ISSN 1611-1699/eISSN 2029-4433

JOURNAL of BUSINESS ECONOMICS & MANAGEMENT

2025
Volume 26
Issue 6
Pages 1264–1283
https://doi.org/10.3846/jbem.2025.23893

ARE RENEWABLE ENERGY STOCKS, INVESTOR SENTIMENT, AND THE CRYPTOCURRENCY MARKET-RELATED?

Chi Wei SU[1, 2, 3], Xin Yue SONG[4], Meng QIN[5✉], Oana-Ramona LOBONŢ[6], Muhammad UMAR[7, 8]

[1]School of Finance, Yunnan University of Finance and Economics, Kunming, China
[2] Faculty of Finance, City University of Macau, Macao, China
[3]School of Economics, Qingdao University, Qingdao, China
[4]School of Public Administration, Sichuan University, Chengdu, China
[5]School of Marxism, Qingdao University, Qingdao, China
[6]Finance, Business Information Systems and Modelling Department, Faculty of Economics and Business Administration, West University of Timisoara, Timisoara, Romania
[7]Adnan Kassar School of Business, Lebanese American University, Beirut, Lebanon
[8]Doctoral School of Economics and Business Administration, Faculty of Economics and Business Administration, West University of Timisoara, Timisoara, Romania

Article History:
- received 10 September 2024
- accepted 22 April 2025

Abstract. This paper applies wavelet quantile correlation to research on the relationship among renewable energy stocks, investor sentiment, and the cryptocurrency market. The empirical results indicated that under extremely negative conditions, in both the short and medium run, renewable energy stocks and cryptocurrencies are negatively correlated, implying that during such periods, renewable energy stocks can be used as a safe haven for cryptocurrencies. The opposite happens when the market is average or booming. This indicates that investors tend to invest simultaneously in these two promising asset classes when the market performs well. Under varied market conditions, FGI correlates positively with cryptocurrency, demonstrating sentiment influences price patterns. Moreover, the correlation between FGI and renewable energy stocks further validates the relationship between cryptocurrencies and renewable energy stocks. These findings can be used to improve the prediction of market trends by investors using sentiment indices and to devise more effective portfolio diversification strategies that minimize risk amid an evolving market.

Keywords: renewable energy stocks, investor sentiment, cryptocurrency, wavelet, quantile correlation, portfolio diversification.

JEL Classification: C32, E44, G12.

✉Corresponding author. E-mail: ***meng575316928@126.com***

1. Introduction

This paper analyses the correlation between renewable energy stocks, investor sentiment (FGI), and the cryptocurrency market, with further analysis of these two factors' potential roles in asset al.ocation and risk management in the cryptocurrency market. The cryptocurrency market, known for its tremendous volatility and unpredictability, has attracted the interest of investors worldwide. Cryptocurrencies are an alternative to other investments, as the opportunity has been perceived to be viable given that direct transaction within a network eliminates intermediaries, such as traditional banks (Fang et al., 2019; Liu et al., 2024). While there is considerable attention that has been given to how traditional cryptocurrencies influence financial markets, their negative impacts on the environment are often ignored (Yadav et al., 2025). According to the Bitcoin Energy Consumption Index published by Digiconomist, a single transaction in Bitcoin consumes an amount of electricity equal to what the average household in the U.S. uses in 53 days (Le, 2023). The significant consumption of energy gives rise to concerns over the future sustainability of the environment (Naeem & Karim, 2021; Su et al., 2025b). To mitigate this issue, there has been a rise in the allocation of investments towards both cryptocurrencies and renewable energy equities (Yadav et al., 2025). This trend allows investors to pursue financial benefits while concurrently reducing negative environmental impacts (Li & Meng, 2022). For instance, Tesla has chosen to discontinue its endorsement of cryptocurrency transactions due to apprehensions related to climate change. This has brought about the need to analyse the environmental effects of Bitcoin mining in terms of sustainable development. This divestment leads to a decrease in the price of Bitcoin (BTCP), and this forces investors to compare the economic benefits of Bitcoin with the support for green investment opportunities. Therefore, investors are forced to be more careful in their high-risk investments (Sharma et al., 2023). As traditional cryptocurrencies increasingly impact the environment, investors face a choice between pursuing the economic benefits of Bitcoin or opting for green investment opportunities to diversify risk (Naeem & Karim, 2021; Qi et al., 2024). Thus, the inclusion of renewable energy equities in an investment portfolio can enhance diversification by effectively reducing total risk while seeking to preserve value or hedge against the hazards of holding cryptocurrency (Dias et al., 2023).

Furthermore, the essence of cryptocurrencies makes them unlike conventional assets in many aspects since most of the times they are regarded as being void of intrinsic values and lack an inherent relationship with a particular fiat currency (Gaies et al., 2023). Due to this aspect, valuation for cryptocurrencies often has strong effects resulting from psychological forces like fear and greed that eventually enhance uncertainty and volatility in markets (Chen et al., 2021). This, in turn, has a significant effect on the investment decisions made by investors (Bandelj, 2009; Vargas-Sierra & Orts, 2023). Moreover, the perception and attitude of investors play a vital role in creating and managing a well-balanced investment portfolio that efficiently manages risk (Yang & Wu, 2019; Qin et al., 2024b). Consequently, the integration of FGI in the analysis can bring a deeper understanding of the interrelationships between renewable energy stocks and cryptocurrencies, thus assisting investors further in better risk management and improved portfolios.

