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Does climate risk as barometers for specific clean energy indices? Insights from quartiles and time-frequency perspective

Hongjun Zeng [a], Mohammad Zoynul Abedin [b,*], Vineet Upreti [b]

[a] *Department of Financial Planning and Tax, School of Accounting, Information Systems and Supply Chain, RMIT University, Melbourne, Australia*
[b] *School of Management, Swansea University, Bay Campus, Fabian Way, Swansea SA1 8EN, Wales, United Kingdom*

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ABSTRACT

This study presents the first analysis of the nexus between the Southern Oscillation Index (SOI), a measure of climate risk, and segmented clean energy indices (such as solar, renewable, and bioenergy). Our research findings indicate that (i) the Granger quantile causality significance of SOI on segmented clean energy indices is asymmetric across different conditional quantiles. Significant predictability of SOI is observed only at the 0.25 and 0.75 quantile levels for all segmented clean energy indices, except for the WilderHill Clean Energy Index and NASDAQ OMX Fuel Cell Index. (ii) The clean energy market is significantly influenced by SOI under bullish market conditions. Impacts of SOI on all clean energy markets are nearly negligible when clean energy indices are at the median and lower quantile levels. (iii) The influence of strong La Niña episodes on segmented clean energy indices is more pronounced than during periods of intense El Niño phenomena. (iv) SOI exhibited a positive correlation at mid-term and long-term frequencies with segmented Clean Energy sectors, excluding bioenergy, for the majority of the sample period. Our conclusions provide deeper insights for investors managing clean energy investments in extreme climate conditions. Additionally, they offer useful information for policymakers to formulate viable economic policies addressing climate change, ensuring energy security, and facilitating a safer transition to clean energy.

1. Introduction

Recently, significant impacts on global clean energy investments have been observed, including the COVID-19 and subsequent global energy crises, making clean energy an increasingly important asset for economic recovery, climate protection, and energy transition (Tian et al., 2022). Currently, governments and international organizations are continually increasing their support for clean energy through policy guidance, fiscal incentives, and technological innovation, thereby promoting the development of clean energy (de Jesus Fernandez and Watson, 2022). Additionally, it is crucial to mention that Russian-Ukrainian war directly heightened the high instability of traditional energy markets and exacerbated uncertainty in traditional energy. In order to reduce dependence on fossil fuels to ensure supply chain security and mitigate energy supply chain security risks, many countries have increased institutional and policy support for clean energy in response to the strong uncertainty in the crude oil market arising from geopolitical factors (Hussain et al., 2023).

Therefore, in this document, we investigated the influence of the daily Southern Oscillation Index on segmented clean energy markets. The Southern Oscillation Index, a crucial atmospheric indicator measuring global climate change, played an irreplaceable role in studies on the societal and economic impacts of extreme weather (Islam et al., 1980). According to relevant theories, this index served as a primary measure of the El Niño-Southern Oscillation (ENSO) phenomenon, reflecting the interaction between sea surface temperatures in the tropical Pacific Ocean and atmospheric circulation. Most importantly, by monitoring and analyzing the variations in the Southern Oscillation Index (SOI), a thorough understanding of atmospheric circulation patterns in the climate system, particularly the development and evolution of El Niño and La Niña events, was attainable (Henchiri et al., 2021).

It is essential to clarify that the SOI is not an extreme climate event itself, but rather an indicator of the ENSO system, measuring air pressure differences between specific locations. While El Niño and La Niña are natural climate phenomena not directly caused by fossil fuel consumption, there is growing evidence that anthropogenic climate change, largely driven by greenhouse gas emissions from fossil fuels, may be indirectly influencing ENSO events. This influence is complex,

* Corresponding author.
E-mail addresses: hongjun.zeng@student.rmit.edu.au (H. Zeng), m.z.abedin@swansea.ac.uk (M.Z. Abedin), v.upreti@swansea.ac.uk (V. Upreti).

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potentially altering ENSO characteristics such as amplitude, frequency, or spatial pattern. The relationship between fossil fuel use, climate change, and ENSO remains an active area of research in climate science, highlighting the intricate interactions within the global climate system (McPhaden, 1999; Cai et al., 2018; Timmermann et al., 2018; McPhaden et al., 2020).

Given the preceding discourse, it is projected that the evolution and deployment of renewable energy sources will have a great correlation with climate change mitigation. Primarily, diminishing dependence on fossil fuels can substantially decrease carbon emissions. Consequently, adopting renewable energy could, to a certain degree, decelerate the progression of climate change, which in turn, may lessen both the occurrence and severity of severe weather phenomena (Bernai, 2013). While the ENSO phenomenon, as indicated by the SOI, is a natural climate variability, understanding its potential impacts on energy markets, including clean energy, is crucial for effective energy planning and risk management.

On another note, according to behavioral finance perspectives, climate change factors gradually became key influencers of investor decision-making and market behavior (Masini and Menichetti, 2012). Additionally, the study by Campiglio et al. (2023) confirmed that investors indeed responded to climate-related risks, which consequently led to variations in the prices of financial assets. With the ongoing increase in environmental risks due to climate change and growing societal attention to sustainable development, these factors impacted investor decisions through various channels (Zhang, 2022).

The financial risks triggered by climate transition to a low-carbon economy have become focal concerns for market participants (Bolton and Kacperczyk, 2021). However, there is a significant gap in the literature regarding the drivers of climate risk across segmented clean energy markets. While Wei et al. (2022) briefly examined the effects of the ENSO on the clean energies in the US and the EU, they did not delve into the asymmetric shocks of the SOI on segmented clean energy markets. It is crucial to acknowledge that the realm of clean energy spans distinct market segments, including solar energy, wind power, and bioenergy. Understanding how these different segments respond to climate indicators like the SOI can provide valuable insights for investors and policymakers in the transition towards a more sustainable energy system.

In summary, the primary research questions addressed in this paper are: (1) Is there a correlation between the SOI (Climate Risk) and the market performance of segmented clean energy markets? (2) Does the Southern Oscillation Index exhibit return predictability for segmented clean energy markets, and is the predictability heterogeneous across different segmented clean energy indices? (3) How does predictability vary under different climatic and market conditions (different quantiles)? The results of this analysis aim to provide market participants with valuable perspectives for appropriate policy and investment considerations. (4) How did the local or overall correlation between SOI and segmented Clean Energy Indices vary across different times and scales (with scale being correlated with frequency)?

In this article, we employed various approaches to analyze the quantile causality and impact of the Southern Oscillation Index on segmented clean energy indices. Quantile regression, a crucial tool for studying heterogeneity and heterogeneous effects, was used (Koenker and Xiao, 2004). Specifically, (1) we initially adopted the quantile granger causality method to investigate how segmented clean energy indices were causally affected by extreme weather events during different quantiles (market conditions) periods. The main advantage of quantile Granger causality methods was their ability to provide a distribution of nonlinear causal relationships from the Southern Oscillation Index to segmented clean energy indices' market performance at specific quantiles (different market conditions). (2) Through the use of Quantile-on-Quantile Regression (QQR), the heterogeneous impacts of the Southern Oscillation Index, encompassing both La Niña and El Niño periods, were measured on segmented clean energy markets across varying market states (different quantiles). This approach provided market participants with the advantage of analyzing the asymmetric or heterogeneous responses of the clean energy stock market to La Niña and El Niño events during both bull and bear markets. In contrast, traditional linear regression methods, such as OLS or general quantile regression approaches, were incapable of yielding such nuanced results. (3) For robustness analysis, we adopted the cross-quantile (CQ) approach introduced by Han et al. (2016). The CQ method provided an intuitive understanding of non-linear and directional predictability across quantiles. Therefore, this allowed for a more detailed examination of the connection across the returns of segmented clean energy indices and Southern Oscillation Index shocks. This method also enabled us to estimate the extreme climate (SOI) shocks faced by each segmented clean energy index and its distribution attributes. Another advantage of this approach was that it could handle heavy-tailed sequences in time series data and did not require estimating conditional and variance ratios from traditional correlation plots and nonlinear estimators (Han et al., 2016). (4) Wavelet coherence analysis is a widely employed and practical technique, as it takes into account the frequency domain. Indeed, relying solely on time-domain analysis is insufficient for observing all data characteristics (Kumar and Foufoula-Georgiou, 1997). Wavelet coherence transforms the original sequence into decomposed sequences, enabling different non-stationary time series with varying degrees of local coherence in high or low frequencies to be identified (Park et al., 2014). This allows us to simultaneously identify the temporal relationships between the Southern Oscillation Index and Clean Energy Indices at all time domain and frequency domain.

This study has contributed incrementally to existing literature in several respects: (1) Previous research has often been confined to low-frequency data on extreme weather (monthly data), while studies utilising high-frequency data on extreme weather indices have been lacking. The advantage of high-frequency time series data over low-frequency data lies in its more detailed and accurate information due to a higher number of observation points (Andersen and Bollerslev, 1997). Moreover, high-frequency data is suitable for detailed analysis, real-time decision-making, and providing more accurate model predictions (Ghil and Vautard, 1991). (2) The influence of extreme climate shocks on energy has been a continual focus for market participants. This research systematically examined the influence of the Southern Oscillation Index on segment clean energy sectors using a range of methods. The results from these methods are of significant importance to the literature in energy and sustainability. (3) This paper revealed the heterogeneity of the impact of SOI on segmented clean energy sectors under different market conditions and extreme weather states. The contribution of this article allows the academic community, business sector, general public, and government to gain an in-depth understanding of the connection between extreme climate change and clean energy markets performance. It provides a more accurate reference for risk management for investors, assisting market participants in making informed decisions in today's environment of increasingly prevalent and severe extreme weather disasters and heightened financial market uncertainty. (4) Due to the inherent connection between the SOI index and the clean energy market, this study proved highly valuable for investors with different investment preferences and time horizons. By considering SOI as a specific driving factor, the paper identified the interdependence between SOI and segmented Clean Energy Indices across various time scales.

Our empirical estimates emphasize: (1) We found a significant overall Granger causal relationship between SOI and all segmented clean energy sectors at heterogeneous quantile levels. However, the Granger causality of SOI on segmented clean energy indices is inconsistent at different conditional quantiles. (2) Clean energy is more likely to be significantly influenced by SOI in upward market conditions than in bearish market conditions. In other words, we did not observe any significant co-movement between SOI and segmented clean energies when both were at median and lower quantiles. (3) The influence of strong La Niña periods on segmented clean energy indices is greater than during intense El Niño periods. (4) SOI was observed to exhibit predictability only at mid-term and long-term frequencies for Clean Energy sectors, excluding BI.

The structure of this article is organized as bellows: Section 2 checks prior papers. Section 3 details the methodology and data. Analysis and discussion of the empirical findings are outlined in Section 4. Concluding remarks, along with implications for market stakeholders, will be offered in Section 5.

2. Literature review

2.1. Dynamic nexus between climate change and other financial markets

Nawaz et al. (2021) explored the correlation between green financing in N-11 countries and BRICS nations and their extreme climate mitigation situations, finding a close association. Hammoudeh et al. (2020) asserted that carbon emission quotas significantly impact the prices of green bonds. Nasir et al. (2019) observed that an increase in the share of foreign direct investment in the ASEAN-5 countries led to exacerbated environmental degradation in these economies. Meo and Abd Karim (2022) applied QQR to explore the connection between green financial assets and CO2 emissions across heterogeneous quantiles. Their results suggested that the development of green financial assets represents the most advantageous financial strategy for lowering carbon emissions. Ren et al. (2020) checked the correlation between Chinese level of green development, the share of China's non-oil energy consumption, and Chinese carbon intensity. Their conclusions affirmed that an increase in Chinese level of green financial development, coupled with support for and application of non-fossil energy, accelerated the reduction of Chinese carbon intensity.

