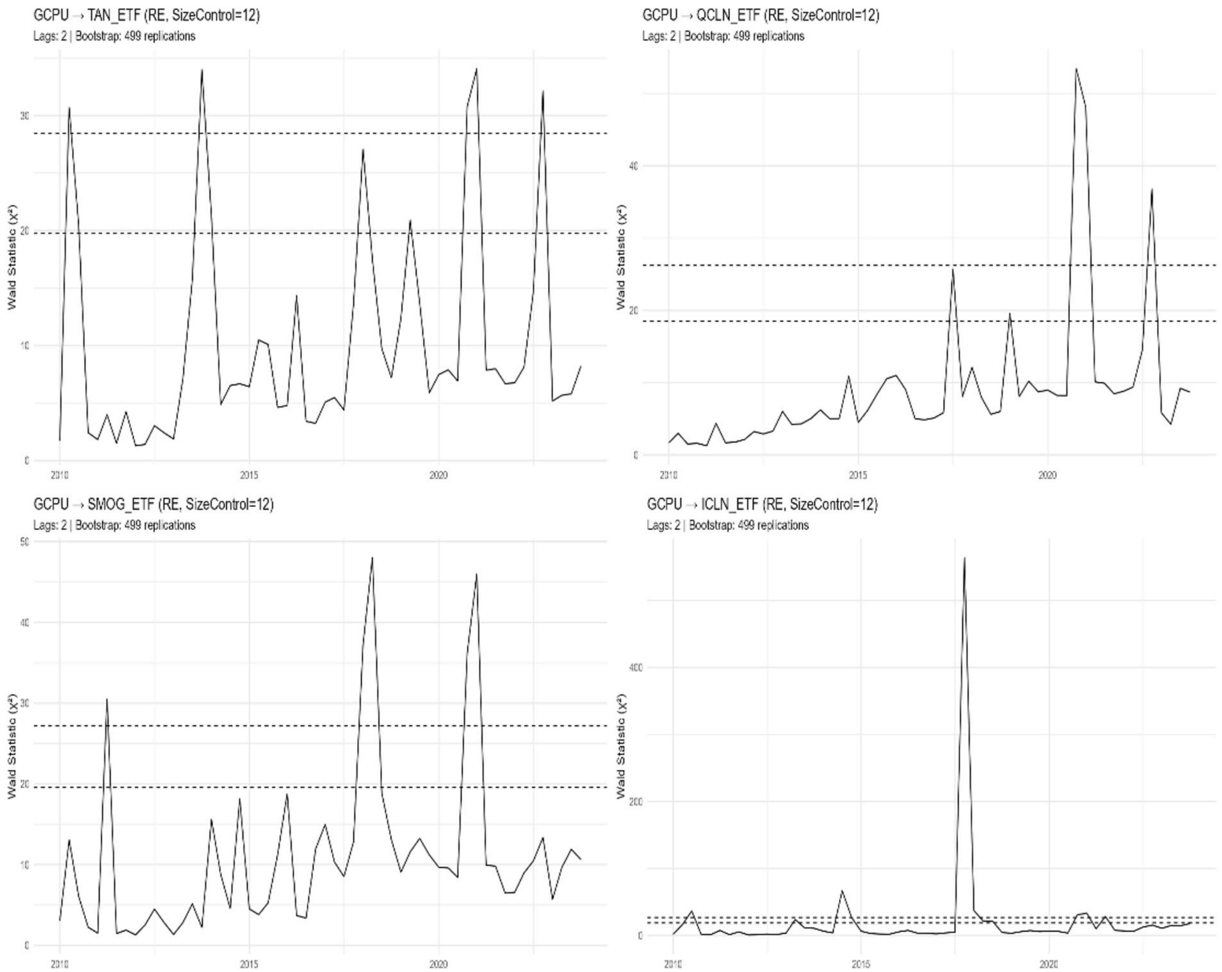

Fig. 20. Recursive expanding: GCPU → renewable energy ETFs, size control/windows = 12.

Table 11
CPU → renewable energy ETFs, size control/windows = 36.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	4.173	5.307/6.802/10.276	15.642***	6.154/8.45/14.933	16.545**	9.39/11.845/18.695
QCLN	5.359*	5.227/6.833/10.589	14.647***	6.051/8.18/13.807	14.647**	9.319/11.795/17.378
SMOG	2.828	5.578/7.228/11.17	13.531**	6.478/8.789/14.661	14.436**	9.686/12.167/18.641
ICLN	2.547	5.572/7.268/11.057	20.086***	6.088/8.379/13.668	20.701***	9.565/12.024/17.726

around 2020, we see an increase in relationship around 2021.

Table 8 and Figs. 12–14 give us the results for the ETF to GCPU direction, the 36-month specification yields the clearest and most compelling evidence of long-run causality. The results are very similar to ETF to CPU at 36-months. The decreasing pattern from 2020 becomes very clear and all ETFs show statistical significance across all three algorithms except for the recursive algorithm of iShares Global Clean Energy ETF (ICLN). These results confirm that renewable ETFs are powerful leading indicators of global climate policy uncertainty at longer horizons, especially during early 2010–2013 and again in mid-2010s episodes linked to major international climate agreements. Like the CPU, post-2020, these relationships weaken, indicating a potential structural shift in how financial and policy uncertainty interact (see Fig. 15).

Climate Policy Uncertainty to Renewable Energy ETFs.