This study provides multiple valuable contributions to the current literature. The cryptocurrency market has significantly developed, and with this development comes increased interest in its market dynamics and environmental effects. Previous research primarily focuses on the relationship between cryptocurrencies and traditional assets (Naeem et al., 2023; Su et al., 2023). However, systematic analysis of the linkages between renewable energy stocks and cryptocurrencies remains insufficient. The correlation between FGI and the cryptocurrency market has not been fully explored. Therefore, this paper fills the gap and explores the relationship among renewable energy stocks, FGI, and the cryptocurrency market to support investors and policymakers effectively. Moreover, while traditional methods can reveal directional and dynamic links, they fail to capture tail dependencies effectively, thus failing to comprehensively reflect the market conditions (Kumar & Padakandla, 2022; Qin et al., 2024c). Hence, we employ the wavelet quantile correlation (WQC) approach that captures interlinkages between different quantiles at various temporal horizons (Patel et al., 2023). The results indicate that renewable energy stocks are negatively correlated with cryptocurrencies over the short and medium horizon under extremely negative market conditions. This means that during economic downturns, investors tend to shift their capital from cryptocurrencies to renewable energy equities, as they attempt to reduce the risk exposure and seek more dependable returns. The association in stable or booming markets is positive, meaning that the integration of renewable energy equities into cryptocurrency investment portfolios can maximize overall investment performance and diversify risk. Additionally, investor sentiment is also positively correlated with cryptocurrency prices across different market conditions, showing that sentiment is one of the important drivers of the changes in the price of cryptocurrencies. Furthermore, the relationship between FGI and renewable energy stocks varies depending on market conditions, indirectly corroborating the correlation between renewable energy stocks and cryptocurrencies. These findings help investors include renewable energy stocks in their portfolios containing high-risk cryptocurrency investments to optimise asset al. ocation and reduce cryptocurrency holdings when sentiment indicators deteriorate, thereby better-managing risk exposure.

This study is sequentially structured with the organization: Section 2 offers a broad literature review regarding the relevant materials. Section 3 presents the theoretical mechanisms. Section 4 provides an in-depth discussion of the wavelet quantile correlation (WQC) methodology. Section 5 provides a description of the data. Section 6 summarises the results of the empirical inquiry. Section 7 focuses on the ultimate results and their ramifications.

2. Literature review

2.1. Cryptocurrency market and renewable energy stocks nexus

It is essential to comprehend the connection between the renewable energy stock market and cryptocurrencies, as the substantial energy consumption associated with cryptocurrency mining and trading is significant. Bastian-Pinto et al. (2021) confirm the validity of Bitcoin as a safeguard for investments in green energy. According to Ren and Lucey (2022), there is a generally favourable link between the renewable energy index and cryptocurrency, with the correlation fluctuating over time. Annamalaisamy and Vepur Jayaraman (2024) discover that renewable energy stocks and Bitcoin demonstrate robust and favourable performance during COVID-19. Tiwari et al. (2024) also affirm this perspective, demonstrating a favourable correlation between BTCP and renewable energy stocks amidst the COVID-19 pandemic and the Russo-Ukrainian War. In contrast, Symitsi and Chalvatzis (2018) state that Bitcoin has a lasting influence on the volatility of renewable energy stocks, resulting in adverse effects between them. Naeem and Karim (2021) contend that renewable energy exhibits a greater hedging ratio and efficacy against BTCP, implying a negative correlation between renewable energy and Bitcoin. Angelini et al. (2022) have discovered a noteworthy adverse spillover impact between renewable energy sources and BTCP, suggesting a possible substitution effect between the two. Dias et al. (2023) provide additional evidence supporting the notion that renewable energy assets can serve as a safeguard against the potential decrease in cryptocurrency prices.

Despite these outcomes, various studies have concluded that there is no meaningful correlation between cryptocurrencies and the renewable energy sector. According to Pham et al. (2022), cryptocurrencies like Bitcoin and Ethereum do not strongly associate with green assets during relatively stable market conditions. Li and Meng (2022) argue that cryptocurrencies do not significantly affect price movements in the renewable energy stock market compared to other currencies. Dogan et al. (2022) have also identified that no causal relationship exists between Bitcoin trading and renewable energy trading volume in the cryptocurrency market crash of 2014, indicating that long-run viability for investments in cryptocurrencies does not exist.

2.2. Cryptocurrency market and investor sentiment nexus

Since cryptocurrencies share similar characteristics with speculative stocks, investor perspectives and sentiments may influence them (Celeste et al., 2020). Selmi et al. (2018) observe that investors panic and transfer funds to cryptocurrencies as a safe-haven asset during market volatility, increasing cryptocurrency prices. Corbet et al. (2020) demonstrate that macroeconomic announcements that convey pessimistic sentiment typically impact cryptocurrency returns positively. Before the COVID-19 pandemic, Mokni et al. (2022) argued that FGI significantly positively affected cryptocurrency returns, indicating that greater investor greed increases cryptocurrency returns across all quantiles. Gaies et al. (2023) also show that the occurrence of extreme events triggers continued greed among investors, thereby pushing up BTCP. Additionally, Suleman et al. (2025) confirm that during COVID-19, investor greed and extreme greed significantly positively impact the cryptocurrency market. Kulbhaskar and Subramaniam (2023) believe that positive news boosts FGI, thus increasing the returns on cryptocurrencies. Bakhtiar et al. (2023) employ the FGI to represent investor sentiment, indicating that investors become cautious when the FGI is low, leading to lower returns on cryptocurrencies. Wang et al. (2024) point out that when investors become extremely greedy, a herding effect driven by FGI leads to more synchronised movements in cryptocurrency prices, suggesting that sentiment has a positive impact on cryptocurrency prices.