2.2. Dynamic nexus between extreme weather and other markets

Saura et al. (2023) highlighted the profound impact that extreme weather conditions have on climate policies and financial markets worldwide, leading to notable effects on the global economic landscape. Tetteh and Amoah (2021) identified a marked adverse relationship between temperature, wind speed, and the performance of stock markets. Furthermore, Zhu et al. (2023) investigated how extreme weather affects the pricing of emission quotas in China, pointing out the heightened sensitivity of carbon prices to such conditions, especially noting a positive relationship during periods of extreme heat. Wei et al. (2023) quantified climate change indices and the time-varying connections between carbon emission market, crude oil market, and clean energies. Their study concluded that climate change indices generally dominate the studied factors, with information spillover occurring mainly at a frequency of 1–3 months. Wei et al. (2022) investigated the impact of extreme climate change on the performance of renewable energy stock markets. They found that, under most market states, the ENSO index significantly impacted Europe's clean energy stock market, while its influence on the United States' clean energy market was relatively insignificant.

2.3. Extreme weather and energy markets (clean energy markets)

Ding et al. (2022) highlighted the significant positive causal relationship among investor attention to climate change and the time-frequency connectedness in clean energy markets. This phenomenon suggests a brighter market outlook for renewable energy stocks due to the increasing focus of market participants on climate change issues. Ren et al. (2023) discovered that the dynamic bidirectional causal connection between the climate policy uncertainty (CPU) of US and the clean energy market varied over time. Specifically, CPU and dependence on clean energy significantly increase during extreme weather events or major climate policy announcements. Batten et al. (2021) confirmed that climate change-induced extreme weather leads to more intense fluctuations in carbon market prices. The conclusions of Zou et al.'s (2023) research revealed that extreme weather events have long-term adverse effects on water quality in nature, persisting not only in the year of the event but also remaining challenging to eliminate within ten years after the occurrence.

This study will explore the quantile-related connection between the Southern Oscillation Index and segmented clean energy indices, an area that previous research has yet to delve into. Specifically, by analyzing the linkage effects of SOI with segmented clean energy indices at different quantile levels, it provides an in-depth understanding of the dependency structure between extreme climate shocks and the clean energy under various market states. This, in turn, offers valuable information for decision-making support regarding risk management and market regulation for market participants.

3. Econometric methodology and data

3.1. QADF unit root test

Traditional unit root tests often face critique for their limitation to only ascertain the presence or absence of a unit root at a conditional central tendency. The introduction of the QADF (Quantile Augmented Dickey-Fuller) unit root test by Koenker and Xiao (2004), further refined by Galvao Jr (2009), marked a significant advancement by including a linear time trend and various covariates. This method's strength lies in its ability to explore the integration features across different distribution quantiles. Consider a scenario where X_t represents a time series that is both strictly stationary and ergodic, Ω_t denotes the σ-field induced by $(X_{t-1},\ldots,X_{t-s})$, and $F_X(.\backslash\Omega_t^X)$ is the conditional distribution of X_t when given Ω. The application of the QADF unit root test involves defining a model as follows:

$$Q_\tau^X\left(X_t\backslash\Omega_t^X\right)=\lambda_1(\tau)+\lambda_2(\tau)t+\beta(\tau)X_{t-1}+\sum_{j-1}^{p}\beta_j(\tau)\Delta X_{t-j}+F_u^{-1}(\tau) \tag{1}$$

In this model, $Q_\tau^X(.\backslash\Omega_t^Y)$ represents the b-quantile for variable$F_X(.\backslash\Omega_t^X)$, while $\lambda_1(\tau)$ is identified as the component for intercepts, and the trend over time is delineated by t. $\beta(\tau)$ serves as an index for persistence, with F_u indicating the shared distribution function for errors. Through model estimation, it becomes possible to deduce the persistence index $\widehat{\beta}$ across different distribution quantiles. The QADF test's null hypothesis is established as $H_0:\beta(\tau)=1$.

3.2. Granger quantiles causality

Firstly, we use Granger quantile causality method, which introduced by Troster (2018), to test Granger causality in different quantiles among indices. This method can obtain non-linear and conditional level quantile Granger causality. Let $\mathscr{F}_{t-1}^Y=\{Y_{t-1},Y_{t-2},\ldots,Y_{t-p}\}$ and $\mathscr{F}_{t-1}^X=\{X_{t-1},X_{t-2},\ldots,X_{t-p}\}$ be the former information sets of Y_t and X_t, respectively. Then we would like to test the null hypothesis that X_t does not the Granger cause of Y_t as: $F_Y\left(w|\mathscr{F}_{t-1}^Y,\mathscr{F}_{t-1}^X\right)=F_Y\left(w|\mathscr{F}_{t-1}^Y\right)$, for all $w\in\mathbb{R}$, where $F_Y\left(\cdot|\mathscr{F}_{t-1}^Y,\mathscr{F}_{t-1}^X\right)$ is the conditional distribution of Y_t given $\mathscr{F}_{t-1}=\left(\mathscr{F}_{t-1}^Y,\mathscr{F}_{t-1}^X\right)'$. Let $q_Y^\tau(\cdot\mathscr{F}_{t-1})$ be the τ-quantile of $F_Y(\cdot\mathscr{F}_{t-1})$. Then, $Pr\{Y_t\le q_Y^\tau(Y_t|\mathscr{F}_{t-1})|\mathscr{F}_{t-1}\}=E\{1(Y_t\le q_Y^\tau(Y_t|\mathscr{F}_{t-1}))|\mathscr{F}_{t-1}\}$, for an parameter function $1(\cdot)$ so that we can show Eq. (1) as

$$H_0:E\left\{\psi_\tau\left(Y_t-m_\tau\left(\mathscr{F}_{t-1}^Y,\theta_0(\tau)\right)\right)|\mathscr{F}_{t-1}\right\}=0,\text{for all }\tau\in(0,1) \tag{2}$$

where $m_\tau\left(\mathscr{F}_{t-1}^Y,\theta_0(\tau)\right)$ is a parametric modelling of $q_Y^\tau(|\mathscr{F}_{t-1}),m_\tau\in\mathscr{M}=\{m_\tau(\cdot,\theta(\tau))|\theta(\cdot):\tau\mapsto\theta(\tau)\in\Theta\subset R^p$, for $\tau\in Q\subset(0,1)\}$. As Troster (2018), we can transfer Eq. (2) to an unconditional null hypothesis as:

$$H_0^{X \nrightarrow Y}: E\{\psi_\tau(Y_t - m_\tau(\mathscr{F}_{t-1}^Y \theta_0(\tau)))exp(iv'\mathscr{F}_{t-1})\} = 0, \text{a.s.for all } \tau \in Q \quad (3)$$

against,

$$H_A^{X \nrightarrow Y}: E\{\psi_\tau(Y_t - m_\tau(\mathscr{F}_{t-1}^Y, \theta_0(\tau)))exp(i\boldsymbol{v}'\mathscr{F}_{t-1})\} \neq 0, \text{for any } \tau \in Q, \quad (4)$$

for a weighting framework $exp(iv'\mathscr{F}_{t-1}) := exp[i(v_1(Y_{t-1}, X_{t-1})' + \ldots + v_p(Y_{t-n}, X_{t-n})')]$, for all $v \in \mathbb{R}^n$ with $n \le p$, and $i = \sqrt{-1}$. And we may apply the estimation statistic to check the null hypothesis of Eq. (3):

$$G_T(\boldsymbol{v}, \tau) \equiv \frac{1}{\sqrt{T}} \sum_{t=1}^{T} \psi_\tau(Y_t - m_\tau(\mathscr{F}_{t-1}^Y, \theta_T(\tau)))exp(i\boldsymbol{v}'\mathscr{F}_{t-1}), \quad (5)$$

where $\theta_T(\cdot)$ is a consistent parameter of $\theta_0(\cdot)$. Moreover, as Troster (2018), we use a functional norm of $G_T(v, \tau)$, which has greater power than $G_T(v, \tau)$, for testing $H_0^{X \nrightarrow Y}$ of Eq. (3):

$$S_T := \int_{\mathscr{T}} \int_V G_T(\boldsymbol{v}, \tau)^2 dF_v(\boldsymbol{v}) dF_\tau(\tau), \quad (6)$$

where $F_v(\cdot)$ represented a normal distribution of weights, and variable $F_\tau(\cdot)$ conformed to a uniform distribution across a grid $Q \subset (0, 1)$ consisting of equidistant quantiles, the null hypothesis of Granger non-causality was rejected upon observing that S_T was significantly large. Subsequently, we demonstrated the subsampling method proposed by Troster (2018) for the estimation of the p-values associated with variable S_T, utilising a subsample $b = [5T^{2/5}]$, wherein '[]' denotes the floor function.

3.3. The QQR approach

The QQR method emerged as a suitable technique to analyze the bearish interrelationship between the SOI and the designated clean energy indices (Zeng et al., 2024a). This is attributed to the capacity of quantiles to capture asymmetry within the high and low distributions, as illustrated below:

$$\text{SOI}_t = \beta^\theta(CE_t) + u_t^\theta \quad (7)$$

Where, SOI_t and CE_t represent the Southern Oscillation Index and designate the clean energy index for the period t. θ corresponds to the θ^{th}-indicated quantile of the conditional distribution of SOI_t, while u_t^θ pertains to the quantile of the error. Furthermore, the conditional quantile denoted by θ^{th} is set to zero.

A significant drawback of the quantile regression framework lies in its inability to discern the distinct impacts of varying degrees of positive or negative shocks from the other examined variables on the Southern Oscillation Index. Consequently, we employed a local linear regression approach to explore the asymmetric effects of the additional indicators on the Southern Oscillation Index. And we can conduct a first-order Taylor expansion of the quantile of variable X_t in the subsequent manner:

$$\beta^\theta(CE_t) \approx \beta^\theta(CE^\tau) + \beta^{\theta'}(CE^\tau)(CE_t - CE^\tau) \quad (8)$$

Where, $\beta^{\theta'}$ signifies the partial derivative of $\beta^\theta(CE_t)$, serving as an indicator of the marginal impact akin to a slope. Evidently, θ embodies the functional configuration of both $\beta^\theta(CE^\tau)$ and $\beta^{\theta'}(CE^\tau)$, whereas CE and CE^τ adopt τ as their functional form. Consequently, both θ and τ assume the role of functional forms $\beta^{\theta'}(CE^\tau)$ and $\beta^\theta(CE^\tau)$, respectively. Should we express $\beta^\theta(CE^\tau)$ and $\beta^{\theta'}(CE^\tau)$ by $\beta_0(\theta, \tau)$ and $\beta_1(\theta, \tau)$, correspondingly, the presentation follows as depicted below:

$$\beta^\theta(CE_t) \approx \beta_0(\theta, \tau) + \beta_1(\theta, \tau)(CE_t - CE^\tau) \quad (9)$$

If we have fundamental QQR Eq. (1), as follows,

$$\text{SOI}_t = \beta_0(\theta, \tau) + \beta_1(\underset{*}{\theta}, \tau)(CE_t - CE^\tau) + u_t^\theta \quad (10)$$

The symbol (*) furnished the conditional quantile of the clean energy index denoted as θ^{th}. These equations elucidate the interrelation linking quantiles of SOI with various other indicators. A comparable minimization approach was employed to derive an equation akin to that of ordinary least squares (OLS).

$$min_{b_0, b_1} \sum_{i=1}^{n} \rho_\theta[CO2_t - b_0 - b_1(\widehat{X} - \widehat{X^\tau})]K\left(\frac{F_{n(\hat{X})-\tau}}{n}\right) \quad (11)$$

The quantile loss function, denoted as $\rho_\theta(u) = u(\theta - I(u < 0))$, was exemplified by the expression $\rho_\theta(u)$. The kernel density function, represented as *K(.)*, was accompanied by the kernel density function bandwidth parameter denoted as n. Drawing from prior research, such as the work of Sim and Zhou (2015), a bandwidth of $h = 0.05$ for the density function was selected as the optimal parameter within the QQR framework.

