THE CLEAN ENERGY-ECOLOGY INTERRELATEDNESS: EVIDENCE FROM THE S&P DOW JONES INDICES

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1. Introduction

While energy is essential for growth and development, it is also essential to recognize that “sustainable energy” fosters “environmental sustainability.” The compelling link between clean energy (CE) and ecology raises intriguing questions: Do rapidly advancing CE technologies, which drive the shift toward

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sustainable energy, positively impact ecology through improved water and waste management practices and efficient industrial systems? Can this nexus be analyzed by examining the returns of ecology-focused and clean energy firms? With private investment in CEs gaining momentum, particularly as a significant step toward mitigating climate change, it is crucial to evaluate the impact of these technologies on the performance of ecology-related firms (Hastik et al., 2015).

This research article investigates the clean energy–ecology nexus by analyzing the performance of clean energy and ecology-focused firms. Understanding the interrelationship between clean energy and ecology in the frequency domain allows for more nuanced conclusions. While the conventional time-domain causality approach gives an overall perspective of causal relationships, the frequency-domain causality approach can dissect these connections across various frequencies. This study adds to the clean energy–ecology nexus literature by employing the inferential framework developed by Farne and Montanari (2018) (FM approach) to unravel the causality between index returns of energy and ecology firms. The FM approach offers a distinct advantage by identifying prominent causalities, facilitating precise inference on "unconditional/conditional Granger-causality." In contrast, the widely used Breitung and Candelon (2006) test examines Granger-causality at individual frequencies. The FM approach surpasses existing methods of frequency-domain causality inference by functioning as a robust inferential tool, enabling substantive insights into the causal dynamics between clean energy and ecological variables.

This study is the first to investigate the interconnectedness between clean energy and ecology. It empirically examines the bivariate dependence structure among clean energy and ecology stock price indices. Methodologically, this study aligns with literature that revisits various economic nexuses, including the inflation-growth relationship (Tiwari et al., 2019), the interplay of energy and economic growth (Tiwari, 2014), dynamic linkages between renewable energy stocks and crude oil prices

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(Ferrer et al., 2018), and the interconnectedness between oil prices, clean energy, and technology stock returns (Nasreen et al., 2020).

The paper is organized as follows: Section 2 details the data and methods used in the study, Section 3 presents the empirical findings, and Section 4 provides the main conclusions.

2. Data and Methods

2.1. Data: Our time-series data for this analysis is sourced from the S&P Dow Jones Indices LLC Database. We utilize the S&P Global Eco Index (ECOR), S&P Global Clean Energy Index (ENER), and the S&P 500 Index (SPR) for equity-based indices that are internationally recognized for their robust methodologies and insights into market dynamics. The primary sample consists of daily returns from August 4, 2009, to December 29, 2017, totaling 2,190 observations. Additionally, an out-of-sample period from August 2, 2017, to July 31, 2019, includes 517 observations to validate the main results.

Table 1 presents descriptive statistics and unit root test outcomes. The returns of the three indices show asymmetrical distributions, evidenced by negative skewness (less than one) and leptokurtic distribution with excess kurtosis. The Jarque-Bera test indicates data non-normality. Both the ADF and PP tests reveal non-stationarity; however, the Zivot-Andrews (ZA) and KPSS tests confirm stationarity, considering an endogenous structural break (ZA) and fractional integration (KPSS), thus suggesting stationarity of the returns series. The Ljung-Box test shows no serial correlation, while the ARCH-LM test reveals an ARCH effect, indicating conditional heteroscedasticity in all three series. Table 2 reports various nonlinearity test results. The Teraesvirta and White neural network tests, along with the Keenan and Tsay tests, confirm nonlinearity at a 1% significance level. Consequently, based on the findings in Tables 1 and 2, one can conclude that linear or parametric models may yield biased estimates, limiting the validity of drawn conclusions and policy implications.

Further, Figure 1 presents the time series plots of the returns for ecology (ECOR), energy (ENER), and S&P 500 (SPR) indices, showing similar overall trends across these series. Figure 2 illustrates the rolling correlation between ECOR and ENER using a 25-day window, indicating a noticeable decline in correlation strength since 2016. This plot further reveals the time-varying nature of the correlation, suggesting that linear or time-constant models are unsuitable for analyzing this relationship. The results in Figure 2 support the use of the frequency-domain (FM) approach in this study to effectively address the research question.

2.2. Granger-Causality Spectra: The concept of "causality," commonly known as Granger-causality (GC) and popularized by Granger (1969), holds considerable importance from both theoretical and practical perspectives (Berzuini

Table 1
SUMMARY STATISTICS[a]

	Mean	Median	Max	Min	Std. Dev.	Skew-ness	Kur-tosis	Jarque-Bera
ECOR	0.0030	0.0101	0.011	−0.013	0.002	−0.54*	7.35*	1691.9*
ENER	−0.0059	0.0070	0.011	−0.012	0.002	−0.27*	5.41*	512.6*
SPR	0.0001	0.0001	0.007	−0.01	0.001	−0.47*	7.61*	1859.4*

	ADF	PP	ZA	KPSS	Ljung-Box	Ljung-Box^2	ARCH-LM(10)	Obs.
ECOR	−12.66	−1697.97	−13.77*	0.06	38.6*	591.6*	267.5*	2012
ENER	−11.56	−1647.91	−12.91*	0.24	69.8*	547.5*	270.5*	2012
SPR	−13.25	−1985.15	−14.54*	0.02	32.8*	1055.0*	446.8*	2012

[a]*is for significance at a 1% level of significance. Unit root and stationarity tests assume Constant.

et al., 2012). Contributions by Pierce (1979) and Geweke (1982, 1984) introduced the foundational ideas of frequency domain causality, specifically "unconditional and conditional Granger causality." Building on this, Breitung and Candelon (2006) developed a framework to test short- and long-run Granger causality (GC) within the frequency domain, demonstrating its effectiveness in examining the predictive power of interest rates on real economic growth. These advancements sparked renewed interest in frequency-based GC methods (Nishiyama, 1997).