Moreover, several investigations present contrasting perspectives. Chen et al. (2021) argue that there is a negative correlation between the rising dread of the coronavirus and the profitability of Bitcoin. Zhu et al. (2023) find that extreme market conditions cause considerable anxiety among policymakers and investors, with a significant negative correlation between investor returns and BTCP during bear markets. Anamika et al. (2023) observe that cryptocurrency prices tend to increase when there is a decline in FGI in the stock market since cryptocurrencies are occasionally considered a viable alternative investment option. Osman et al. (2024) further state that during the COVID-19 pandemic, stock market sentiment negatively led to the price returns of Bitcoin and Ethereum. Maghyereh and Ziadat (2024) also support this view, suggesting that investor behaviours such as herding and panic trigger massive sell-offs in cryptocurrencies during specific periods.

In general, there is still disagreement in the literature about the relationship between renewable energy stocks, FGI, and the cryptocurrency market. While prior studies have indicated a relationship between cryptocurrencies and FGI, research integrating the renewable energy market into analytical frameworks remains in its infancy, lacking systematic exploration and empirical validation. Furthermore, the extant literature has insufficiently addressed the complex relationships across multiple time scales and poorly investigated properties such as heavy-tailed distributions, outliers, and tail dependence, thereby limiting our overall understanding of the market intricacies. To address these limitations, this research employs the wavelet quantile correlation (WQC) technique, which is effective in determining the relationship at multiple time scales and quantiles with a special focus on tail dependence (Kumar & Padakandla, 2022), thereby providing a more comprehensive and detailed analysis.

3. Theoretical analysis

3.1. Cryptocurrency market and renewable energy stocks

The general equilibrium framework proposed by Kanamura (2020) can be applied to examine the relationship between renewable energy stocks (denoted as ECO) and cryptocurrency prices (denoted as BTCP). The model is particularly important when assessing the linkages among asset markets because of its ability to capture the extensive dynamics of inter-market connections (Wang et al., 2023). This framework allows an examination of the dynamic changes happening in cryptocurrency trading while allowing for an analysis of how these changes interact with demand for ECO. The equilibrium prices of ECO and BTCP can be expressed as:

$$ECO_t = \left(1+\beta_1 \frac{D_t}{c_1}\right)^{\frac{1}{\beta_1}}; \quad (1)$$

$$BTCP_t = \left(1+\beta_2 \frac{\overline{S_t} - S_t}{c_2}\right)^{\frac{1}{\beta_2}}; \quad (2)$$

$$dD_t = \mu_D dt + \vartheta_D d; \quad (3)$$

$$dS_t = \chi\left(ECO_t\right) dD_t + \vartheta_s dw_t, \quad (4)$$

where ECO_t is the Box-Cox inverse function of the supply curve and the D_t process for demand in Equations (1) and (3). $BTCP_t$ is calculated using the Box-Cox inversion transformation on Equation (2) and linked to the supply mechanism S_t in Equation (4), suggesting that $BTCP$ is correlated with ECO through $\chi\left(ECO_t\right)$. Moreover, $\overline{S_t}$ is set as a constant, marking the maximum of S_t. Hence, $E\left[dv_t, dw_t\right] = \rho d_t \sqrt{b^2 - 4ac}$. Employing Ito's Lemma as outlined by Kanamura (2020), we can derive:

$$\bar{\vartheta}_{BTCP} = \sqrt{\chi\left(ECO_t\right)^2 \vartheta_D^2 + \vartheta_S^2 - 2\rho\chi\left(ECO_t\right)\vartheta_D \vartheta_S}; \quad (5)$$

$$\rho_{ECO,BTCP} = \frac{1}{dt} corr\left(\frac{dBTCP_t}{BTCP_t}, \frac{dECO_t}{ECO_t}\right) = \frac{-\chi\left(ECO_t\right)\vartheta_D + \rho\vartheta_S}{\bar{\vartheta}_{BTCP}}. \quad (6)$$

The correlation coefficient between ECO and $BTCP$, denoted as $\rho_{ECO,BTCP}$, is explored by developing a partial differential equation: $\frac{\partial \rho_{ECO,BTCP}}{\partial ECO} = -\frac{\vartheta_D \vartheta_S^2}{\bar{\vartheta}_{CP}^3}\left(1-\rho^2\right)\frac{\partial \chi}{\partial ECO}$. When $\frac{\partial \chi}{\partial ECO} < 0$, $\frac{\partial \rho_{ECO,BTCP}}{\partial ECO} > 0$ and $\rho_{ECO,BTCP}$ is a positive function of ECO, suggesting that an increase in ECO strengthens its positive correlation with BTCP, especially if $-\chi\left(ECO_t\right)\vartheta_D + \rho\vartheta_S > 0$ and the opposite holds. Conversely, if $\frac{\partial \chi}{\partial ECO} > 0$, $\frac{\partial \rho_{ECO,BTCP}}{\partial ECO} < 0$ and $\rho_{ECO,BTCP}$ exhibits a decline with ECO, signifying that an decrease in ECO strengthens its negative correlation with $BTCP$ when $-\chi\left(ECO_t\right)\vartheta_D + \rho\vartheta_S > 0$ and vice versa. Thus, we can offer a deduction relying on the previously provided theory: renewable energy stocks demonstrate an association with cryptocurrency pricing, even though the orientation of this association remains unclear.