At the 12-month horizon (see Table 9 and Figs. 15, 16 and 17), the rolling-window specification reveals very strong and volatile causal influence from policy uncertainty to renewable ETFs. For the CPU to ETF direction, all four ETFs show highly significant results under RO and RE. By contrast, the Forward Expanding Algorithm remain insignificant, confirming that short-term causality only appears when local fluctuations are captured dynamically. For Forward Expanding algorithm, we see some increasing trend from 2009

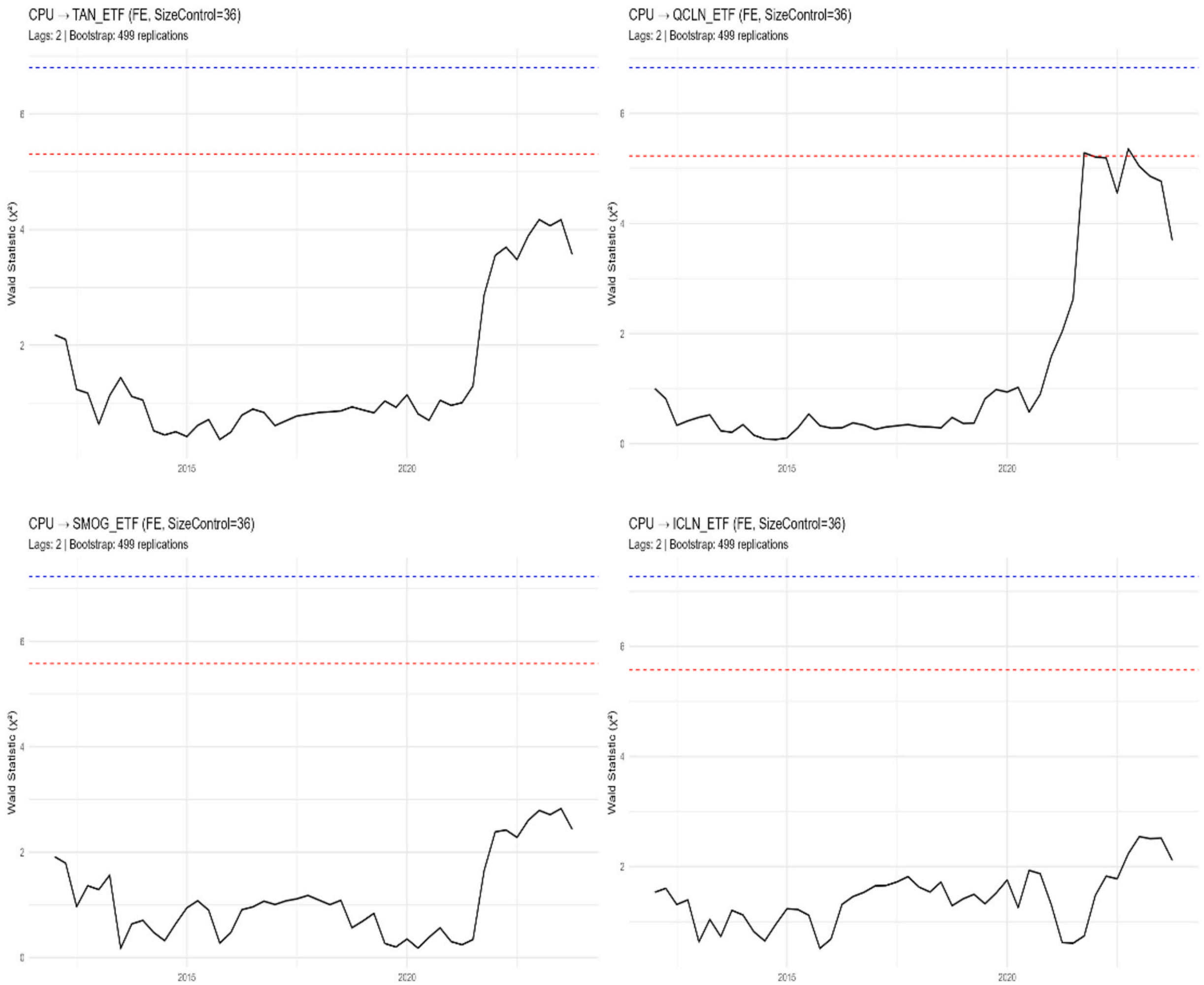

Fig. 21. Forward expanding: CPU → renewable energy ETFs, size control/windows = 36.

to 2011 then the relationship stays flattened till 2020 where we see an increase to 2022 before the relationship starts to decrease again. For the Rolling Window and Recursive Expanding algorithms, the relationship is very volatile.

Table 10 and Figs. 18–20 are the results for the GCPU to ETF direction (see Fig. 17). The results are very similar to the CPU to ETF direction. Again, the Rolling Window and Recursive Expanding algorithms show statistically significant relationships with the results of the Forward Expanding window not being statistically significant. These repeated bursts show that global climate policy uncertainty has stronger and more widespread short-run effects on renewable ETFs than domestic CPU. The fact that FE and RE results remain muted further highlights the episodic and shock-driven nature of this short-term causality. The results are very similar to that of CPU.

Table 11 and Figs. 21–23 show the results for CPU to ETFs at 36 months' window. The rolling window and Recursive Expanding specifications again provides the clearest evidence of causality. For CPU to ETFs, all four ETFs show significant results under Rolling Window and Recursive Expanding algorithms. This indicates that over longer horizons, domestic climate policy uncertainty exerts meaningful and sustained influence on ETF dynamics. Forward Expanding results, however, remain weak, with only QCLN showing marginal significance. The trends are like the trends for CPU at the 12-month horizon, very stable influence from CPU to renewable energy ETFs up to 2020 where the relationship increases drastically.