This study is motivated by Farne and Montanari (2018), who proposed a bootstrap testing method for assessing "conditional and unconditional GC spectra," which highlights significant causality cycles in relative terms. This method, termed the

Table 2
NONLINEARITY TESTS[a]

	Teraesvirta_NN_Test	White_NN_Test	Keenan_Test	Tsay_Test	Obs.
ECOR	21.477*	11.525*	0.285051	4.346*	2012
ENER	19.325*	12.298*	5.479668	2.446	2012
SPR	17.659*	0.970338	15.89195	2.732*	2012

[a]*is for significance at a 1% level of significance; NN stands for neural network.

Figure 1
ECOLOGY, ENERGY, AND S&P500 RETURNS

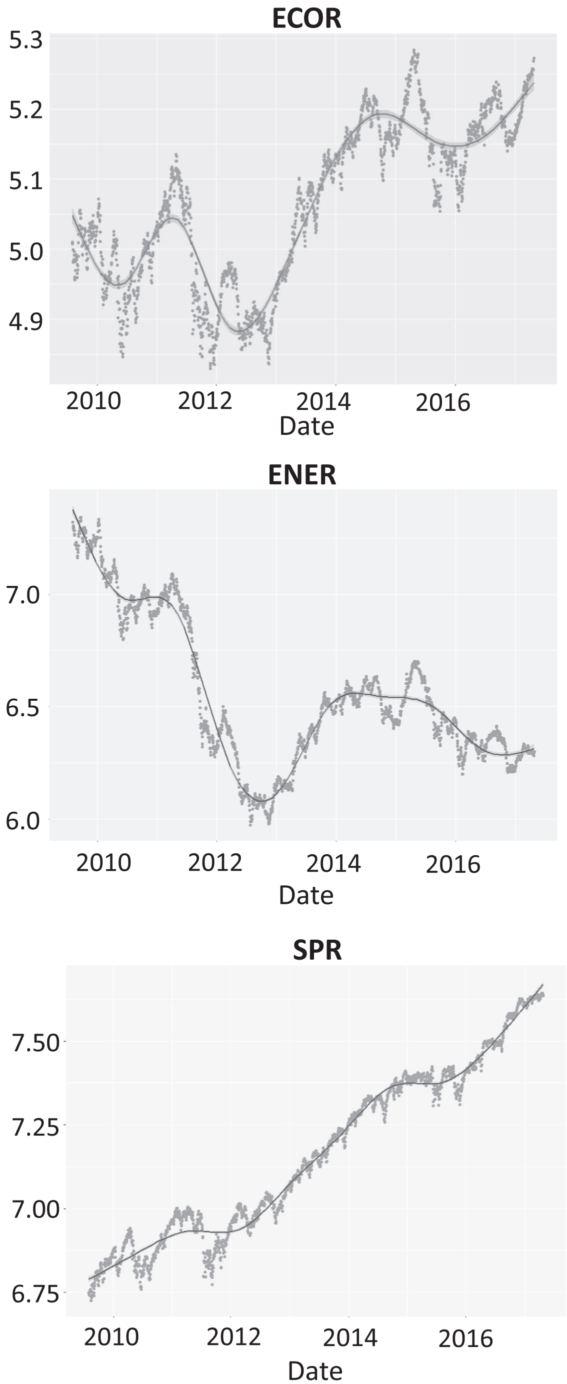
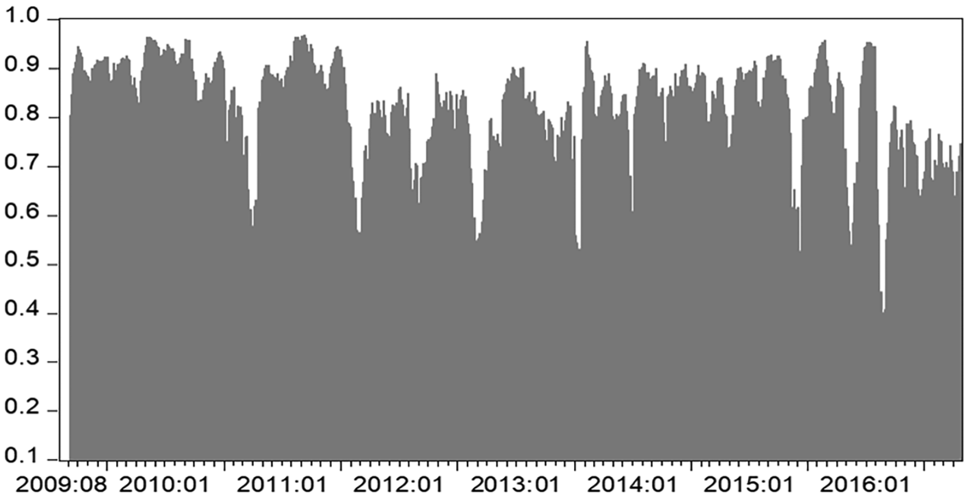


Figure 2
ROLLING CORRELATION PLOT OF ECOR AND ENER



"Farne-Montanari (FM)-bootstrap test for Granger-causalities across frequencies," underpins our approach.