3.2. Cryptocurrency market and investor sentiment

The relationship between investor sentiment (denoted as FGI) and cryptocurrency prices (denoted as BTCP) can be clarified through the intertemporal capital asset pricing model (ICAPM) as described in Cifarelli and Paladino (2010). The model can more accurately represent the correlation between investor mood, asset price, and market movements than the conventional CAPM since it takes into account investors' actions at various time points (Su et al., 2024b). The cryptocurrency market's pricing model is predicated on two fundamental assumptions. First, the market is composed of both reasonable and feedback investors. Reasonable investors acquire cryptocurrencies in accordance with their established investment objectives, while feedback investors scans for trading opportunities by monitoring price movements in the cryptocurrency marketplace. In addition, the demand for cryptocurrencies is inextricably linked to the expectations of investors. When investors assume a more optimistic future, the market demand for cryptocurrencies increases, and vice versa. In this theoretical framework, we implement the FGI metric to gauge investor sentiment to make it possible to dig more into the relationship between investor sentiment and the demand for cryptocurrencies.

$$R_t = \frac{E_{t-1}\left(BTCP_t\right) - BTCP^f}{\mu\left(FGI_t\right)}, \tag{7}$$

where the portion of cryptocurrencies solicited from the rational section is symbolised by R_t. The $\mu\left(FGI_t\right)$ figure is favourable and demonstrates a constantly rising tendency in relation to systemic risk. The expectancy conditioned on *BTCP* is symbolised by $E_{t-1}\left(BTCP_t\right)$, and the free of risk return is expressed by $BTCP^f$. If every participant in the cryptocurrency market performs rationally, the value of R_t is equal to 1. The conventional capital asset pricing model (CAPM), as established by Sharpe (1964), can be illustrated through Equation (7), which n also be described as Equation (8). As a result, we observe that an increase in *BTCP* is associated with a higher level of *FGI*.

$$E_{t-1}\left(BTCP_t\right) = BTCP^f + \mu\left(FGI_t\right). \tag{8}$$

Furthermore, the remainder of investors in the cryptocurrency market adjust their current investment proportions from the previous *BTCP*. Afterwards, taking into consideration the feedback cohort, the ratio of cryptocurrency demands (F_t) is expressed as:

$$F_t = \tau BTCP_{t-1}, \tag{9}$$

where $\tau > 0$ implies that the feedback organises invests in cryptocurrency when *BTCP* rises (or declines) in the preceding interval. When the rational and feedback batches get involved in the cryptocurrency market, the equation $R_t + F_t = 1$ holds true:

$$E_{t-1}\left(BTCP\right) = BTCP^f + \mu\left(FGI_t\right) - \tau\mu\left(GFI_t\right)BTCP_{t-1}. \tag{10}$$

The expression $-\tau\mu\left(FGI_t\right)BTCP_{t-1}$ is incorporated into Equation (8) by Equation (10), which generates instability in *BTCP*. As a consequence of the overarching coefficient $\mu\left(FGI_t\right)$ being

$1-\tau BTCP_{t-1}\left(\tau BTCP_{t-1}=F_t\right)$, the relationship between FGI and $BTCP$ remains significant. Consequently, the ICAPM framework is employed in this study to probe the hypothesis that BTCP is correlated with investor sentiment, as measured by the FGI.

Building on the previous analysis, we apply the wavelet quantile coherence (WQC) approach to further analyse the relationship between renewable energy stocks, FGI, and the cryptocurrency market. The WQC method is an advanced econometric tool that effectively detects dependencies at different frequencies and time scales, making it especially suited for characterizing the nonlinear and time-dependent properties of the market (Uche et al., 2024). By using this approach, we aim to better understand the relationships between variables, hence providing meaningful inferences for investors to improve asset al.ocation and risk management while also providing vital support to policymakers.

4. Methodology

Wavelet analysis divides data into multiple frequencies components, which can reveal both long-term and short-term properties. At the same time, quantile correlation assesses the variations in relationships among variables across varying conditions (Jalal & Gopinathan, 2023). Therefore, building on the wavelet quantile correlation (WQC) methodology introduced by Kumar and Padakandla (2022), we examine the temporal heterogeneity and tail dependence across diverse time scales and quantiles. This method represents an extension of quantile correlation methods based on the work of Li et al. (2015). The quantile correlation of the variables X and Y is defined in the following:

Take $Q_{\tau,X}$ be the τ^{th} quantile of X and $Q_{\tau,Y(X)}$ denote the τ^{th} quantile of Y given X. The condition for $Q_{\tau,Y(X)}$ to be unaffected by X is that $I\left(Y-Q_{\tau,Y}\right)>0$ and X remains independently. In addition, $I(.)$ is a function that serves as an indicator. Furthermore, by considering the range $0<\tau<1$, we may calculate the quantile covariance in the manner below:

$$q\operatorname{cov}_t\left\{Y,X\right\}=\operatorname{cov}\left\{I\left(Y-Q_{\tau,Y}>0\right),X\right\}=E\left\{\phi_\tau\left(Y-Q_{\tau,Y}\right)\left(X-E\left(X\right)\right)\right\}, \tag{11}$$

where $0<\tau<1$ and $\phi_\tau\left(w\right)=\tau-I(w<0)$. In accordance with the approach established by Li et al. (2015), we compute the quantile correlation applying the following formula:

$$q\operatorname{cov}_t\left(X,Y\right)=\frac{q\operatorname{cov}_t\left(Y,X\right)}{\sqrt{\operatorname{var}\left(\phi_\tau\left(Y-Q_{\tau,Y}\right)\right)\operatorname{var}\left(X\right)}}. \tag{12}$$