For the GCPU to ETF direction given in Table 12 and Figs. 24–26, the 36-month results are more consistent and robust across the board. Under Rolling window and Recursive Expanding algorithm, all four ETFs achieve significance at the 5 % level. While the magnitudes are smaller than at the 12-month horizon, the persistence of significance across all ETFs confirms that global policy uncertainty exerts a broad and systematic long-run impact. Again, the Forward specification shows weak relationship, reinforcing that causal influence is best captured by rolling windows. However, the trend in the relationship is consistent for all three algorithms: forward expanding, rolling window, and recursive expanding.

The weaker signals observed under the forward expanding (FE) specification likely reflect its cumulative nature, which gives equal weight to early observations and can dilute later structural shifts, whereas rolling (RO) and recursive evolving (RE) windows emphasize local dynamics and regime changes, respectively. Accordingly, the stronger causality found under RO and RE is evidence of

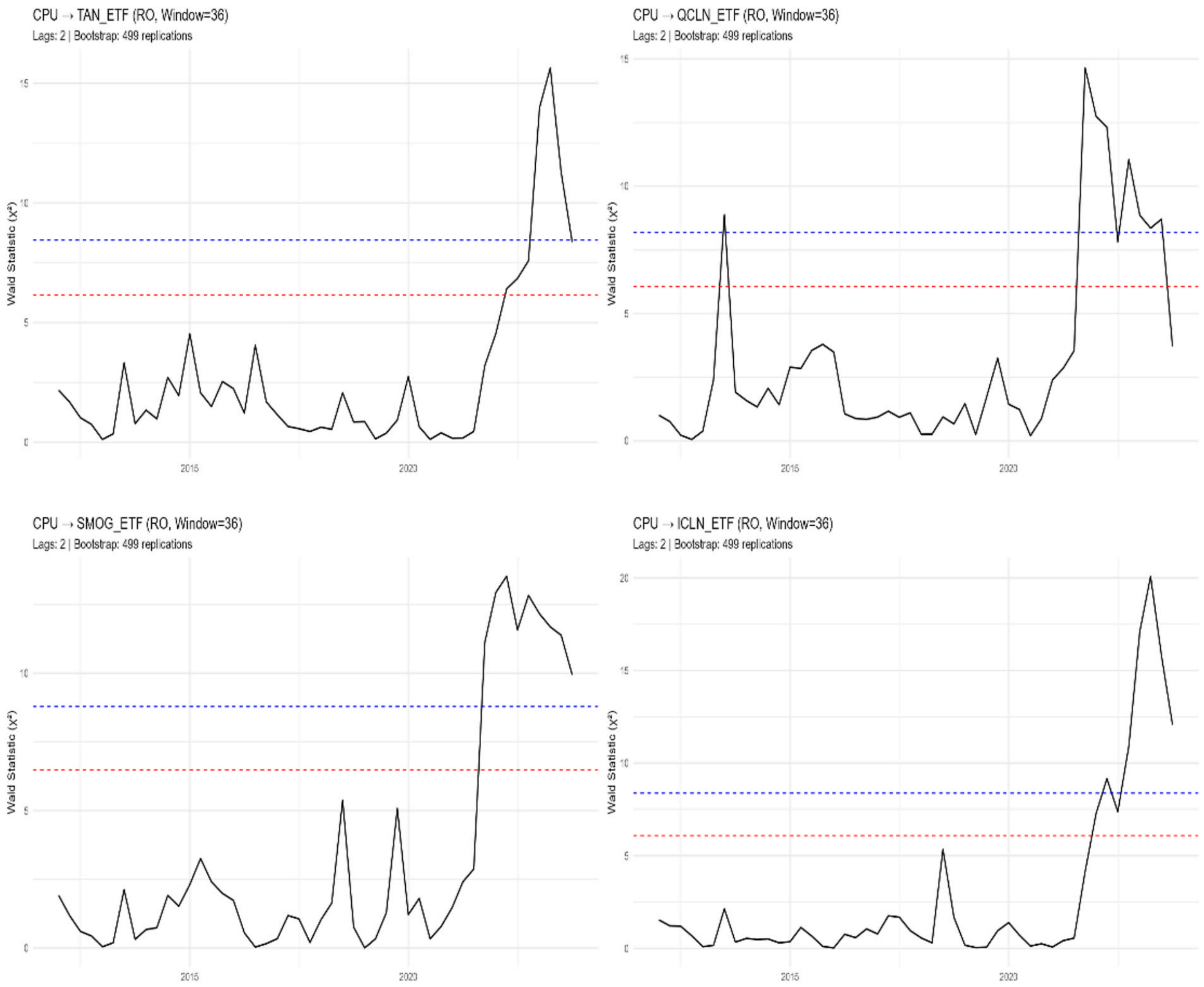

Fig. 22. Rolling window: CPU → renewable energy ETFs, size control/windows = 36.

time-localized or regime-shift episodes, while FE is a conservative benchmark capturing only persistent, cumulative predictability.