The assumption is that the historical values of a time series Y_t can forecast another time series X_t at time t as Y_{t-1}, Y_{t-2}, … complement substantial information to the historical values of X_t, i.e., X_{t-1}, X_{t-2}, … in predicting X_t. This argument leads to the statement that "Y_t Granger causes X_t."

Following the GC spectral theory approach in Ding et al. (2006), when X_t and Y_t are jointly in the covariance of stationarity, they follow a non-singular VAR(k) model. Then, specifying Zt = [Xt, Yt]′, Farne and Montanari (2018) write the following equation (1):

$$Z_t = A_1 Z_{t-1} + \ldots + A_k Z_{t-k} + \in_t \quad (1)$$

where $\in_t \sim N_2(0, \Sigma_2)$, Σ_2 is a 2×2 covariance matrix; $A_1, \ldots., A_k$ are 2×2 coefficient matrices.

For each frequency ω, the transfer function for $P(\omega)$ of Z_t in equation (1) can be written as equation (2):

$$P(\omega) = \left(\mathrm{I} - \sum_{j=1}^{k} A_j e^{-ijw} \right)^{-1}, \quad -\pi \le \omega \le \pi \quad (2)$$

Following Geweke (1982), the unconditional GC spectrum of the effect variable X_t with reference to the cause variable Y_t can be defined as equation (3):

$$h_Y \to X(\omega) = ln\left(\frac{h_X X(\omega)}{\widetilde{P}_X X(\omega)\sigma_2 \widetilde{P}_X X(\omega)^*}\right) \tag{3}$$

Similarly, the unconditional GC spectrum of the effect variable X_t concerning the cause variable Y_t can be specified as:

$$h_Y \to X/W(\omega) = ln\left(\frac{h_X * X * (\omega)}{Q_X X(\omega)\sigma_X Q_X X(\omega)^*}\right) \tag{4}$$

Both $h_Y \to X(\omega)$ and $h_Y \to X/W(\omega)$ range from 0 to ∞, with $-\pi \leq \omega \leq \pi$. Whereas, $h_Y \to X(\omega)$ denotes the relationship power between Y to X at frequency ω, $h_Y \to X/W(\omega)$ is the relationship strength from Y to X at frequency ω, given that Wt is a conditioning variable (Farne & Montanari, 2018).

Because of the rich causality structure, causality tests employed in macroeconomic series generally flag most of the causalities as significant. Therefore, Farne and Montanari (2018) suggest a suppletive bootstrap test method to explicate the most prominent ones. This method tests at each frequency (ω), the null hypothesis H_0: $t(\omega) = t_{med}$ against the alternative H_1: $t(\omega) > t_{med}$, where the functional $t(\omega)$ may be the unconditional $GCh_Y \to X(\omega)$, the conditional $GCh_Y \to X/W(\omega)$ or their difference $h_Y \to X(\omega) - h_Y \to X/W(\omega)$, and t_{med} is the median of $t(\omega)$ across frequencies (Farne & Montanari, 2018).

Following Politis and Romano (1994), Ding et al. (2006), and Breitung and Candelon (2006), this method approximates the distribution of each $t(\omega)$ as: $h_Y \to X(\omega)$ and $h_Y \to X/W(\omega)$ are unknown. The bootstrap series obtained are conditionally stationary Markov chains.

Because of the complete stochastic behavior of X_t^*, Y_t^* and W_t^* is explained by the conditional distributions of X_t^*/X_{t-1}^*, Y_t^*/Y_{t-1}^* and Z_t^*/Z_{t-1}^*, the computation of "conditional and unconditional GC spectra" on the data series. Thus, Farne and Montanari (2018) argue that the strength of this approach lies in testing each GC estimated on the original series, i.e., X_t, Y_t, and W_t, with the median causality calculated across frequencies on X_t^*, Y_t^* and W_t^*.

2.3. Estimation Strategy: In the testing procedure, first, for the functional, $h_Y \to X(\omega)$, the bootstrap procedure is to replicate N stationary bootstrap series ($ECOR_t^*$, $ENER_t^*$) for actual series ($ECOR_t$, $ENER_t$). Second, for the functionals, $h_Y \to X/W(\omega)$ and $h_Y \to X(\omega) - h_Y \to X/W(\omega)$, we simulate the N bootstrap series ($ECOR_t^*$, $ENER_t^*$, SPR_t^*) for the actual series ($ECOR_t$, $ENER_t$, SPR_t). In our specifications, $ECOR_t$, $ENER_t$, SPR_t denote the series X_t, Y_t, and W_t of the model, where $t = 1, \ldots, 2190$. SPR_t is the conditioning variable, which discounts the mediating power concerning the relationship between ECOR and ENER.

We compute the "unconditional Granger-causality" and the "conditional GC" spectra, followed by performing bootstrap inference on the "unconditional GC" and "conditional GC" spectra. Then, we perform the bootstrap inference on the difference between unconditional/conditional GC spectra. Finally, we perform the BC Test (2006) on the "conditional/unconditional GC" spectra.