Kumar and Padakandla (2022) have broadened the quantile correlation technique by employing a maximal overlap discrete wavelet transform to separate X_t and Y_t. At the j^{th} level, pairs X_t and Y_t are separated employing quantile correlation approaches with the purpose to obtain the wavelet quantile correlation for all levels j. The specific calculating procedure is as described below:

$$WQC_\tau\left(d_j\left[X\right],d_j\left[Y\right]\right)=\frac{qcov_t\left(d_j\left[Y\right],d_j\left[X\right]\right)}{\sqrt{var\left(\phi_\tau\left(d_j\left[Y\right]-Q_{\tau,d_j\left[Y\right]}\right)\right)var\left(d_j\left[X\right]\right)}}. \tag{13}$$

Following Equation (13), X represents the independent series, whereas Y represents the dependent series. We divided the time duration into short-term, medium-term, and long-term scales to capture dynamic relationships across different time horizons. Meanwhile, wavelet quantile correlation effectively reveals the asymmetrical relationships between system parameters and presents the results across different quantiles (Patel et al., 2023; Qin et al., 2025). It also addresses the impact of outliers through quantile decomposition.

5. Data

This study utilises daily data from May 13, 2021, to April 10, 2024, to explore the correlation among renewable energy stocks, investor sentiment and the cryptocurrency market. On May 13, 2021, Tesla announced the suspension of Bitcoin payments due to the adverse environmental impact of Bitcoin mining, leading to a sharp decline in cryptocurrency prices. The study period includes significant occurrences comprising the Bitcoin halving, Ethereum network upgrades, and other key events that could influence market sentiment, including the COVID-19 outbreak in 2022 and the recent Russia-Ukraine conflict. The Fear and Greed Index (FGI) measures investor sentiment towards the cryptocurrency market (Cavalheiro et al., 2024). Additionally, as representatives of the renewable energy stock market, we employ the Wilder Hill Clean Energy Index (ECO), the Europe Renewable Energy Index (REIX), and the Mainland China New Energy Index (CNN) to reflect the renewable energy markets in the U.S., the EU, and China, correspondingly (Ferrer et al., 2018; Yang et al., 2021). These three indices provide comprehensive coverage, as the first two indices reflect the overall situation of clean energy in developed countries, while the last index shows some aspects of clean energy in developing countries. Furthermore, this study selects the closing prices of Bitcoin (BTCP), Ethereum (ETHP), and Litecoin (LTCP) to measure the performance of the cryptocurrency market. With the exception of the CNN data, which is obtained from Wind, all other data are acquired from Bloomberg.

Figure 1 depicts the trends in these variables across the full sampling period. Overall, cryptocurrency prices experience rollercoaster-like fluctuations. We observe that in 2021, due to the impact of the COVID-19 pandemic, BTCP, ETHP, and LTCP all undergo varying degrees of decline (Li & Meng, 2022). Additionally, due to Bitcoin's high energy consumption issues, Tesla announces the suspension of Bitcoin payments, leading to a drop in cryptocurrency prices during this period. In the same year, governments worldwide increase their support for the renewable energy industry, such as the U.S. Clean Energy Plan and the EU's Fit for 55 climate package, resulting in minimal impact of the COVID-19 pandemic on the renewable energy market. Meanwhile, the frequent outbreaks of the pandemic cause fluctuations in financial markets (Qin et al., 2024a), significantly affecting FGI. From late 2021, the onset of the post-pandemic era sees economic recovery, with both renewable energy stocks and cryptocurrencies showing some rebound. In early 2022, the Russo-Ukrainian conflict triggered an energy crisis, initially causing the renewable energy stock market to rise and then decline (Su et al., 2025a). Traditional cryptocurrencies like BTCP and ETHP, due to their high energy consumption, heighten investor concerns about environmental impacts, negatively affecting the prices of these currencies, which show a downward trend. In May of the same year, the TerraUSD (UST) de-pegging incident triggers investor panic, leading to the widespread selling of cryptocurrencies. Therefore, this period is crucial for studying asset price fluctuations.