4.2. Discussion

In this research, we examine how Renewable Energy Exchange-Traded Funds (ETFs) and Climate Policy Uncertainty (CPU)/Global Climate Policy Uncertainty (GCPU) influence each other from January 2010 to June 2025. Using the innovative Time-Varying Granger Causality (TVGC) with forward expanding, rolling window, and recursive evolving algorithms, we uncover new insights into the dynamic interaction between climate policies and renewable ETFs. While earlier studies have tended to analyze renewable energy investments and climate policy uncertainty in isolation, our study integrates both perspectives to provide a more comprehensive view of their evolving connection.

Recent work has highlighted the resilience of renewable ETFs under different forms of uncertainty. Valadkhani (2024) found that renewable ETFs offer greater upside potential than fossil-fuel ETFs but are also exposed to significant downside risk, while Dutta and Dutta (2022) showed that geopolitical risk can lower volatility in renewable energy assets, framing them as safer investments. Our results complement these findings by demonstrating that climate policy uncertainty is an additional, independent driver of renewable ETF performance. Whereas previous studies emphasized market and geopolitical risks, we show that policy-related uncertainty exerts its own strong and time-varying influence, particularly from 2016 onward.

The literature on CPU has similarly emphasized heterogeneous effects across sectors. Ren et al. (2023) documented that CPU influences energy markets differently over time, and Bouri et al. (2022) showed that crises amplify the role of CPU in shifting investor preferences toward green assets. These findings align with our evidence of strengthening causality from CPU to renewable ETFs during periods of policy and market stress, such as the COVID-19 crisis and the 2021–2022 tightening cycle. Unlike prior studies that established correlations or static causal effects, however, our use of time-varying methods allows us to trace the evolution of these relationships and show that the reverse causality (ETF to CPU) weakens over time, a contribution not documented in earlier work.

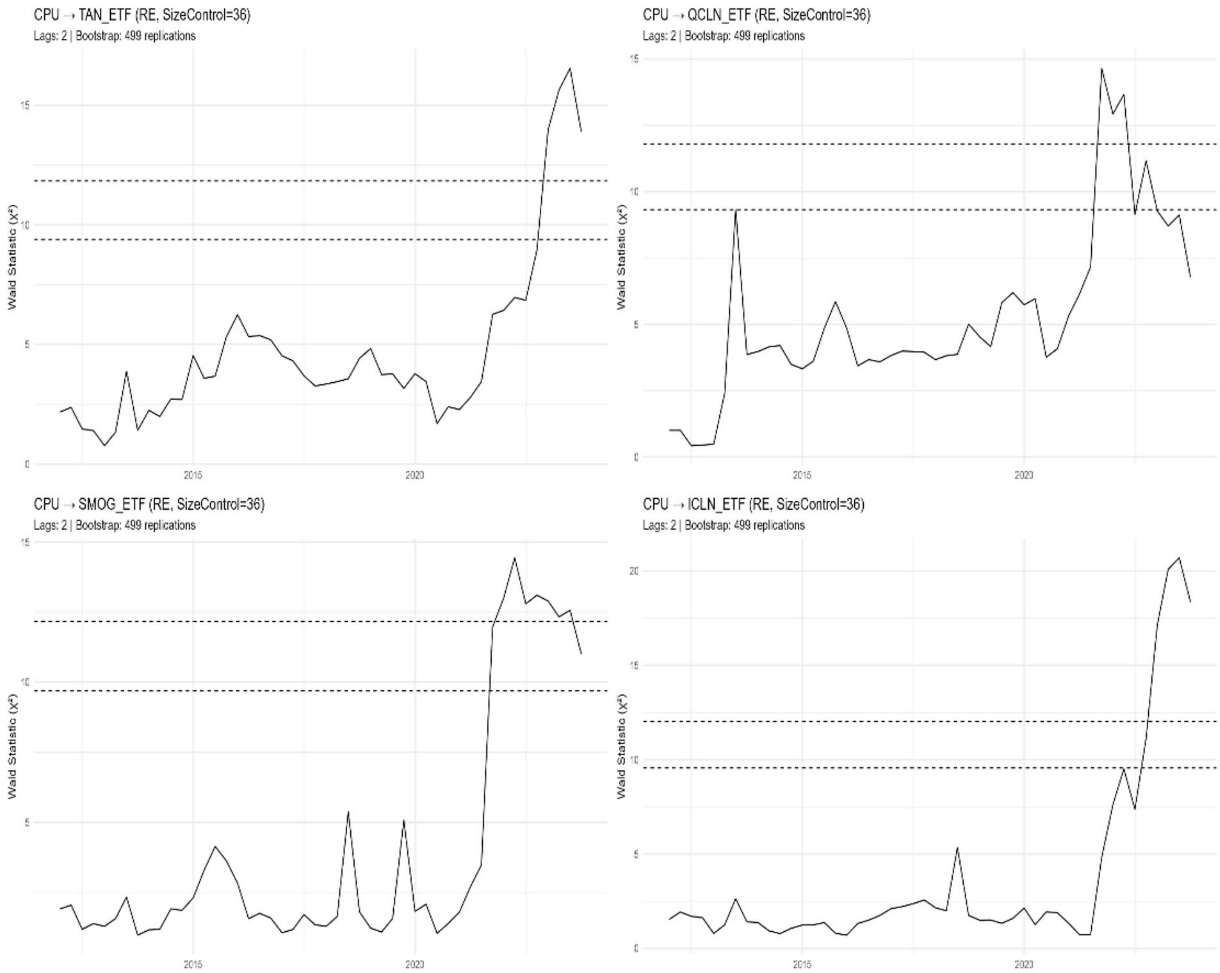

Fig. 23. Recursive expanding: CPU → renewable energy ETFs, size control/windows = 36.