3. *Results*

Figure 3 shows the "Conditional GC" from ENER to ECOR. This result shows that GC running from ENER to ECOR conditioning on SPR is significant at the 0.5% level and highly pronounced throughout the whole frequency range. Figure 4 demonstrates the Granger difference conditional from ENER to ECOR. We find the remarkable amplification power of SPR as it moves from lower to higher frequencies. Figure 5 indicates the unconditional GC inference flowing from ENER to ECOR and ECOR to ENER. This result supports the evidence provided in Figure 3 and reinforces our understanding that the GC between ECOR and ENER as it is significant at the 1% level up to frequency 0.2, i.e., for approximately 31 days.

Figure 3
CONDITIONAL GRANGER CAUSALITY FROM ENER TO ECOR

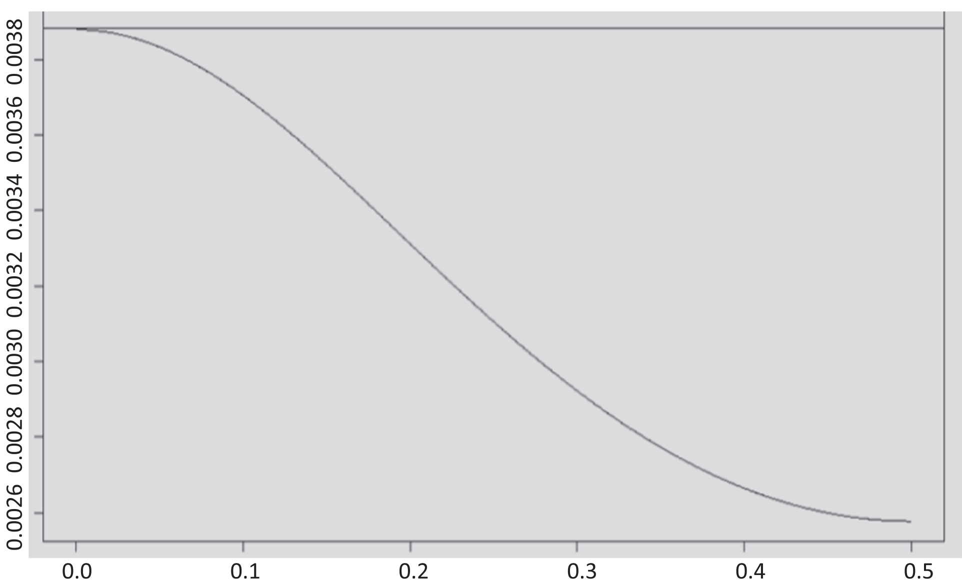


Figure 4
GRANGER DIFFERENCE CONDITIONAL FROM ENER TO ECOR

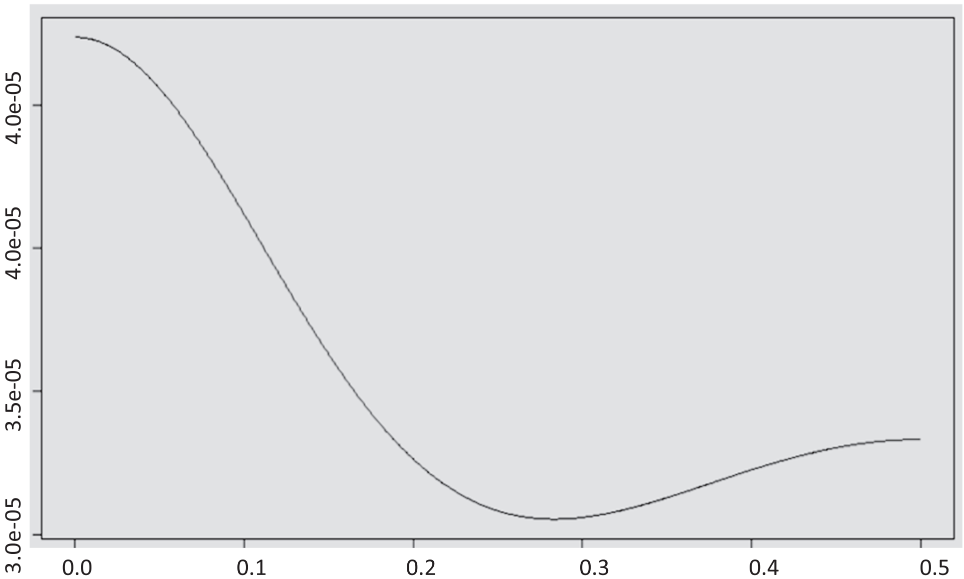
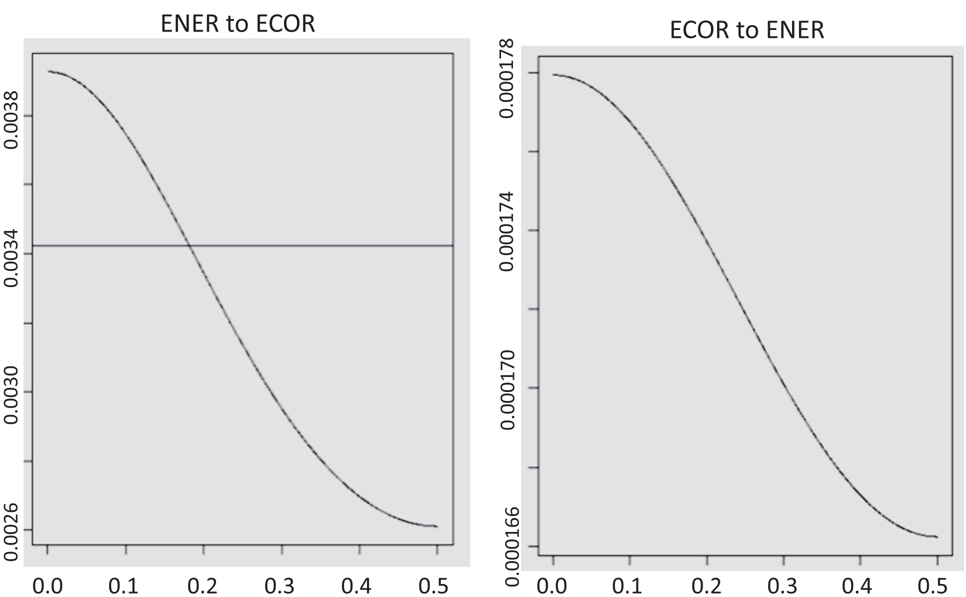