3.4. Wavelet transform coherence (WTC)

In the analysis of the index series within the time-frequency domain, we employed the continuous wavelet transform. The Wavelet Transform Coherence (WTC) proved to be efficacious in capturing localized dependencies within both the temporal and frequency domains of the series. The cross-wavelet estimation of two index series $x(t)$ and $y(t)$ can be indicated as:

$$W_n^{XY}(u, s) = W_n^X(s, \tau) W_n^{Y^*}(s, \tau) \quad (12)$$

where u points out the position, s is the scale, and * demonstrates the complex conjugate. The WTC can be estimated as bellows:

$$R_n^2(s, \tau) = \frac{\left|S(s^{-1} W_n^{XY}(s, \tau))\right|^2)}{S\left(s^{-1}|W_X(s, \tau)|^2\right) S\left(s^{-1}|W_Y(s, \tau)|^2\right)} \quad (13)$$

where S can indicates smoothing process for all time and frequency domain at the same moment. $R_n{}^2(s, \tau)$ is in the span $0 \le R^2(s, \tau) \le 1$.

3.5. Cross quantile (CQ) approach

We employed the cross-quantilogram (CQ) method as proposed by Han et al. (2016). The CQ method evaluates the dependence between two time series with respect to their respective counter-conditional quantiles. The predictability of these series was assessed using a Ljung-Box Q-type test, in line with the recommendations of Han et al. (2016). The CQ approach analyses two time series to identify lead-lag causal connections among specific quantiles, thereby estimating their dependence pattern. As a result, this method provides distinct advantages in forecasting the connections of significant lags and the ensuing potential structures of cross-correlations. The CQ for the quantile-hit procedure is delineated as follows:

$$\rho_a(k) = \frac{E[\Phi_{a1}(x_{1,t} - q_1(\alpha_1))\Phi_{a2}(x_{2,t-k} - q_2(\alpha_2))]}{\sqrt{E[\Phi_{a1}^2(x_{1,t} - q_1(\alpha_1))]}\sqrt{E[\Phi_{a2}^2(x_{2,t} - q_2(\alpha_2))]}} \quad (14)$$

where $k = 0, +1, +2, \ldots$, points out the time lags, and $\psi_a(\mu) \equiv 1[\mu < 0] - \alpha$ is the signal element, $[x_{i,t} - q_i(\alpha_i)]$ indicates quantile striking procedure, and $\rho_a(k)$ estimates a quantile-based cross-connection element.

3.6. Data

We obtained daily closing price data for the Clean Energy Index from Datastream, covering the period from January 1, 2017, to April 1, 2023.

Recognizing the significant impact of the United States' energy policy on the global economy, as Zeng et al. (2023) and Zeng et al. (2024b), we used the WilderHill Clean Energy Index (WILDER) and the Standard & Poor's Global Clean Energy Index (SP) as representative benchmarks for the clean energy stock market. Subsequently, the subdivided clean energy indices considered encompassed the Nasdaq OMX Bio/Clean Fuels Index (BI), Nasdaq OMX Renewable Energy Index (RE), Nasdaq OMX Geothermal Index (GEO), Nasdaq OMX Fuel Cell Index (FUEL), Nasdaq OMX Solar Index (SOLAR), and Nasdaq OMX Wind Index (WIND).

In addition, for this paper, we utilized daily data for the SOI, with the time span aligning with that of the clean energy indices. The daily SOI data were obtained from the Australian Government Bureau of Meteorology's website (http://www.bom.gov.au/?ref=logo). Following the processing method of Wei et al. (2022), to facilitate subsequent empirical analysis, the returns of the clean energy indices were calculated as the natural logarithm of the first difference of the closing prices, while the SOI index data remained unchanged. It is crucial to emphasize that we did not perform a first-order logarithmic differencing on the SOI index for two reasons. Firstly, as a unique climate mark, the SOI differs in data characteristics from financial indices, and logarithmic differencing would eliminate its inherent climatic information. It is noteworthy that an SOI value exceeding 8 signifies the occurrence of La Niña (an SOI below −8 indicates an El Niño event). Secondly, the SOI is considered directly applicable for economic analysis, given its typically proven time series stationarity (Bastianin et al., 2018), as validated in Fig. 1. So, the first-order logarithmic differencing is not applicable to SOI data.

It should be emphasized that SOI, as a crucial indicator reflecting ENSO, was closely related to global climate change, extreme weather events, agricultural production, and energy demand, making it an indispensable reference indicator for assessing climate risk (Iwakiri and Watanabe, 2021; Odériz et al., 2020). So global extreme weather events can be captured through the changing trends in the Southern Oscillation Index (SOI) (Atems et al., 2020). As discussed in the introduction section, the original data of the SOI comprises extreme upward and downward phases attributed to the El Niño and La Niña phenomena. To allow for a brief observation of the changing trends in the SOI, Fig. 1 illustrates the dynamic variations in the Southern Oscillation Index. Intuitively, we can observe signs of the El Niño and La Niña phenomena alternating over time. It is noteworthy that, after 2020, the duration of the global climate oscillation cycle influenced by La Niña became more persistent.

Furthermore, from Fig. 2, it can be observed that the return series of WILDER exhibited lower volatility relative to other subdivided clean energy indices. It is worth noting that we observed heightened oscillations in all subdivided clean energy indices post the outbreak of COVID-19 compared to the period preceding the COVID-19 outbreak.

4. Empirical findings

Table 1 presents the summary statistics for the Southern Oscillation Index (SOI) and the subdivided clean energy indices. It is observed that BI has a negative average return, whereas SOI and the remaining clean energy indices exhibit positive average returns, with FUEL having the highest average return among all clean energy indices. Concerning variance, FUEL has the maximum variance among all clean energy indices, while RE has the minimum variance. Simultaneously, FUEL's volatility (measured by the variance of returns) is significantly higher than that of other clean energy indices. Except for SOI, all other sequences have kurtosis values exceeding 3. Additionally, skewness values for all return sequences are non-zero, indicating asymmetry in the distributions. In other words, the time series for all indices exhibit peakedness, fat tails, and a departure from Gaussian distribution. Furthermore, the J-B test confirms that the sequences for all indices are not normally distributed.

Before employing a series of quantile-related econometric methods, we attempted to ensure the stability of returns on the SOI and segmented clean energy across various quantile distributions by utilising the Quantile Augmented Dickey-Fuller (QADF) unit root test (Bakhsh et al., 2024). Specifically, the QADF test, by examining the dynamics at different quantiles, allowed for a more detailed analysis of the time series' stability under varying market conditions. Our QADF examination was conducted across significant sub-quantiles ranging from 0.05 to 0.95. By comparing the t-statistic values with the 5 % critical value (CV), we determined the presence or absence of unit roots at the quantiles. The findings of the QADF test, as presented in Table 2, clearly indicate the rejection of the null hypothesis (presence of unit root), demonstrating that both the SOI and the segmented clean energy index were stable

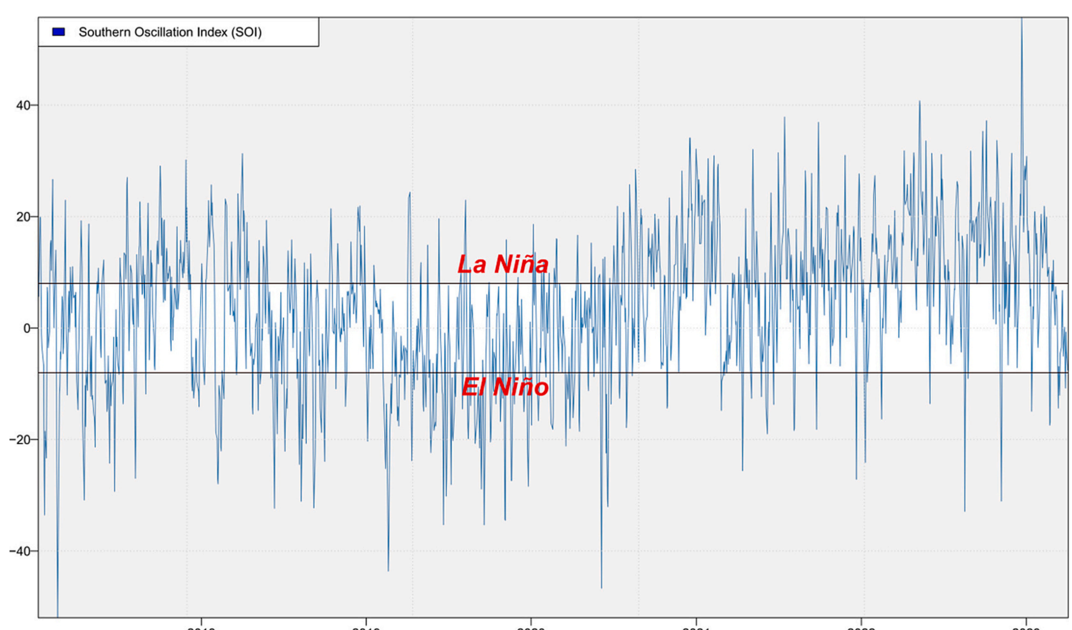


Fig. 1. Trend plot of the Southern Oscillation Index (SOI).
Notes: An SOI value exceeding 8 signified the occurrence of La Niña, while an SOI below −8 indicated an El Niño event.