Table 12
GCPU → renewable energy ETFs, size control/windows = 36.

	Forward		Rolling Window		Recursive	
ETF	WALD	P90/P95/P99	WALD	P90/P95/P99	WALD	P90/P95/P99
TAN	3.83	5.127/6.773/10.849	9.328**	6.154/8.522/14.788	10.976*	10.499/13.624/21.83
QCLN	4.486	4.8/6.203/9.26	8.658**	6.052/8.285/13.932	10.089	10.335/13.093/19.692
SMOG	2.965	4.819/6.236/9.559	9.364**	6.221/8.441/14.661	12.716*	10.869/14.039/21.142
ICLN	1.901	4.711/6.182/9.49	9.841**	6.094/8.306/14.559	11.018*	10.296/13.337/20.546

Other recent contributions further illustrate the breadth of CPU's effects. Guo et al. (2022) found non-linear impacts of CPU on energy prices, while our study extends this line of inquiry to renewable ETFs specifically, revealing that there is a bidirectional relationship between Renewable Energy ETFs and Climate Policy Uncertainties. Olasehinde-Williams et al. (2023) emphasized the importance of clear policy frameworks to stabilize sustainable investments; our findings directly support this argument, showing that the renewable sector is sensitive to climate policy signals. Dai and Zhang (2023) highlighted mixed CPU impacts on Chinese banks, pointing to sector-specific vulnerabilities. While our analysis does not focus on banking, our evidence that renewable ETFs are increasingly exposed to CPU suggests potential spillovers to financial institutions heavily invested in these assets.

Taken together, our results contribute two key advances relative to the literature. First, they integrate insights from renewable energy finance and climate policy uncertainty studies, which have mostly developed separately, thereby highlighting CPU as a central determinant of renewable investment performance. Second, by applying a time-varying approach, we uncover asymmetry and temporal evolution in the bidirectional relationship – CPU's growing impact on ETFs alongside ETFs' declining influence on CPU which extends beyond the static or sector-specific findings of earlier studies.

The weaker ETF → CPU causality observed after 2020 may reflect the dominance of broad macro-financial shocks rather than a