Figure 5
UNCONDITIONAL GRANGER CAUSALITY INFERENCE



3.1. Robustness Test: To provide further evidence supporting the main results, we repeat the "FM-bootstrap test for Granger-causalities across frequencies" using the out-of-sample data for August 2, 2017 to July 31, 2019. Figure 6 exhibits the "Conditional GC" in the out-of-sample data. Figure 6 shows that GC flows from ENER to ECOR conditioning on SPR at a 5% significance level throughout the frequency range. This result supports the evidence in Figure 3, as the results are fairly similar. Figure 7 shows the Granger difference conditional from ENER to ECOR in the out-of-sample data. We find remarkable fluctuation in the amplification power of SPR as it moves from lower to higher frequencies. However, the significance is well within a significance level of 0.1% up to 0.45 and is similar to that in Figure 4.

Figure 8 reveals the unconditional GC inference flowing from ENER to ECOR and ECOR to ENER in the out-of-sample data. This result supports the evidence provided in Figure 6 and re-emphasizes the GC moving from ENER to ECOR, as it is significant at the 5% level throughout the whole frequency range.

3.2. Additional Robustness Tests: Frequency domain analysis with Granger causality tests typically examines the gain function of the applied matching filter on the input variable, overlooking the phase shift introduced by the filter's inherent properties. Breitung and Schreiber (2018), however, enhanced frequency domain causality analysis by introducing an autoregressive filter that enables estimating the