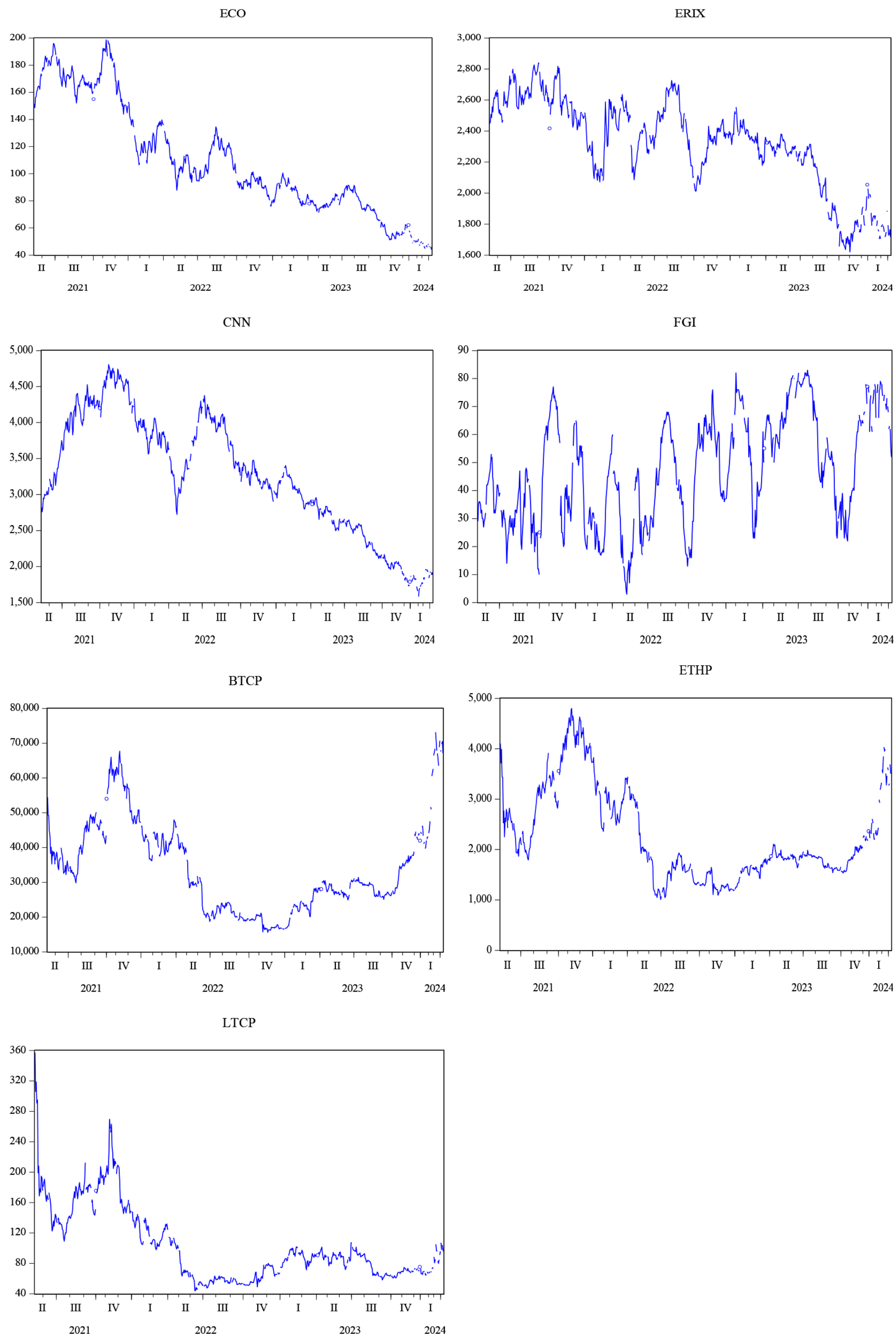


Figure 1. The trends of the related series

Table 1 presents the results of the descriptive statistics. To ensure the stability of the data, all variables are subjected to first-order differencing. According to the results, the mean values for ECO, ERIX, CNN, FGI, BTCP, ETHP, and LTCP are –0.167, –1.141, –1.458, 0.036, 19.727, –0.919, –0.408 respectively. From the skewness results, ECO, ERIX, CNN, and BTCP exhibit right skewness, while FGI, ETHP, and LTCP show left skewness. All variables have kurtosis values over 3, indicating a leptokurtic distribution, which suggests that these variables are more likely to exhibit tail dependencies under extreme conditions. Through the Jarque-Bera test, the null hypothesis of normal distribution is rejected at the 1% significance level for these series. Moreover, these variables have been confirmed to be stationary by conducting augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

Table 1. Descriptive statistics for each index

	ECO	ERIX	CNN	FGI	BTCP	ETHP	LTCP
Observations	641	641	641	641	641	641	641
Mean	–0.167	–1.141	–1.458	0.036	19.727	–0.919	–0.408
Median	–0.250	–1.130	–6.988	0.000	–32.470	0.920	0.005
Maximum	11.730	246.980	303.365	17.000	10556.960	617.398	44.212
Minimum	–10.410	–204.240	–239.290	–26.000	–5967.780	–902.555	–95.945
Std. Dev.	3.206	46.618	71.728	4.780	1528.119	129.070	7.774
Skewness	0.242	0.099	0.235	–0.568	0.889128	–0.556	–3.345
Kurtosis	3.824	5.844	4.080	5.572	10.597	10.106	44.841
Jarque-Bera	24.404***	217.022***	37.022***	211.134***	1625.917***	1381.761***	47953.250***
ADF	–25.055***	–24.373***	–26.115***	–27.439***	–24.891***	–27.012***	–28.564***
KPSS	0.059	0.077	0.414	0.018	0.018	0.288	0.442

Note: Std.Dev. is Stand Deviation. Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test unit root and stationarity, correspondingly. *** represents significance at the 1% level.