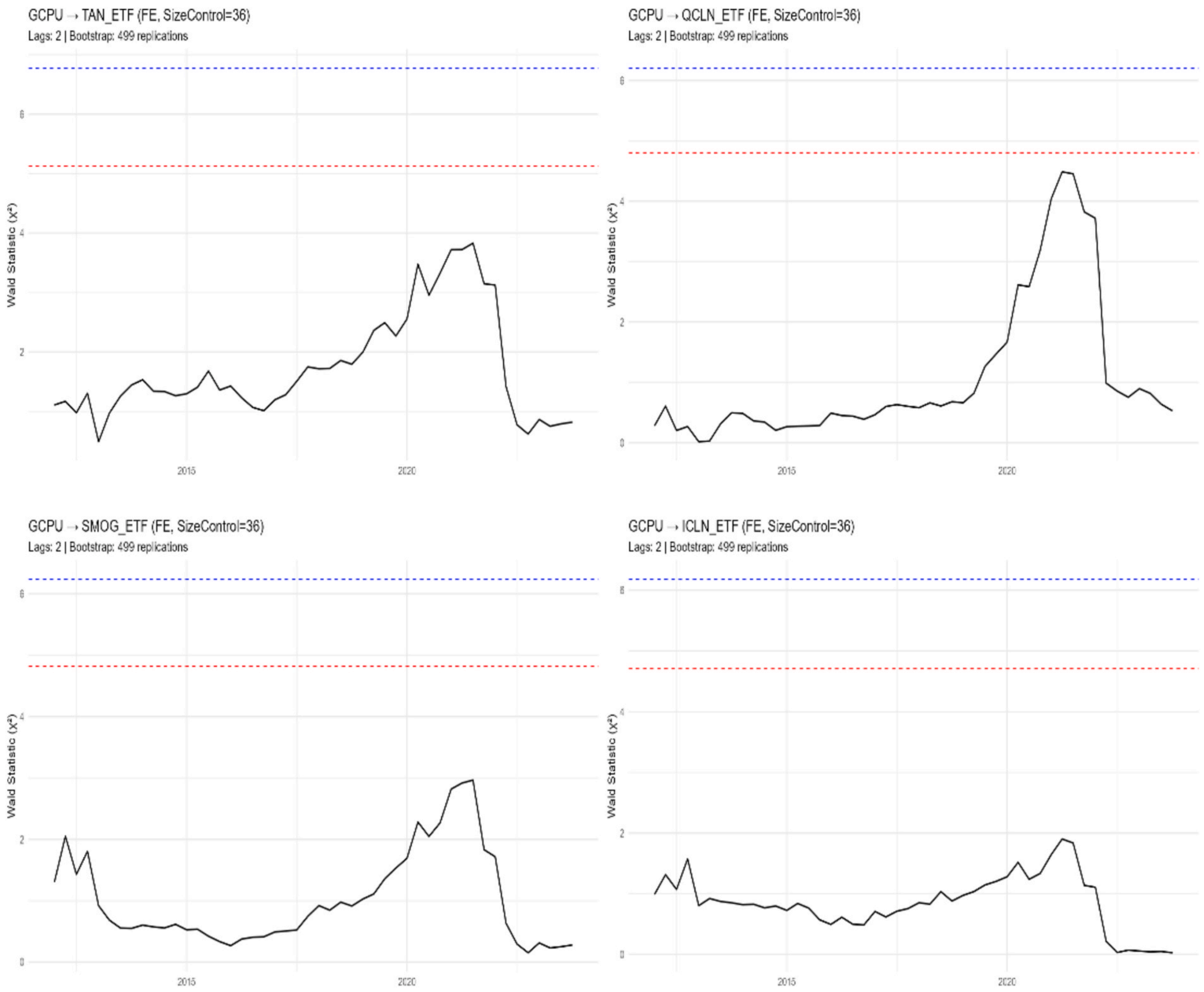

Fig. 24. Forward expanding: GCPU → renewable energy ETFs, size control/windows = 36.

structural change in the relationship. The COVID-19 crisis, global inflation, monetary tightening and the Russia–Ukraine conflict increased overall policy uncertainty to such a degree that sector-level signals from renewable ETFs were overshadowed. In such conditions, markets tend to focus on broad risk factors, which may explain the reduced predictive power of renewable ETFs for policy uncertainty in the later period.

Our findings that climate policy uncertainty (CPU) increasingly drives renewable ETF dynamics align with emerging evidence that technological and organizational transformations amplify market sensitivity to policy signals (Gao, Cai, et al., 2025). document an exponential surge in research on artificial intelligence (AI)-driven renewable energy systems since 2019, showing how rapid technological upgrading has intensified the pace of renewable transitions. This suggests that accelerating innovation may heighten investor sensitivity to policy-related uncertainty, thereby strengthening CPU's influence on renewable asset valuations. Similarly (Gao, Tan, et al., 2025a),show that participation in intelligent manufacturing pilot programs significantly improves firms' ESG performance by stimulating green innovation and improving financial resource allocation, implying that firms with stronger technological capabilities may react more sharply to policy shifts. In a related policy context (Gao, Tan, et al., 2025b), find that digital trade policies – through cross-border e-commerce pilot zones – reduce carbon emissions by improving resource allocation efficiency, industrial upgrading, and green technology adoption. These studies support the idea that policy – driven technological and digital reforms can magnify the responsiveness of renewable-related sectors to policy uncertainty shocks.

At the same time, our results also resonate with work showing that CPU can constrain renewable transitions through real-economy channels (Gao et al., 2025). find that CPU hinders urban renewable energy transition by exacerbating capital and labor misallocation and suppressing industrial structure upgrading, with particularly strong effects in non-capital and inland cities and under high regulatory intensity. This highlights how CPU can affect not only financial valuations but also the structural foundations of renewable expansion. Likewise (Yin et al., 2025), demonstrate that climate risk perception promotes firm ESG performance by fostering green innovation, increasing environmental protection investment, and reducing information asymmetry. Together, these findings suggest that the relationship between CPU and renewable investments likely reflects a balance between these opposing channels: technological