Figure 6
CONDITIONAL GRANGER-CAUSALITY ENER TO ECOR IN OUT-OF-SAMPLE DATA

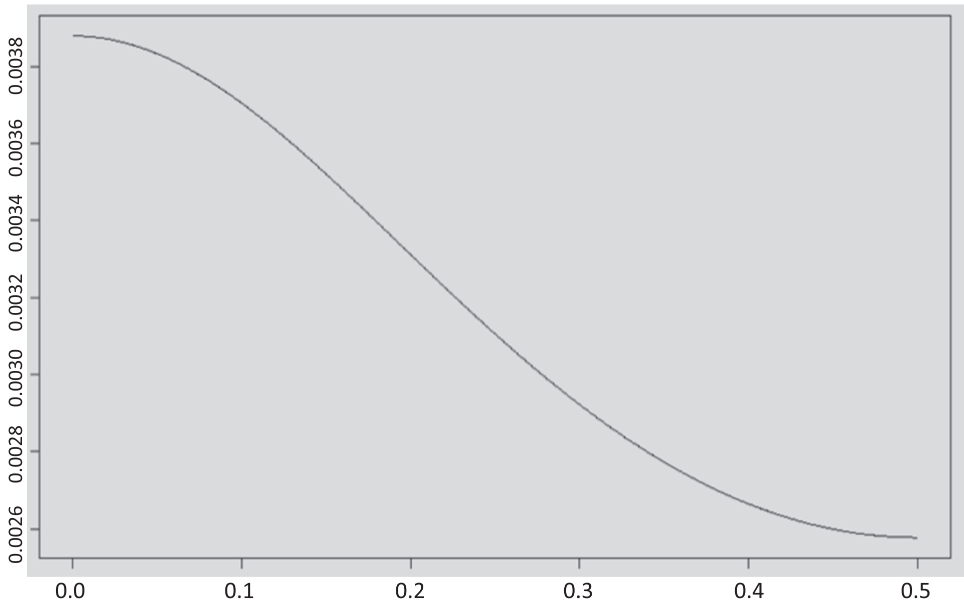


Figure 7
GRANGER DIFFERENCE CONDITIONAL FROM ENER TO ECOR
IN OUT-OF-SAMPLE DATA

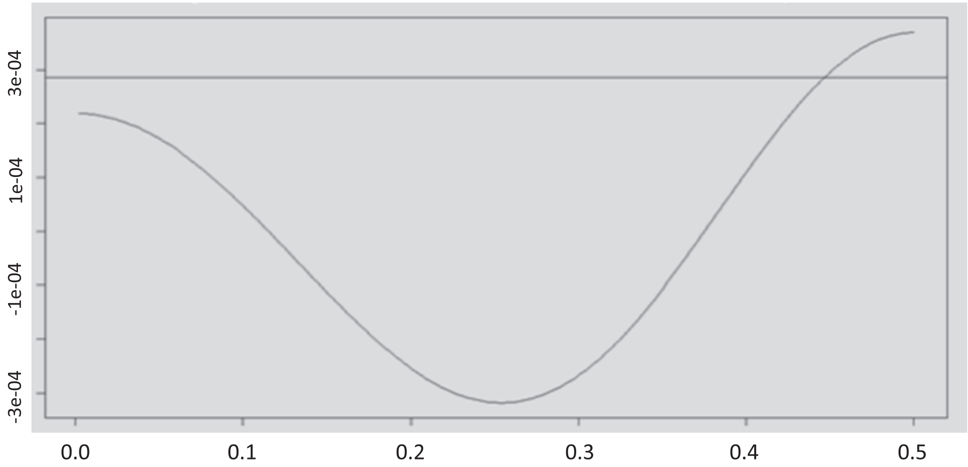


Figure 8
UNCONDITIONAL GRANGER CAUSALITY INFERENCE IN OUT-OF-SAMPLE DATA

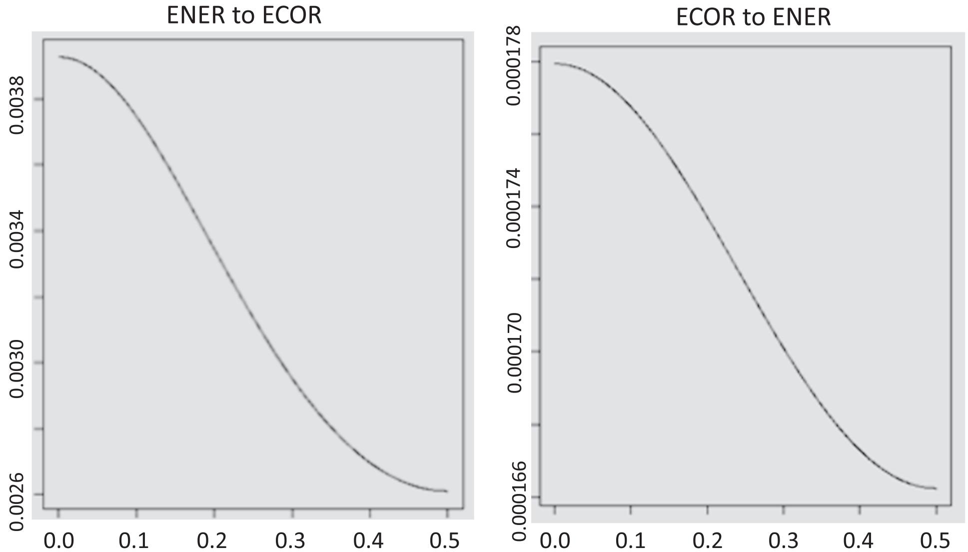


Figure 9
FREQUENCY-WISE BC TESTS ON ECOR (TARGET) AND ENER (CAUSE)