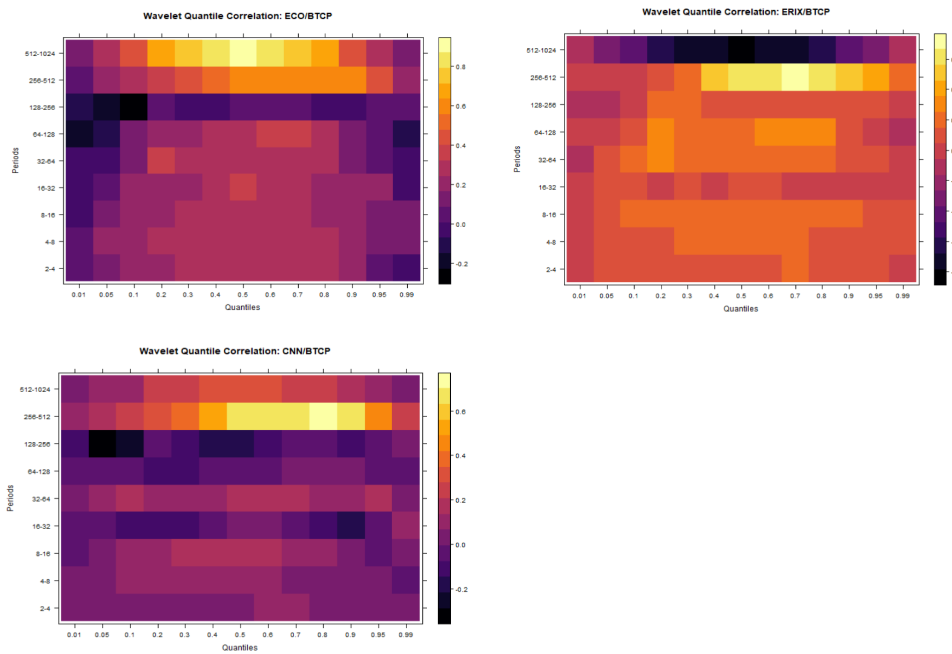
6. Empirical results

In applying wavelet quantile correlation analysis, we divide the time span into short-term (1–256 days), medium-term (257–512 days), and long-term (512–1024 days), as indicated on the left side of every heatmap (Patel et al., 2023). This categorisation allows a deeper exploration of the dynamic relationships between variables at different time scales. Each heatmap's right-hand colour bar indicates how strongly the data in the model are correlated (Kumar & Padakandla, 2022). This classification approach aids in a more thorough understanding of the interactions among the variables.

Figure 2 presents a comprehensive sample correlation analysis between renewable energy stocks and cryptocurrencies. Specifically, Figure 2a describes the quantile correlation between renewable energy stocks and BTCP. In the lower quantile (1–256 days), ECO and CNN exhibit a strong negative correlation with BTCP, while ERIX shows a weak negative correlation with BTCP. This can be clarified through investors perceiving Bitcoin as high-risk and environmentally unfriendly during times of poor market performance. Consequently, they tend to treat stocks like ECO, which are more stable, growth-oriented, and environmentally friendly, as safe-haven assets, incorporating them into their portfolios to reduce risk and promote sustainable economic development (Dias et al., 2023). For instance, in 2021, Tesla announced that it would no longer accept Bitcoin payments, the value of BTCP dropped precipitously. This decision is made in light of the environmental impact that the rapid increase in Bitcoin mining and transactions has occurred. This move not only causes short-term volatility in the Bitcoin market but also makes investors more cautious about the environmental impact of cryptocurrencies. Consequently, increasing investors are concentrating their attention on the renewable energy sector. These investors focus on minimum risk and sustainable development by investing their funds in the stock of renewable energy companies like ECO. The stocks of renewable energy are positively correlated with BTCP in the medium quantile, ranging between 256 and 512 days. This means that investors can combine Bitcoin with renewable energy stocks in their portfolios during relatively stable market periods, as suggested by Tiwari et al. (2024). This approach would permit investors to achieve value growth sustainably by diversifying against potential risks using Bitcoin's vulnerability to fluctuations in the market. Figure 2b depicts the quantile correlation of renewable energy stocks and ETHP. It can be observed that in the low quantile (1–256 days), ECO and CNN move negatively with ETHP. For instance, during 2021–2022, the world markets often faced financial volatility in the markets due to the COVID-19 pandemic (Su et al., 2024a). Given the high volatility of cryptocurrencies such as Ethereum, investors typically perceive them as high-risk assets, especially when market uncertainty intensifies, leading them to avoid such investments. In contrast, renewable energy stocks with stable returns and government incentives, such as ECO, are often considered safe-haven assets during this turbulent market environment. By reallocating funds to these assets, investors effectively reduce risk exposure and seek relatively stable returns, thereby achieving safer and more sustainable investment choices in uncertain market conditions. Additionally, in the medium quantile (256–512 days) and higher quantiles (1–256 days, 256–512 days), ECO and CNN show a positive correlation with ETHP. This is consistent with the analysis for BTCP, indicating that in periods of economic stability and prosperity, investors can enhance their portfolios by investing in renewable energy stocks and cryptocurrencies concurrently to attain greater returns. Figure 2c describes the quantile correlation between renewable energy stocks and LTCP. In the lower quantile (1–256 days, 256–512 days), ECO and ERIX exhibit a negative correlation with LTCP. In early 2022, due to the outbreak of the Russia-Ukraine war, global financial markets experience significant volatility (Li & Su, 2024), severely impacting the cryptocurrency market, with LTCP notably declining. During the same period, the energy crisis caused by the conflict between Russia and Ukraine led many governments to increase their support for renewable energy sources. For instance, the Biden administration advocates for the Clean Energy Plan, while the EU unveils the Fit for 55 climate package. These initiatives enhance the long-term demand for green energy, and renewable energy stocks demonstrate relatively strong performance, attracting investors who are seeking secure and stable assets.