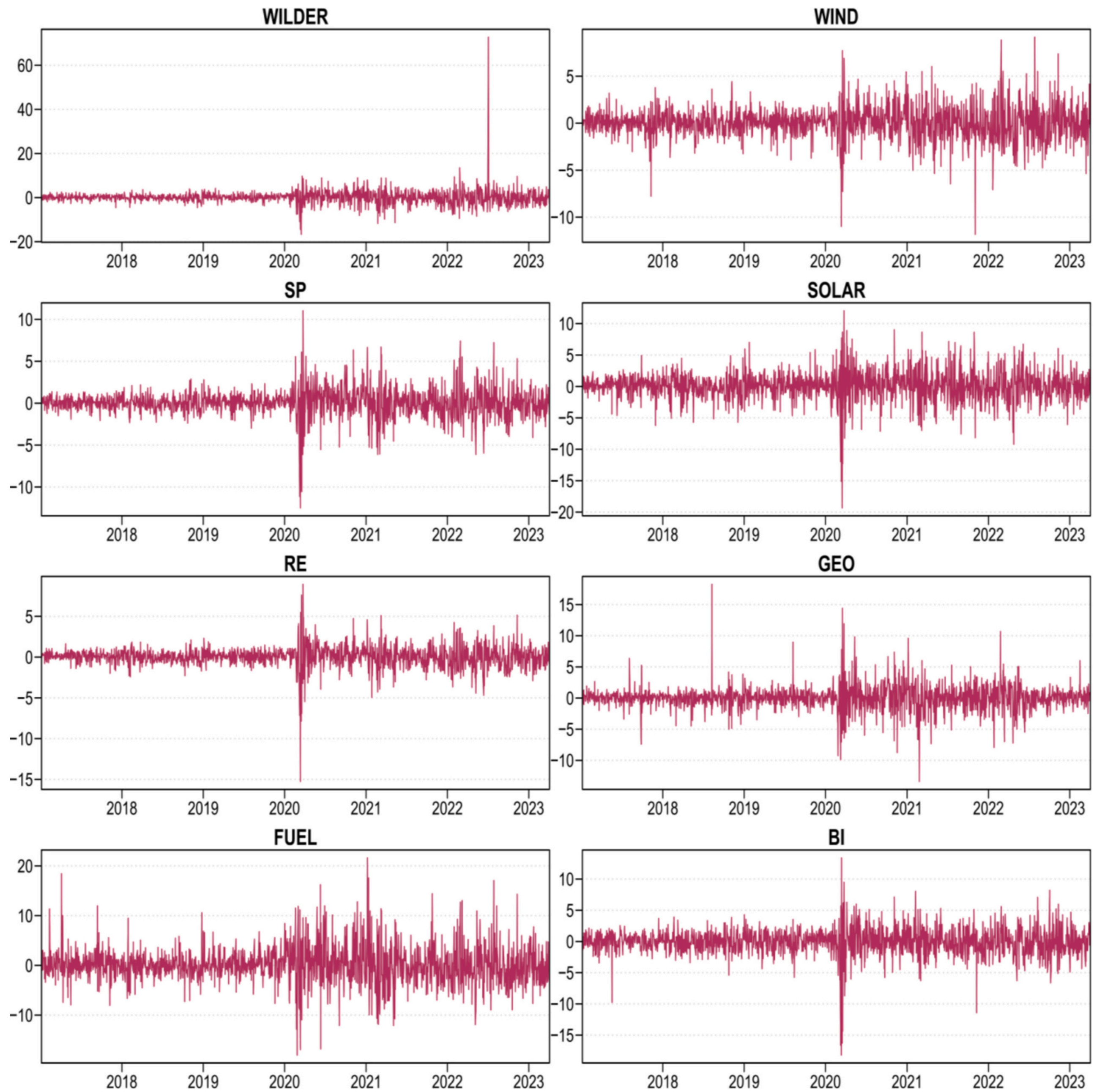


Fig. 2. Dynamics of clean energy indices.

Table 1
Summary statistics.

	SOI	WILDER	WIND	SP	SOLAR	RE	GEO	FUEL	BI
Mean	3.536	0.093	0.041	0.055	0.097	0.047	0.035	0.125	−0.006
Variance	183.890	9.918	3.001	2.698	5.607	1.620	4.052	14.244	4.803
Skewness	−0.204	7.566	−0.141	−0.462	−0.567	−1.102	0.520	0.396	−1.016
Kurtosis	0.326	179.656	4.610	8.449	5.954	18.452	10.825	3.325	9.993
JB	17.881***	2,138,566.366***	1403.687***	4752.359***	2416.962***	22,720.674***	7780.493***	768.921***	6841.583***

Notes: J-B means Jarque and Bera (1980) normality check. ***, **, * point out significance at 1 %, 5 % and 10 % significance level.

across heterogeneous quantile levels. Overall, this test verified the stability of the original return series for the SOI and segmented clean energy index following first-order differencing, thereby ensuring the reliability of conclusions derived from the subsequent application of quantile-related methods.

Due to the distinct characteristics and market attributes of subdivided clean energy indices, the impact of extreme weather on these indices may depend on the phases of extreme climate variations. Given the heterogeneity across specific percentiles, we employed the Granger Quantile Causality method in this section.

Regarding the influence of SOI on subdivided clean energy indices, as depicted in Table 3, we initially discerned relatively intricate results

Table 2
The QADF unit root test results.

	SOI		WILDER		WIND	
	t-stat	CV (5 %)	*t*-stat	CV (5 %)	*t*-stat	CV (5 %)
0.05	−2.982	−2.3148	−11.854	−2.1285	−5.941	−2.2036
0.1	−2.806	−2.4081	−17.842	−2.2165	−9.366	−2.2668
0.25	−5.244	−2.5264	−40.728	−2.2402	−16.102	−2.3334
0.5	−8.299	−2.5634	−59.286	−2.2446	−26.302	−2.3514
0.75	−8.835	−2.5134	−40.978	−2.2021	−20.704	−2.3292
0.9	−7.468	−2.3814	−24.507	−2.1861	−11.699	−2.2652
0.95	−5.221	−2.2928	−15.888	−2.1158	−7.031	−2.1867
	SP		SOLAR		RE	
	t-stat	CV (5 %)	*t*-stat	CV (5 %)	*t*-stat	CV (5 %)
0.05	−3.655	−2.2132	−4.995	−2.184	−3.036	−2.1809
0.1	−7.047	−2.2745	−6.457	−2.2384	−4.832	−2.2378
0.25	−15.062	−2.3154	−14.461	−2.2993	−10.823	−2.2959
0.5	−22.07	−2.3336	−22.216	−2.3092	−19.657	−2.3057
0.75	−18.622	−2.3152	−17.44	−2.2856	−22.125	−2.2725
0.9	−9.087	−2.2566	−8.417	−2.2144	−12.762	−2.2102
0.95	−7.659	−2.2122	−8.076	−2.1368	−8.394	−2.1574
	GEO		FUEL		BI	
	t-stat	CV (5 %)	*t*-stat	CV (5 %)	*t*-stat	CV (5 %)
0.05	−4.126	−2.1906	−8.676	−2.1552	−3.59	−2.1817
0.1	−6.476	−2.2334	−12.249	−2.2301	−7.098	−2.2343
0.25	−14.878	−2.2777	−23.745	−2.3043	−13.229	−2.2981
0.5	−23.938	−2.2658	−30.684	−2.3398	−19.037	−2.3161
0.75	−19.587	−2.2433	−21.495	−2.3392	−18.023	−2.2725
0.9	−9.256	−2.2091	−12.081	−2.2903	−10.971	−2.194
0.95	−6.513	−2.1799	−7.389	−2.2201	−8.891	−2.1239

Notes: The table presents the critical value (CV) of the estimate at the 5 % significance level and the corresponding *t*-statistic values.

from the quantile causality relationships. Specifically, we found that SOI exhibited significant positive Granger causal relationships with all clean energy indices on an overall basis. In contrast, the response of most clean energy indices was weakest at the median and more extreme percentiles ($q = 0.05$ and 0.95), as *p*-values were mostly higher than 0.1. It is noteworthy that, at the 0.75 percentile level, the SOI index was identified to have Granger causal relationships with all clean energy indices.

Furthermore, we observed that the Granger causal test results of SOI for the subdivided clean energy market differed at specific conditional percentiles. For example, concerning WILDER, SOI exhibited a significant positive Granger effect within the [0.05, 0.9] conditional percentiles. Simultaneously, for FUEL, a similar Granger causal effect existed only at the 0.75 conditional percentile. Among the other subdivided clean energy indices, Granger causal relationships with SOI were observed at both 0.25 and 0.75 percentiles.

Therefore, we posit that the above results provide limited evidence for the relationship between SOI and subdivided clean energies. It is essential to emphasize that the Granger causal effects of SOI on clean energies are more pronounced at lower and higher tail percentiles ($q =$ 0.25 and 0.75). More precisely, when SOI is at the median ($q = 0.5$) and more extreme percentiles ($q = \{0.05, 0.1, 0.9, 0.95\}$), its impact on the clean energy sector is weak and localized. These findings were derived through individual significance tests for each specific percentile.

However, the Granger Quantile Causality method is a qualitative analysis (Freeman, 1983), incapable of investigating the degree of SOI's influence on the subdivided clean energy sector. Therefore, in the subsequent step, we adopted QQR to comprehensively understand the panoramic relationship between SOI and subdivided clean energy indices across various percentiles.

Fig. 3 presents the empirical findings of cross-quantile impacts of the SOI on the returns of subdivided clean energy markets using the QQR method. As depicted in Fig. 3, the color bars on the right represent the correlation between SOI and clean energy, indicating the impact of SOI at different percentiles on clean energies. It is essential to emphasize that, as shown by the color bars, deeper shades of blue and red respectively represent the minimum and maximum amounts of coefficients. Subsequently, we direct our attention to Fig. 4, focusing on two distinctive phases of the SOI index – the extreme La Niña and El Niño phenomena, denoted by the 0.9 and 0.1 percentiles, as indicative of their connection to the market performance of subdivided clean energy indices (Liang et al., 2022; Zeng et al., 2024c).

4.1. Impact of SOI on RE

Initially, our examination of Fig. 3 focuses on the quantile dependency of the SOI index and the Renewable Energy (RE) index. We promptly observe that when the SOI percentiles range from [0.5, 1], and the RE percentiles range from [0.8, 1], SOI has a positive impact on the RE index. Conversely, when SOI falls within the [0.4, 0.5] percentiles, and the corresponding RE is in the [0.1, 0.2] range, we observe a darker blue color on the color bar, indicating a minimal factual impact of SOI on RE in this percentile block. This seems to underscore the fact that under normal climatic conditions, the influence of SOI on the market performance of RE is limited. Additionally, we note that when SOI is in the high percentiles [0.7, 0.9] (La Niña period), and concurrently RE is in the high percentiles [0.7, 0.9], their correlation coefficient is significantly positive (highlighted in red). This suggests that during the La Niña period, SOI has a substantial positive impact on the RE index. This finding complements the empirical results of Bouri et al. (2021), indicating that the SOI is sensitive to the actual volatility of crude oil prices, with the impact during the La Niña period appearing more significant than during the El Niño period. Considering the substitution effect between clean energy and traditional fossil fuels, this might be explained by the La Niña phenomenon causing abnormal cooling of seawater in the central and eastern region of Pacific, thereby increasing the consumption of renewable energy for heating in North America.

4.2. Impact of SOI on BI

Subsequently, from Fig. 3, we observe that when SOI percentiles range from [0, 0.3], and the Bioenergy (BI) index is at any percentile

Table 3
Findings of quantiles Granger-causality between the SOI and specific clean energy sectors.

	From *SOI* To							
τ	*SOLAR*	*RE*	*GEO*	*FUEL*	*BI*	*WIND*	*WILDER*	*SP*
All	0.001***	0.001***	0.001***	0.001***	0.001***	0.005***	0.001***	0.001***
0.05	0.016	0.053	0.081	0.132	0.047	0.406	0.084*	0.016
0.10	0.003***	0.001***	0.001***	0.008	0.001***	0.035**	0.001***	0.030
0.25	0.001***	0.001***	0.001***	0.001	0.001***	0.003***	0.001***	0.001***
0.50	0.047	0.718	0.953	0.186	0.235	0.862	0.076*	0.115
0.75	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
0.90	0.061	0.001***	0.001***	0.068	0.001***	0.532	0.001***	0.001***
0.95	0.571	0.023	0.026	0.331	0.314	0.576	0.109	0.009***

Note: The table presents p-values from the quantile Granger causality test, covering quantiles from 0.05 to 0.95. We utilized the QAR(1) model to test the null hypothesis of no Granger causality. The size of the sub-sample was 89. The symbols *, **, and *** denote the rejection of the null hypothesis at significance levels of 10 %, 5 %, and 1 %, respectively.