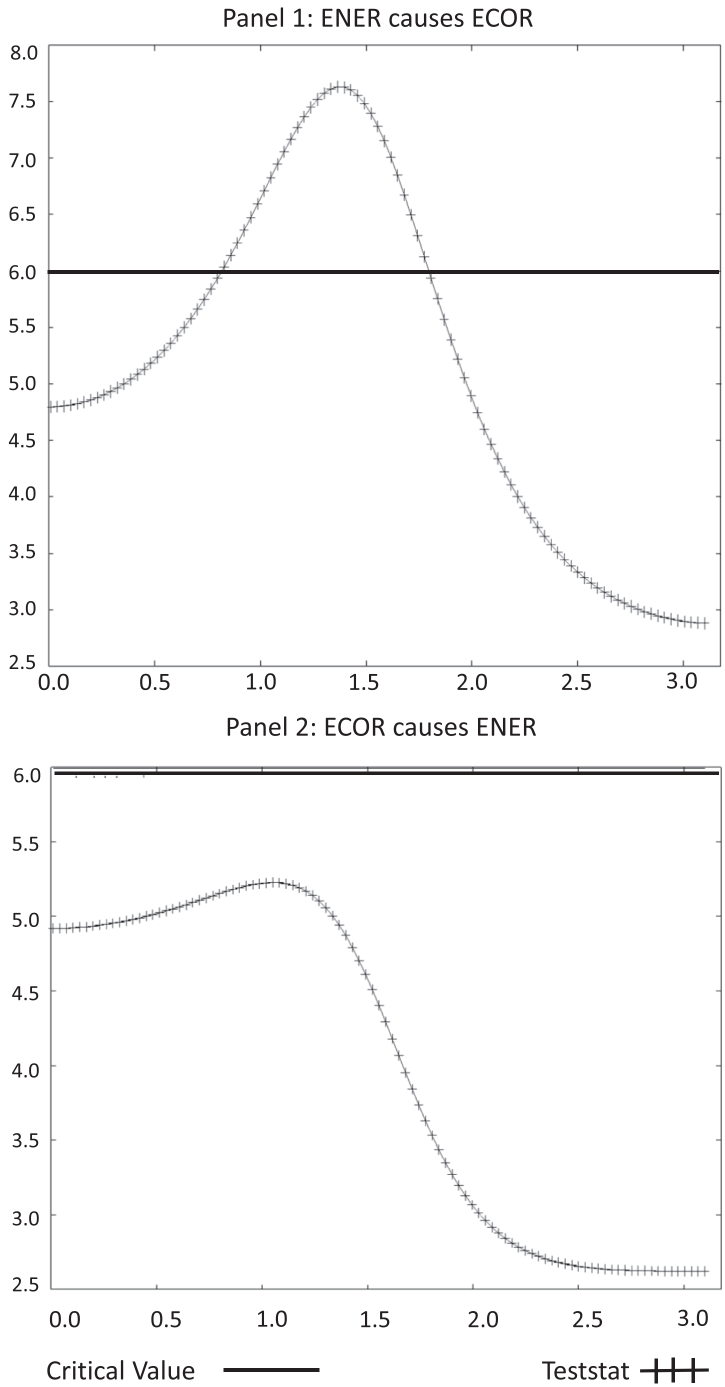


Figure 10
NUMERICAL CHECK OF WHETHER $|F_{\hat{\alpha}}(\omega)|^2 = 0$ AND/OR $|F_{\hat{\beta*}}(\omega)|^2 = 0$

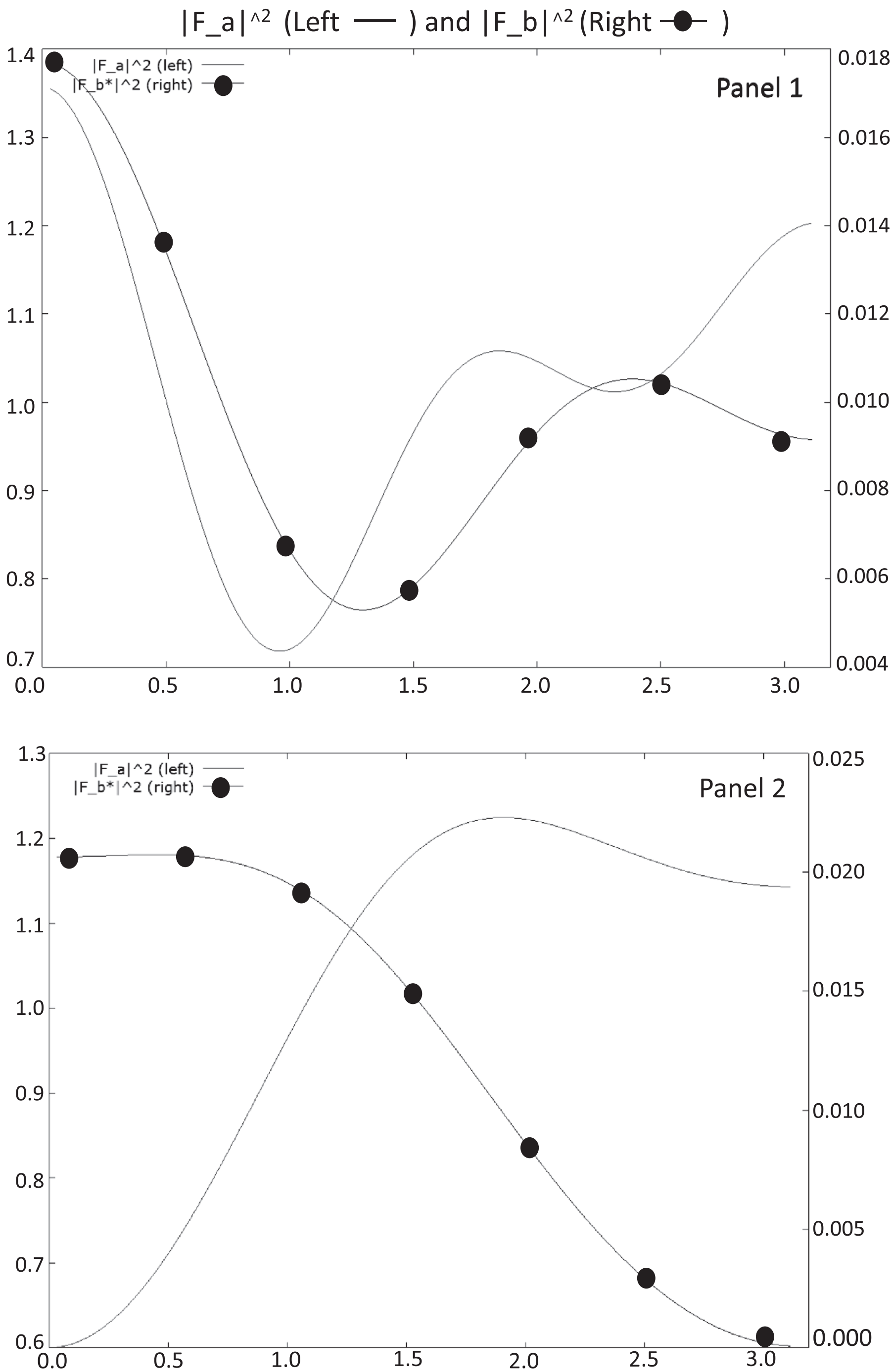
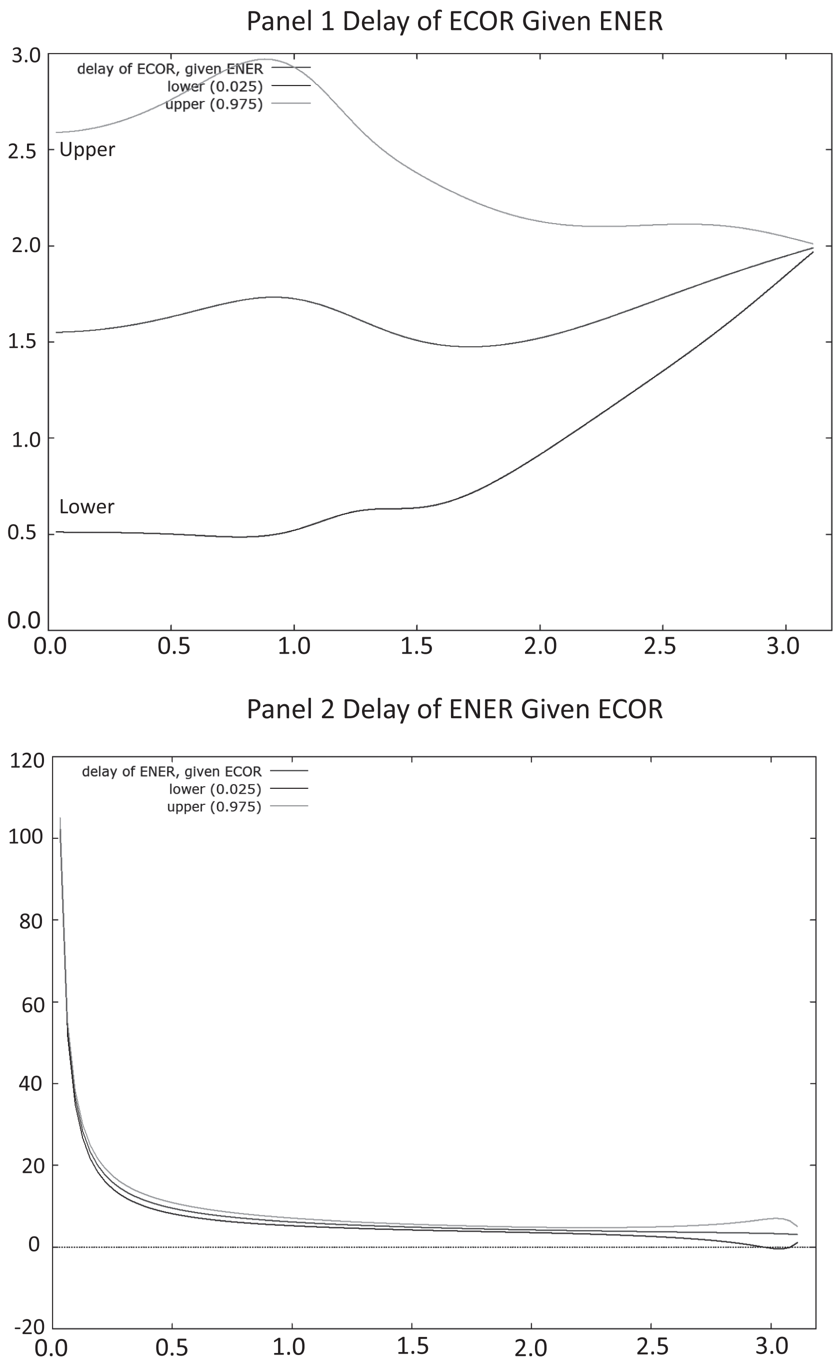