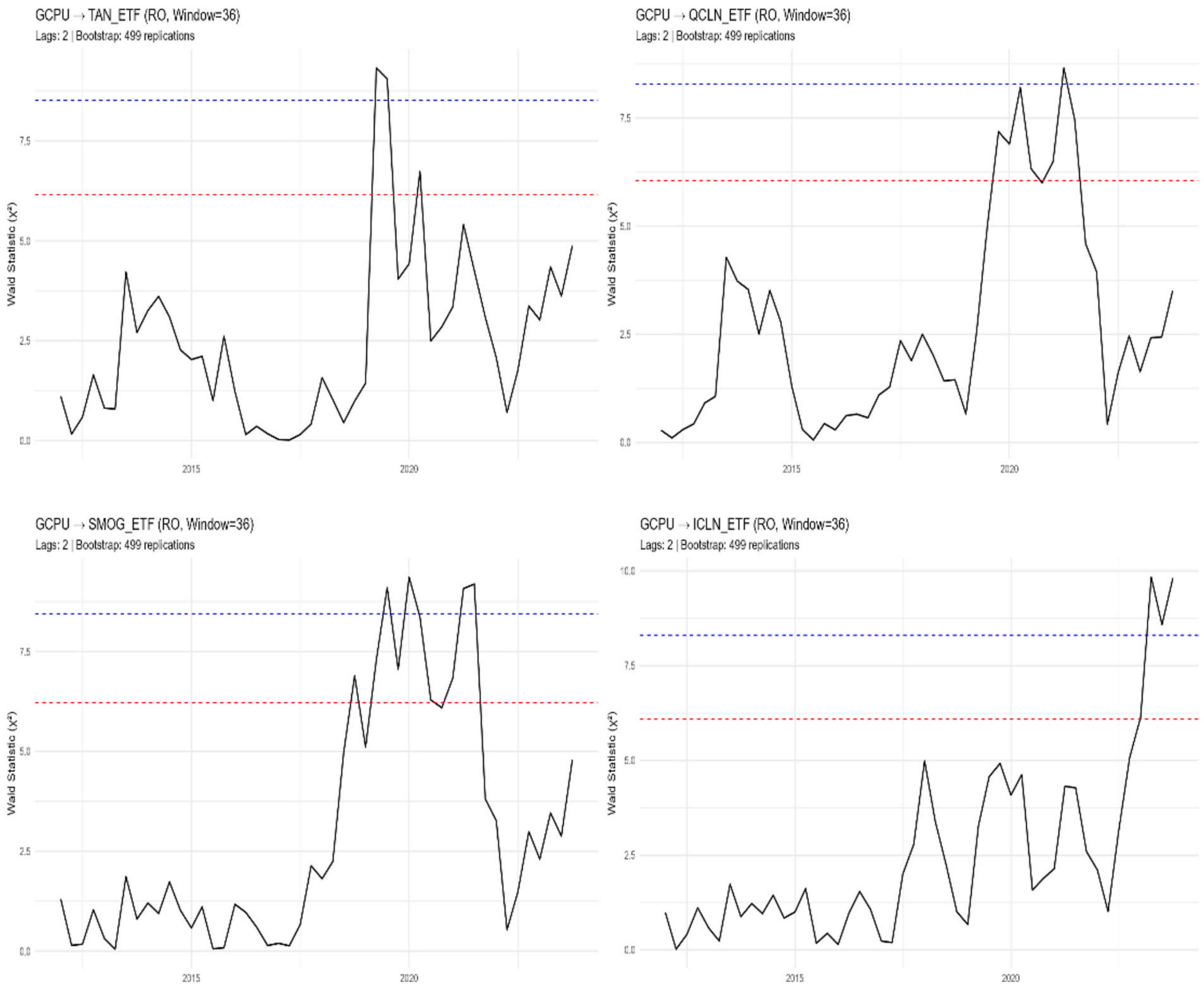

Fig. 25. Rolling window: GCPU → renewable energy ETFs, size control/windows = 36.

capability and green innovation amplify sensitivity, while resource misallocation and industrial rigidity dampen it. This offers a useful conceptual frame for interpreting the strengthening CPU-to-ETF causality we document.

These results point toward future research directions. Scholars could examine whether the CPU–renewable relationship varies across regions with different regulatory regimes or conduct event studies of specific climate policy announcements to assess their impact on renewable markets. In addition, future work could explore how the increasing influence of CPU on renewable ETFs shapes broader portfolio strategies and financial stability in the transition to a low-carbon economy. For example, researchers could investigate how institutional investors adjust asset allocation and hedging strategies in response to heightened CPU, whether exposure to renewable ETFs alters the risk–return trade-offs of diversified portfolios, and how climate policy shocks propagate through financial markets to affect systemic stability. Another avenue is to examine the interaction between CPU and the cost of capital for renewable firms, assessing whether elevated uncertainty raises financing costs or delays project development. Comparative analyses across regions with different regulatory regimes could also shed light on how policy design influences the resilience of both investors and financial systems.

We observe that the influence of renewable energy ETFs on CPU begins to weaken around 2020, which may reflect the maturation and integration of renewable energy investments into the broader financial market, reducing their ability to independently shape perceptions of climate policy uncertainty.

5. Conclusion and policy recommendation

5.1. Conclusions

This study focuses on the following research question: Is there a bidirectional causality between Renewable Energy Exchange-Traded Funds (ETFs) and Climate Policy Uncertainty (CPU)? In line with the objective of the study as a partial contribution to the