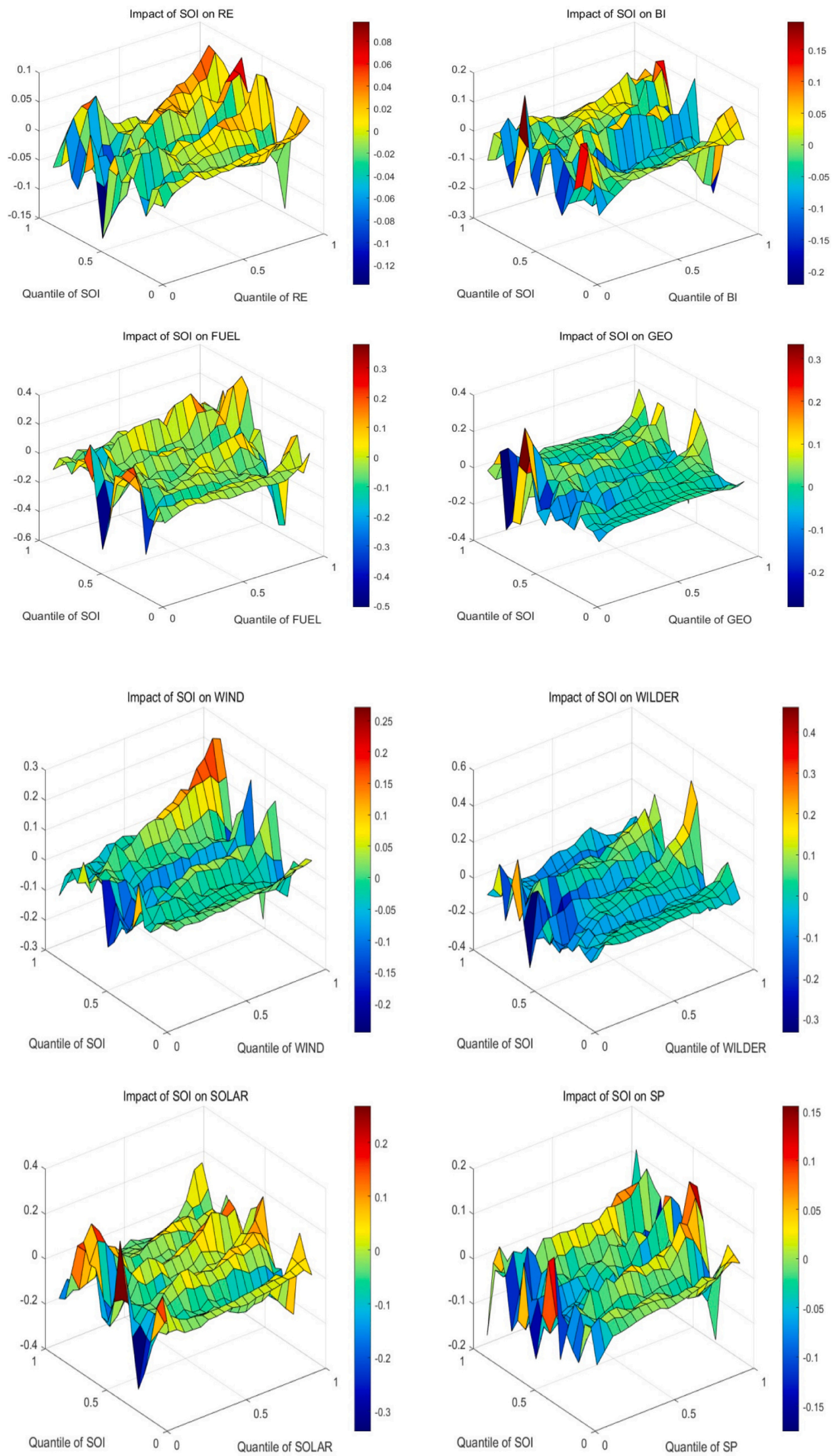
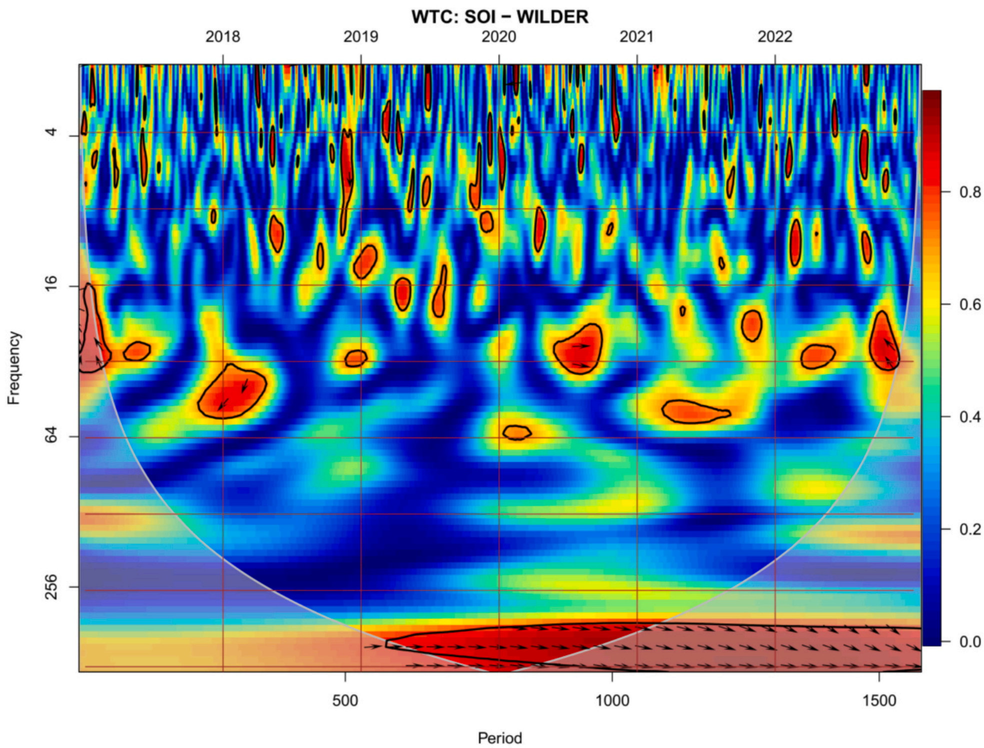


Fig. 3. The QQR findings between SOI and clean energy indices.



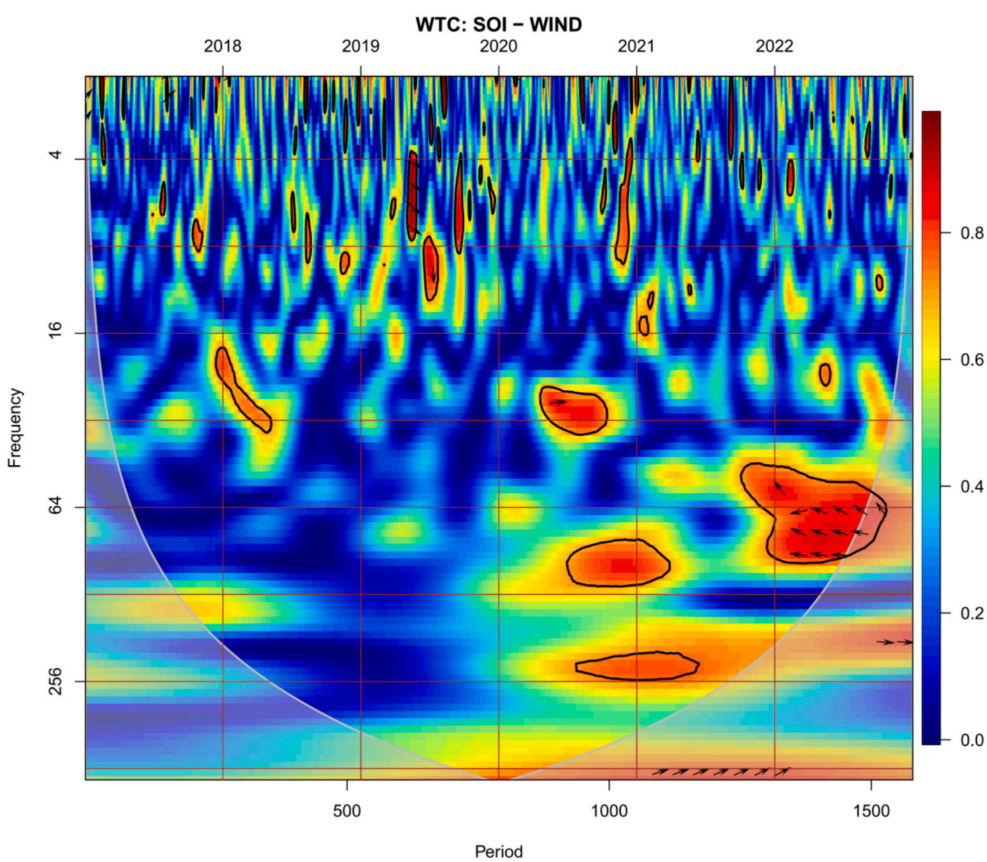


Fig. 4. Wavelet coherence analysis for SOI and 8 clean energy indices.
Note: The figure shows wavelet coherence findings for pairs of SOI and one of specific clean energy indices. The horizontal axis points out time domain (whole sample period), and the vertical axis points out frequency domain (4–256 days). The level of connection is denoted by the color on the right-hand side of the figure; the warmer the color (red means the warmest), the higher the absolute correlation of the pair indices, while the colder color (blue means the coldest) demonstrates a lower correlation of the pair indices. The greater the warmth in the coloration of a region or the emergence of smaller islands of red, the stronger the concordance

between pairs of indices. The arrows serve to demonstrate the in/anti-phase relationship existing among these index pairs. A zero-phase difference signifies that the index pairs move synchronously on a given scale. In instances of in-phase (anti-phase) alignment, the arrows orient to the right (left). Arrows showing to the upper right or lower left signify that the first index is leading (or the second variable is lagging). In contrast, arrows showing to the lower right or upper left suggest that the second index is leading (or the first index is lagging). The outcomes presented in this table document the presence of gray dashed lines, indicating correlations between regions that achieved statistical significance at the 5 % level.

level – meaning SOI is confirmed to be in an extreme El Niño period – SOI generally has a moderate impact on BI. Conversely, as the SOI percentiles approach 1, indicative of the La Niña event, we observe that the impact of SOI on BI becomes more pronounced. This suggests that the cooling of the eastern Pacific during the La Niña event significantly mitigates the impact on bioenergy. A potential reason is that during the El Niño phenomenon, coinciding with a low level of the Mississippi River, challenges were posed to the transportation of various commodities, including grains, affecting the bioenergy supply chain. This river is a crucial waterway for transporting commodities (including oil) from the central and western United States to export points along the Gulf of Mexico (Lambert et al., 2021). Conversely, during the La Niña period, crop prices usually rise, leading to more market volatility in the energy market.[1] Additionally, besides macroeconomic factors, another explanation for the increase in crop prices during the La Niña period may be associated with abundant corn and soybean production in South America.[2] It should be emphasized that, as the main raw materials in biofuels (BI) are ethanol, primarily derived from grains such as corn, wheat, and soybeans, the impact of extreme weather induced La Niña and El Niño phenomena on the maturity and yield of grains is evident (Manochio et al., 2017).