Figure 11
DELTA-METHOD CONFIDENCE INTERVALS FOR THE TIME DELAY
(POINT-WISE, NOMINAL 95% COVERAGE).



time lag between input and response within a specified frequency band. Causality from ENER to ECOR at zero frequency (i.e., in the long term) is well established, so we focus on non-zero frequencies for further insight. Figure 9 presents the results of frequency-specific tests. Panel 1 in Figure 9 shows a significant effect of ENER on ECOR at frequencies between 0.8 and 1.8, while Panel 2 reveals that ECOR has no significant effect on ENER. Thus, as an initial step in our robustness testing, we confirm the presence of Granger causality at certain frequencies, as illustrated in Figure 9.

We then analyze the point estimations of time delays across specific frequencies. To this end, it is essential to conduct a numerical verification to determine if the phase is well-defined or if it vanishes at any point. Accordingly, Figure 10 displays the analysis of the numerical check of whether $|F_{\hat{\alpha}}(\omega)|^2 = 0$ and $|F_{\hat{\beta}*}(\omega)|^2 = 0$ remain significantly above zero across all frequencies shown. We notice that both the progressions of the squared absolute values of $|F_{\hat{\alpha}}(\omega)|^2$ and $|F_{\hat{\beta}*}(\omega)|^2$ are far off from zero in all the reported frequencies. Additionally, we assess the progression of confidence intervals derived using the delta method. Figure 11 illustrates these delta-method confidence intervals for time delays, with periods displayed on the Y-axis. The results indicate the practical relevance of fluctuating Granger-causality in the frequency domain.

4. Conclusion

This study applies the Farne and Montanari (2018) approach to break down the clean energy–ecology nexus. Findings indicate that Granger causality from clean energy to ecology, conditioned on stock prices, is significant at the 0.5% level across the entire frequency spectrum. The main results are validated through a robustness test using the "FM-bootstrap test for Granger-causalities across frequencies" on out-of-sample data. Additional robustness testing, employing the Breitung and Schreiber (2018) method to assess causality within specific time-delay bands, further supports the primary findings. Overall, the results suggest that clean energy technologies positively influence ecology.

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