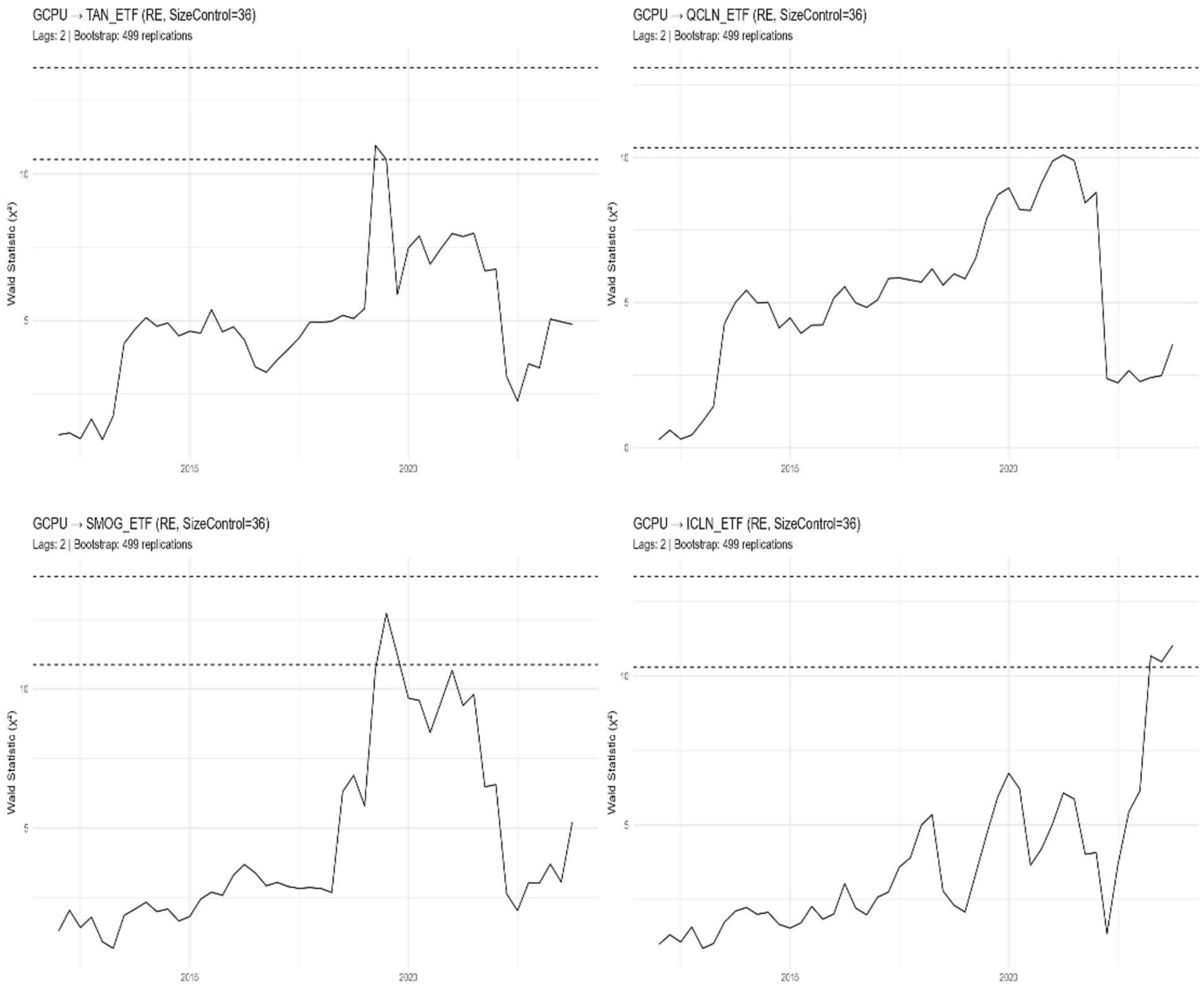

Fig. 26. Recursive expanding: GCPU → renewable energy ETFs, size control/windows = 36.

existing literature, the study aims to determine the causality that exists between CPU and renewable energy ETFs and vice versa. In this study, the Time-Varying Granger Causality test is used, and monthly data from January 2010 to June 2025 are used in the analysis. Forward expanding, rolling window, and recursive evolving algorithms are used.

The results demonstrate that the causal relationship between CPU and renewable energy ETFs is highly time-varying, with periods of strong causality that have evolved into a distinct asymmetric pattern. Specifically, causality from CPU to renewable ETFs strengthens over time, particularly after 2016, while the reverse causality from ETFs to CPU declines after 2020.Therefore, it can be concluded that temporal factors should be considered when examining the relationship between CPU and renewable energy ETFs because the relationship between them is not stable over time.

The increasing impact of CPU on renewable energy ETFs over time likely reflects the rising importance of climate policy in shaping investor expectations, particularly following major initiatives such as the Paris Agreement in 2015 and the Inflation Reduction Act in 2022. These developments have heightened market sensitivity to policy-related uncertainty, reinforcing CPU as a leading predictor of renewable asset performance. By contrast, the diminishing influence of renewable ETFs on CPU is consistent with the maturation and integration of renewable energy markets into the broader financial system, reducing their independent role in shaping perceptions of climate policy uncertainty. While these interpretations are suggestive rather than definitive, they highlight plausible mechanisms driving the observed temporal asymmetry. Future research could, for example, examine firm-level renewable energy stocks to determine whether market maturity effects operate at the individual company level, or conduct event studies of major climate policy announcements (e.g., Paris Agreement ratifications, national clean-energy subsidy rollouts) to directly trace the policy–market uncertainty transmission channel.

5.2. Policy recommendations

As this research has established a bidirectional causal relationship between Climate Policy Uncertainty (CPU) and Renewable

Energy Exchange-Traded Funds (ETFs), investors and policymakers must carefully consider the implications. The growing influence of CPU on renewable energy ETFs, particularly in recent years, underscores that the financial performance of renewable energy investments is increasingly sensitive to policy signals. As a result, investors should monitor changes in climate policy and integrate policy risk into portfolio strategies, while policymakers should design frameworks that minimize uncertainty.

To reduce CPU and foster a stable investment environment, climate policies should be transparent, consistent, and measurable. First, governments should publish long-term climate policy roadmaps with clear targets and timelines, ensuring that market participants can anticipate regulatory trajectories (e.g., phased carbon pricing schemes or renewable energy mandates). Second, policy instruments such as subsidies, tax credits, or renewable portfolio standards should be implemented with predictable review and renewal schedules, rather than ad hoc revisions that heighten uncertainty. Third, transparency can be enhanced through regular public reporting and impact assessments of climate policies, which would allow both investors and the public to evaluate progress against stated goals.

Moreover, assessing the impact of climate policies on renewable energy investment requires robust monitoring and evaluation frameworks. These may include standardized metrics for tracking investment inflows into renewable sectors, econometric evaluations of how policy announcements influence market prices, and international benchmarking against best practices in jurisdictions with successful policy outcomes (e.g., the EU's Green Deal or the U.S. Inflation Reduction Act). Such mechanisms not only reduce uncertainty but also create feedback loops that allow policymakers to adjust policies based on measurable results.

By adopting clear roadmaps, predictable policy instruments, and transparent monitoring systems, policymakers can reduce climate policy uncertainty, thereby lower investment risk and encouraging the flow of capital toward renewable energy. These measures are essential for accelerating the transition to a low-carbon economy while aligning investor incentives with long-term sustainability goals.

Author statement

SAG proposed the original idea, collected the data and wrote introduction and conclusions.

KSB wrote the literature review, the interpretation of the empirical results and overall review of the manuscript.

LAGA helped in the interpretation of the results and conclusions.

Data availability

Data will be made available on request.

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