4.3. Impact of SOI on FUEL

Moreover, we examined the cross-quantile impact of the Southern Oscillation Index (SOI) on FUEL. We observed that the coefficients associated with the percentiles between SOI and FUEL prices were mostly negative. However, when SOI was within the high percentiles [0.7, 0.9], and correspondingly FUEL was in the [0.6, 0.9] percentile range, we found that the color bar displayed a positive color coefficient. This implies that, compared to the El Niño phenomenon, the La Niña phenomenon more readily influenced the market performance of FUEL. A plausible explanation is that the FUEL index primarily tracks companies producing energy using fuel cells. The La Niña phenomenon, causing abnormally cold seawater in the central and eastern Pacific, may lead to colder winters in North America, further highlighting issues of energy supply shortage and a surge in demand for fuel cells (Ren et al., 2023). Another intriguing reason is that the La Niña phenomenon, with its lower temperatures, resulted in nearly a 50 % reduction in the range of electric vehicles, thereby increasing the demand for fuel cells.[3] It should be noted that fuel cells, devices that convert hydrogen or other renewable energy directly into electricity, have been widely researched and applied in the clean energy sector (Eriksson and Gray, 2017). Thus, these fundamental factors can explain the positive influence of the La Niña phenomenon on the index performance of the BI index.

4.4. Impact of SOI on WIND

Next, as depicted in Fig. 3, during the La Niña phenomenon (when SOI is in the high percentiles), the impact of SOI on WIND is pronounced. It is crucial to emphasize that when WIND is within the [0.8, 0.9] percentiles, we observed the peak positive impact of SOI on WIND (with SOI coefficients ranging from 0.15 to 0.25). A relatively convincing explanation is that during the La Niña phenomenon, the strengthening of cold currents would favor wind energy production enterprises. Interestingly, when SOI is at the median, corresponding to all percentiles of WIND, we found that the impact coefficients of SOI on WIND were negative. This implies that under normal climatic conditions, the influence of SOI on the market performance of WIND is weak.

4.5. Impact of SOI on SP

Additionally, as observed in Fig. 3, a negative region of SOI was noted within the [0.1, 0.9] percentiles, corresponding to SP being in the [0.1, 0.2] percentiles. This indicates that, regardless of variations in climate conditions, when SP is in a bear market, SOI consistently has a negative impact. A possible reason is that in bear market conditions, investor sentiment is pessimistic, and there is a decrease in market risk preference, leading to reduced interest among investors in new investment categories (such as clean energy assets). Conversely, when SP is in the high percentiles (bull market), its market performance is closely correlated with SOI, indicating that market improvement creates more favorable conditions for investments in clean energy (Zeng et al., 2025).

4.6. Impact of SOI on SOLAR

Finally, when the Southern Oscillation Index (SOI) was at an extremely low percentile [0, 0.2], corresponding to the period of an extreme El Niño phenomenon, it exerted a positive influence on the returns of SOLAR across all percentiles. Conversely, during the La Niña phenomenon, when SOI was observed at high percentiles, its impact on SOLAR was nearly negligible (indicated by deep blue color). The potential reason is that during El Niño periods, global temperatures rise, and rainfall decreases. The reduced rainfall intensity signifies a decrease in cloud cover and an increase in solar irradiance (Cane, 2005). High solar irradiance significantly boosts the electricity generation capacity of the solar energy industry (Mohammadi and Goudarzi, 2018). Undoubtedly, this is substantial positive news for the market prospects of the solar energy industry, contrasting with the period of the La Niña phenomenon.

4.7. Impact of SOI on WILDER and GEO

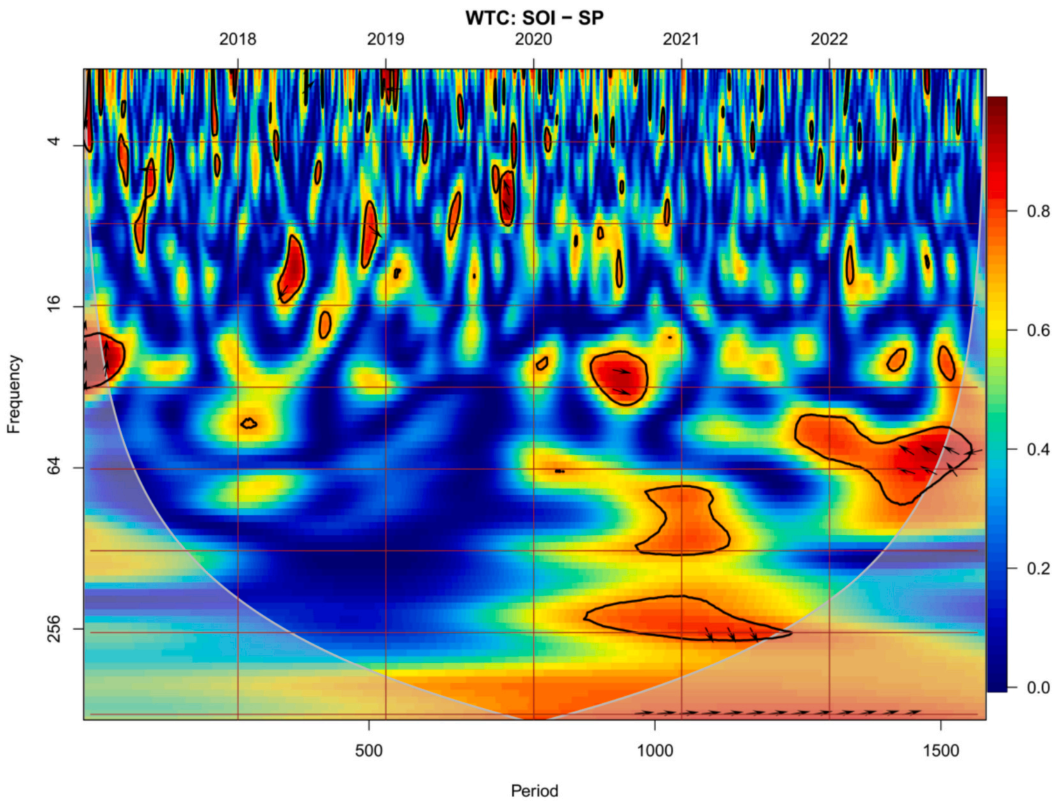
Next, we observed distinctive patterns in the cross-quantile relationship between SOI and the returns of WILDER and GEO in Fig. 3. Specifically, SOI had mostly negative impacts on the returns of WILDER and GEO, with slope coefficients varying with percentiles. Particularly, during a mild La Niña phenomenon when SOI was in the [0.5, 0.6] range, and WILDER and GEO were within the [0.1, 0.2] range, the color bar turned deep blue, indicating significantly negative coefficients. One possible reason is that under normal climatic conditions (characterized by relatively stable and mild weather conditions), demand for clean energy and geothermal energy is relatively low. Investors, being less sensitive to extreme weather changes, may not pay excessive attention to their performance.

In summary, further compelling evidence denotes that the influence of extreme climate shocks on the sub-segmented clean energy index varies heterogeneously across different percentile levels. These further underscores the significant asymmetric influence of SOI on the market

[1] Source: https://www.feedandgrain.com/blogs/feed-grain-pov/blog/15385655/how-will-la-nina-impact-2022-agricultural-production#:~:text=La%20Ni%C3%B1as%20normally%20raises%20crop,and%20fluctuating%20jet%20stream%20patterns

[2] Source: https://www.cmegroup.com/insights/economic-research/2022/how-will-la-nina-impact-ag-markets.html

[3] Source: https://newsroom.aaa.com/2019/02/cold-weather-reduces-electric-vehicle-range/



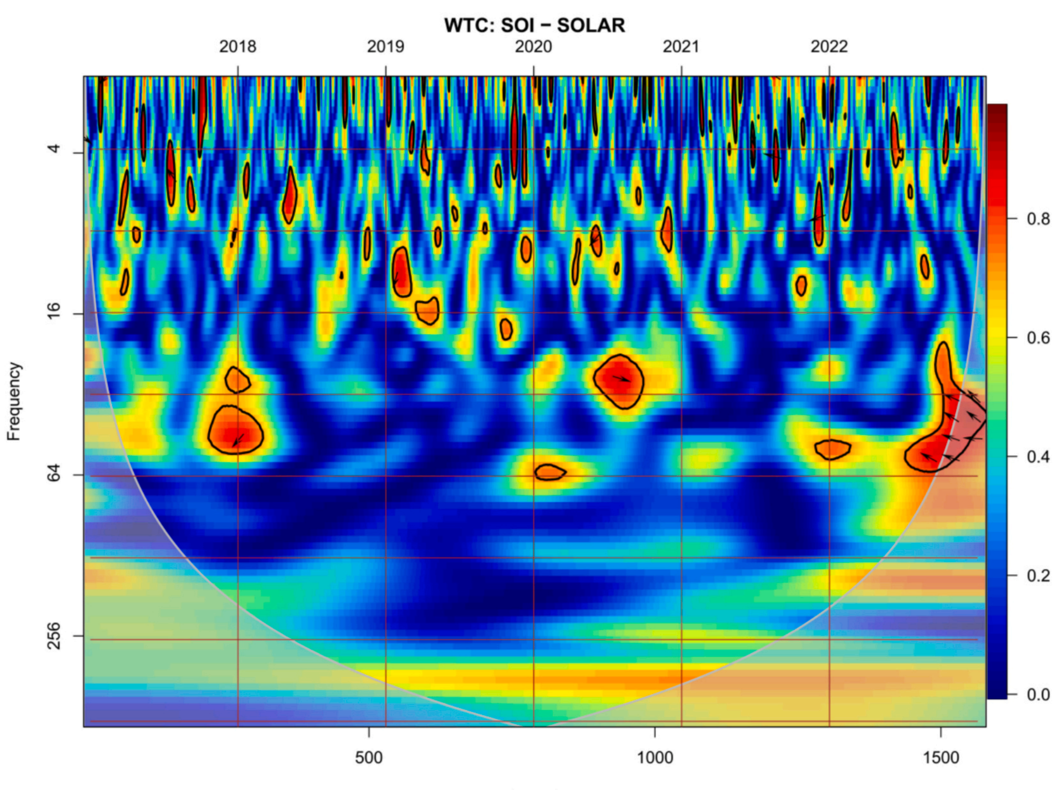


Fig. 4. (*continued*).

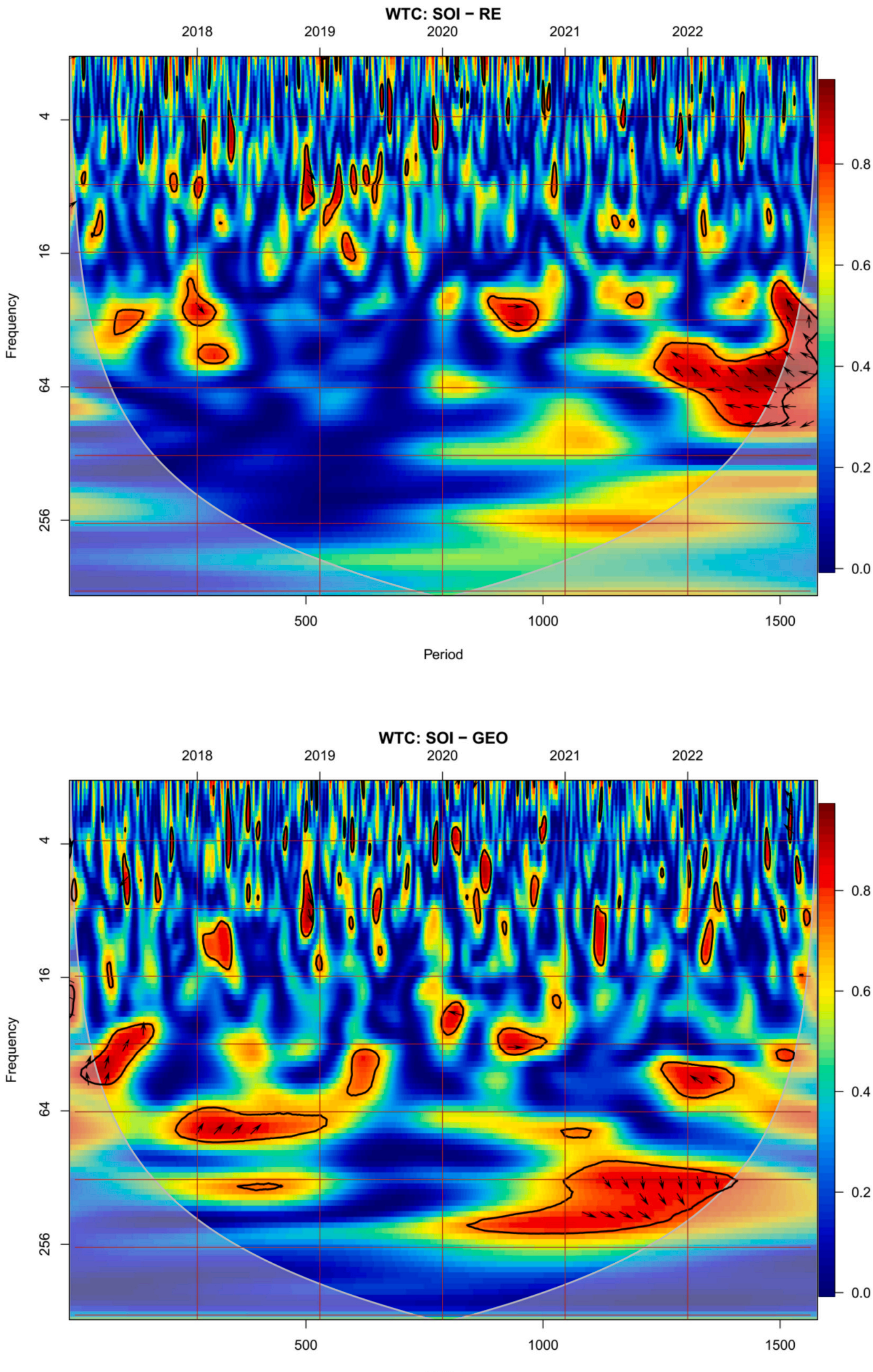
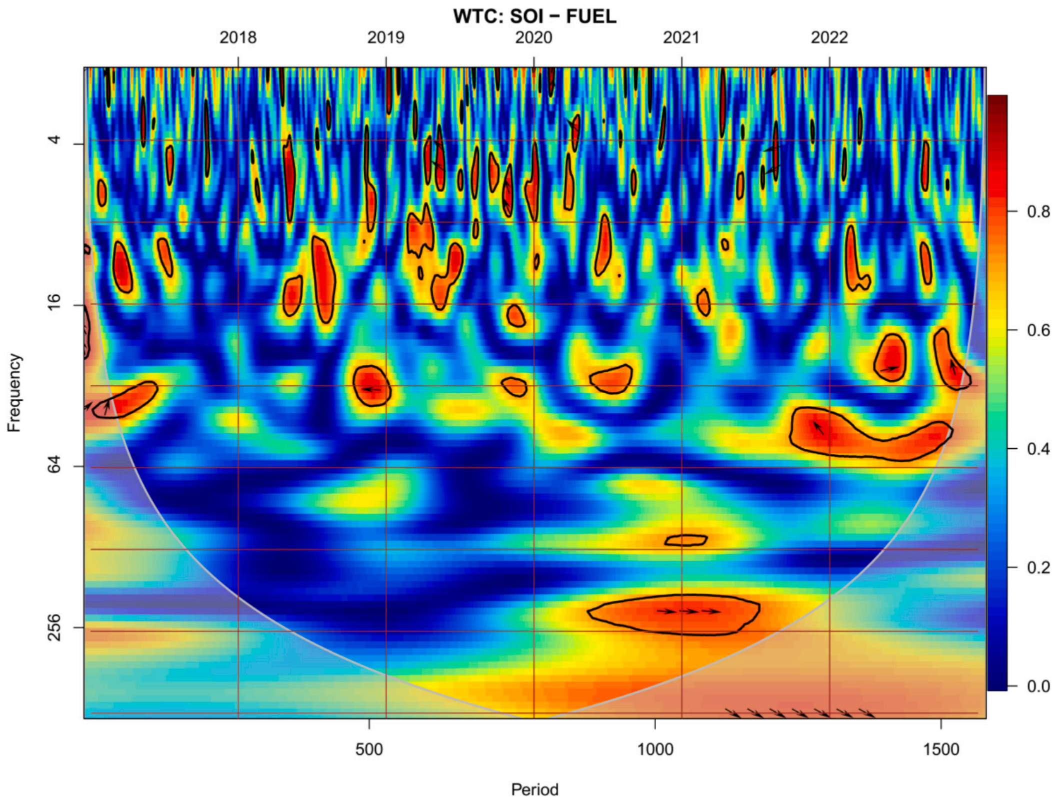


Fig. 4. (*continued*).



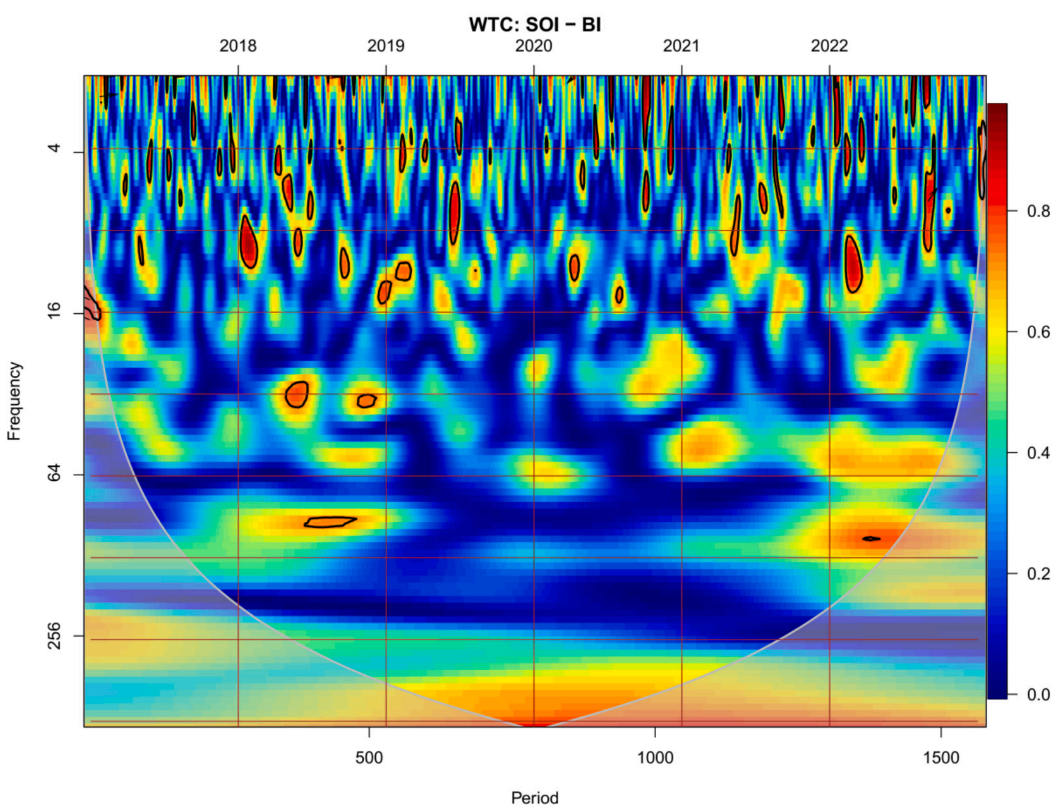


Fig. 4. (*continued*).

performance of clean energy stocks. Additionally, our empirical outcomes are partially aligned with the conclusions of Wei et al. (2023), suggesting that the Southern Oscillation Index does not significantly impact the U.S. renewable energy market under most market conditions.

4.8. Time-frequency wavelet analysis

This subsection further examines the time-frequency interdependence and causality between the Southern Oscillation Index (SOI) and segmented Clean Energy Indices. Specifically, we comprehensively explored the time-frequency coupling patterns of the causal influence of SOI on segmented Clean Energies using the Wavelet Transform

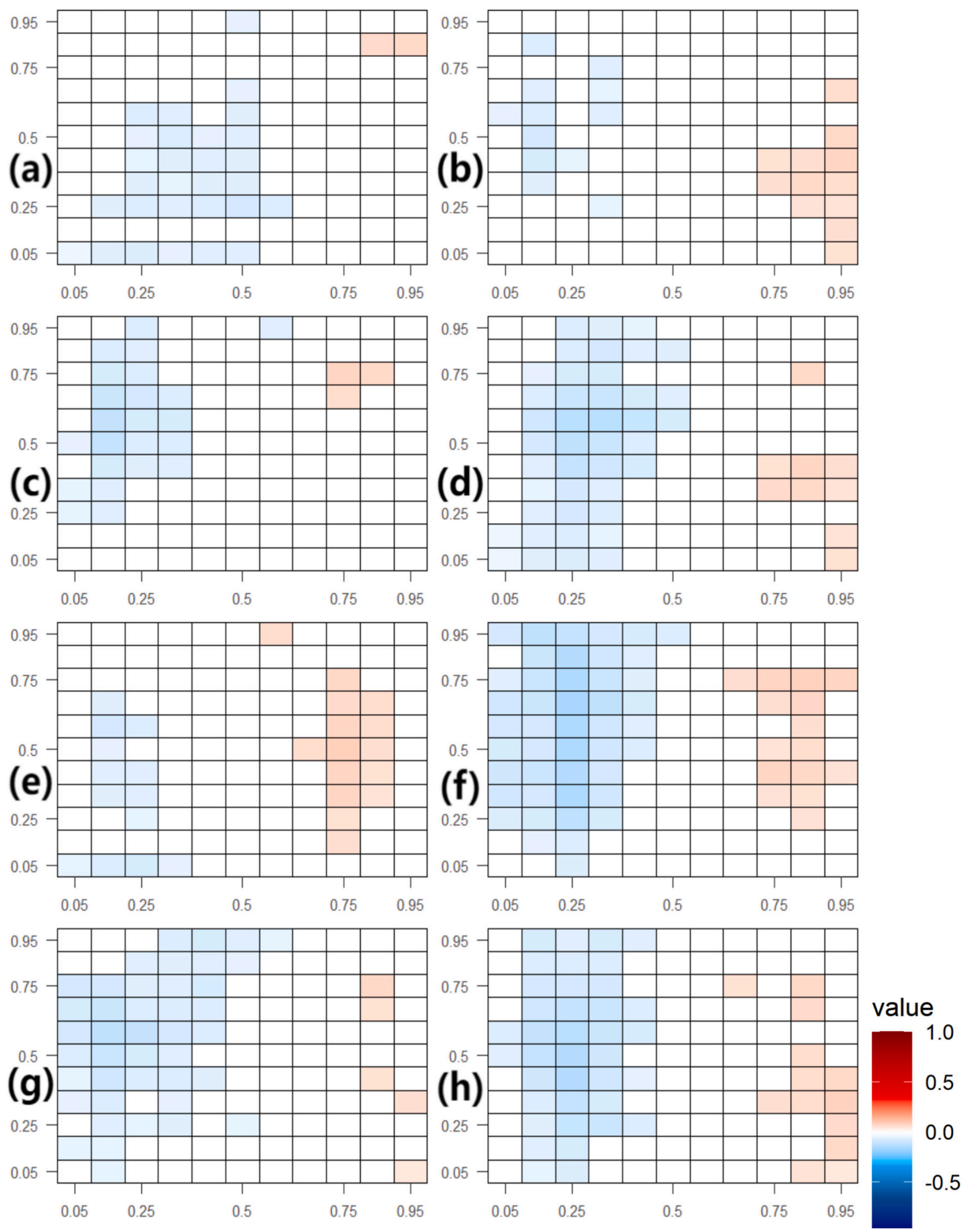


Fig. 5. Heatmaps of the cross-correlation between the Southern Oscillation Index (SOI) and Clean Energy indices.
Notes: These figures portray cross-Quantiles (CQ) through the presentation of heat maps. Quantile degrees lacking great directional predictability have been designated as zero. The colored rectangles demarcate predictable areas where the Ljung-Box check statistic achieves statistical significance. In every heatmap, the horizontal axis corresponds to every clean energy quantile, and the vertical axis corresponds to SOI quantiles (a) SOI-BI; (b) SOI-SOLAR; (c) SOI-FUEL; (d) SOI-SP; (e) SOI-GEO; (f) SOI-WILDER; (g) SOI-RE; (h) SOI-WIND.

Coherence method (WTC). Fig. 4 illustrates the findings of the wavelet coherence among SOI and segmented Clean Energies. A preliminary examination of Fig. 4 reveals that SOI is observed to have significant coupling with Clean Energy Indices at mid-term and long-term frequencies, rather than in the short-term frequency domain.

Taking SOI-WILDER, SOI-SP, SOI-RE, SOI-SOLAR, and SOI-WIND as examples, we observe that from 2020 to 2021, the arrows predominantly point to the right and upwards, pointing a noticeable positive comovement between mid-term SOI and WILDER, SP, RE, SOLAR, and WIND indices. However, after 2022, we observe a negative correlation between SOI-WILDER, SP, RE, SOLAR, and WIND indices at mid-term and long-term frequencies. Notably, the negative correlation is most pronounced (largest red island) between SOI and RE as well as WIND indices. In summary, SOI exerts a positive impact on most of the segmented Clean Energies during most sample periods (primarily before 2022) and at mid-term and long-term frequency scales. Consequently, this suggests that SOI is a significant factor leading to the reliable prediction of most segmented Clean Energy Indices in the mid-run and long-run market performance during the study period.

Similarly, Fig. 4 displays the WTC between SOI and GEO from 2017 to 2023. The majority of arrows also tend to point to the right and upwards, denoting a strong positive association between SOI and GEO at mid-term and long-term frequencies until 2022. Furthermore, Fig. 4 suggests that there is an inverse relationship between SOI and GEO during the research period after 2022. This shows that SOI cannot predict the returns of GEO after 2022.

In a similar manner, the WTC record between SOI and FUEL and BI is presented in Fig. 4. Most arrows in the SOI-FUEL domain point to the right and upwards, indicating predominantly positive coupling in high and mid frequencies from 2017 to 2023. However, at the end of 2021, the arrows for SOI-FUEL begin to turn towards the left and upwards, indicating a negative correlation between SOI-FUEL at mid-term frequencies. Finally, we observe that SOI struggles to serve as a predictor for the BI index since there is no significant temporal and frequency domain coupling between them.

In summary, our results provide positive evidence for the association between SOI and Clean Energy Indices, excluding BI, at mid-term and long-term frequencies.

4.9. Robustness checks

To further validate the sensitivity of the QQR results, we employed the Cross-Quantile (CQ) approach to evaluate the cross-quantile correlation between the SOI and the segmented clean energy index. In Fig. 5, we provide the findings of CQ among the lagged SOI index and the segmented clean energy index for a lag of one period. In this method, the Box-Ljung test was utilized for statistically significant tests of predictability. The red color in the heatmap represents positive correlation, while blue indicates negative correlation. The deeper the shade of red, the stronger the correlation. White denotes the absence of correlation. In every heatmap, the vertical axis means the quantiles of SOI, while the horizontal axis means the quantiles of each segmented clean energy index.

Specifically, in Fig. 5, we observed that, with a lag of 1 (corresponding to daily data), when the clean energy indices were all in relatively high quantiles, the Southern Oscillation Index (SOI) had a positive impact on all clean energy indices. This result shows that under bullish market states (when the market performance of clean energy improves, leading to higher returns), the SOI exhibits a significant positive influence on clean energies. However, when the segmented clean energies were all in the middle to lower quantiles, we did not observe any significant dependency between SOI and clean energy indices. Further observations revealed, for instance, in the case of FUEL and BI, we could only discern a weak connection between SOI during high quantiles (La Niña period) and their corresponding high quantile moments. In other words, this implies that the El Niño phenomenon has no impact on bullish FUEL and BI indices. Conversely, we also noted that during bullish periods for SOLAR and WIND indices, a strong El Niño phenomenon had a positive impact on these indices. These findings suggest that the El Niño pattern typically leads to decreased wind speeds and fluctuating precipitation, thereby influencing SOLAR and WIND indices. In summary, concerning the connection among SOI and segmented clean energies, we observed that the results of the Cross-Quantile (CQ) analysis align with the previous QQR findings, confirming the robustness of our empirical outcomes.

4.10. Discussion

Through the analysis and comparison of the three quantile-based methods mentioned above, we anticipate that the Southern Oscillation Index (SOI) will exert positive impacts on the clean energy during bullish conditions. A tenable interpretation posits that technological progress and the extensive deployment within the clean energy sector are considered the most economical strategies for realising sustainable development objectives amidst aspirations for carbon neutrality (Adenle et al., 2015). As a result, the notable financial returns of the clean energy industry, coupled with apprehensions regarding climatic deterioration, are likely to incentivise a growing cohort of investors to engage proactively in the clean energy marketplace. This is particularly evident during periods of bullish market trends, wherein investor sentiment is markedly positive (Wei et al., 2022). In other words, when the market is bullish, investors' attentions about extreme climate events, such as intense La Niña and El Niño phenomena, favorably contribute to further boosting investor enthusiasm and scale for clean energy investments, thereby resulting in higher asset returns. Unlike in a rising market, during periods of market pressure, investors are often more sensitive to potential loss risks when facing external shocks, exhibit risk aversion, and may unwisely divest assets due to herd effects, further exacerbating the market performance of clean energies.

Moreover, from the standpoint of market fundamentals, on the supply side, the generation of clean energy is substantially contingent upon meteorological conditions (Asif and Muneer, 2007), which may be profoundly affected by La Niña and El Niño phenomena. Consequently, extreme meteorological events could introduce heightened uncertainty into the investment landscape of the clean energy sector, particularly for climate-dependent sources such as wind and solar power (Chen et al., 2021). It is imperative to highlight that, in accordance with data from the US Energy Information Administration, renewable wind energy presently ranks as the fourth-largest electricity industry in the US, surpassed only by natural gas, coal, and nuclear power.[4] Thus, extreme weather may impact the production side of clean energy and catastrophically influence the market performance of clean energy indices and even financial markets through various channels.

Specifically, as we used a clean energy index for the US market, on the one hand, the high sensitivity of the clean energy market to La Niña can be attributed to the fact that, in La Niña years, the western and northern United States experience relatively moist winters, while the southern United States encounters drier and warmer weather (Peltier and Ogle, 2019). Additionally, La Niña brings more hurricanes to the Atlantic, affecting states like Florida and others in the southern regions (Pielke Jr and Landsea, 1999). It is evident that these factors underscore the adverse impact of La Niña on the stability of solar and wind energy outputs in most regions of the US (Watts et al., 2017). Meanwhile, since 2010, La Niña has been linked to rising crop prices in the US (Anderson et al., 2017). This is because La Niña may bring negative weather to major crop-growing regions in the United States, which is unfavorable for the growth of crops such as corn, soybeans, and wheat, affecting the performance of some clean energy indices that use crops as raw materials (e.g., BI).

[4] Source: https://www.eia.gov/tools/faqs/faq.php?id=427&t=3

Finally, our empirical findings indicate that the dynamic interaction between SOI and all Clean Energy Indices, excluding BI, was almost negligible in the short term but strengthened in the mid-run and long run. These results offer crucial insights for market participants investing across different time horizons. For instance, for investors favoring mid-to-long-term trades in clean energy assets, our research outcomes hold significant positive implications, assisting them in making strategic investment decisions to mitigate risks associated with extreme climatic conditions.

5. Conclusions and policy remarks

This study employed a series of quantile-based models and Wavelet method, namely the Granger quantile causality method, Quantile-to-Quantile Regression (QQR), Cross-Quantile (CQ) method and wavelet coherence approach (WTC). We presented a more comprehensive investigation into the impacts and relationships among the SOI and segmented clean energy indices under different market states. Our findings revealed several significantly important discoveries not previously documented in the literature. These findings have substantial implications for policymakers and investors focusing on clean energy and sustainable investment themes, seeking strategies to minimize risks under normal and extreme climate and market states.

Our empirical results indicate that: (1) We found a significant positive Granger causality connection among SOI and all segmented clean energy indices at an overall level, and the Granger causality test results for SOI on segmented clean energy indices differed at specific conditional quantiles. (2) Robust La Niña and El Niño periods could potentially enhance asset returns further during bullish periods (higher quantiles) for most segmented clean energy indices, whereas the correlation among SOI and clean energy indices was nearly nonexistent during market stability periods (medians) and bearish periods (lower quantiles). (3) The impact of intense La Niña periods on segmented clean energy indices was more pronounced than during strong El Niño periods. (4) From the perspective of temporal-frequency connection, it was observed that SOI exhibited predictability solely at the intermediate and long-term frequencies of the Clean Energy Index (excluding the BI).

The above findings distinguished extreme weather as a driving factor influencing various types of clean energy assets, carrying some essential policy implications. Firstly, market participants should closely monitor the impact that the Southern Oscillation Index has on the clean energy market. Additionally, investors can diversify risks by allocating investment portfolios across different clean energy indices based on the heterogeneous response of segmented clean energy to SOI, such as extreme climate risks and financial market risks. Secondly, our study confirms differences in the influence of SOI on the market performance of segmented clean energy indices during bullish, stable, and bearish market periods. This suggests that effective hedging strategies and market regulatory processes should consider the heterogeneity in the response of segmented clean energy indices to SOI impacts under different market conditions. Thirdly, given the asymmetric effects of intense La Niña and El Niño phenomena on segmented clean energy indices, particularly during La Niña periods, policymakers should implement targeted policy interventions to address the influence of SOI shocks and further support the systematic stability and robust development of clean energy to ensure energy security under the carbon-neutral backdrop. Fourth, we observed that SOI had a positive impact on Clean Energy Indices, excluding BI, at mid-term and long-term frequencies. This suggests that market participants in clean energy assets, especially institutional investors and fund managers focusing on mid-term and long-term returns, should concentrate more on developing resilient investment portfolios to mitigate the risks associated with extreme climatic conditions. Finally, useful insights into the predictability of returns on segmented clean energy indices due to SOI can help investors maximize their practical ability to combat extreme climate risks.

There are still some potential issues worthy of further research. For example, exploring the asymmetric impacts of the Southern Oscillation Index on the segmented clean energy market in under uncertainty condition would be worthwhile. If data are available, considering the close and intricate connections among clean energies and climate change in other regions (such as Europe and East Asia) is also appealing.

CRediT authorship contribution statement

Hongjun Zeng: Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Mohammad Zoynul Abedin:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Investigation. **Vineet Upreti:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Investigation.

Declaration of competing interest

We have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.108003.

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