Figure 3 presents a comprehensive sample correlation analysis between FGI and cryptocurrencies. Specifically, Figure 3a describes the quantile correlation between FGI and BTCP. The study indicates that in the long term (512–1024 days), FGI and BTCP exhibit a negative correlation. This is consistent with the findings of Chen et al. (2021), who observed that during prolonged periods of the market, BTCP exhibits characteristics similar to other financial assets rather than the stability associated with traditional safe-haven assets. Investors tend to reduce their investments in high-risk assets such as cryptocurrencies and opt for safe-haven assets or more stable investments to manage risk better in long-term investments (Anastasiou et al., 2021). Within the lowest quantiles (1–256 days, 256–512 days), FGI is positively related

a)



b)

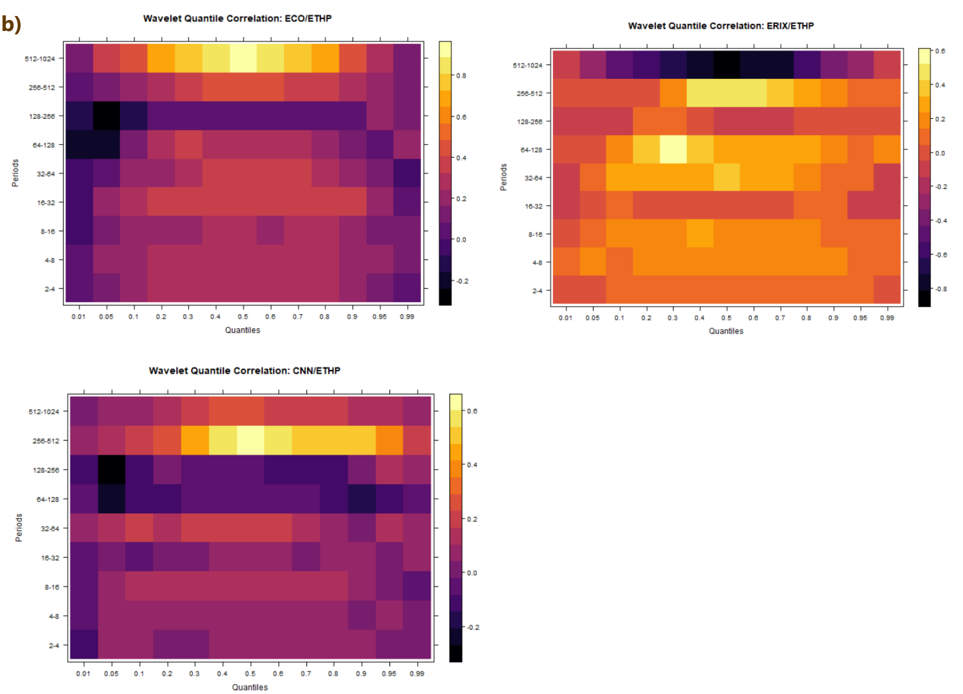


Figure 2. *To be continued*

c)

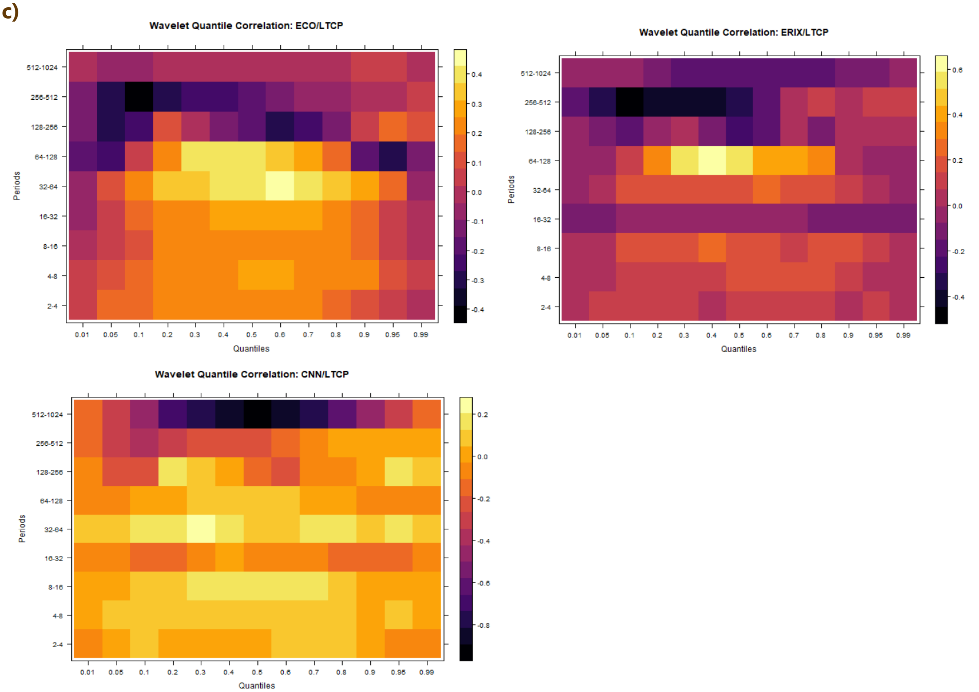


Figure 2. Wavelet correlation between renewable energy stocks and cryptocurrency

to BTCP. This phenomenon can be explained with the nature of Bitcoin as a highly risky and volatile asset. In situations of market panic, investors usually try to decrease their exposure to risk by retracting from the cryptocurrency market and reinvesting their funds in more stable and less risky assets. At medium quantiles (1–256 days, 256–512 days), FGI and BTCP are also positively correlated. That is because, under relatively stable market conditions, investors are more likely to make decisions of trading according to their feelings about the market, and the herd effect brought by FGI leads BTCP to move in a highly synchronous way (Wang et al., 2024). At high quantiles (1–256 days, 256–512 days), FGI and BTCP continue to be positively correlated. This is because, in times of market optimism, FGI is high, and this leads them to increase investments in high-reward but risky assets. As a potentially high-reward asset, Bitcoin has become an ideal choice for speculators. Figure 3b reports the quantile correlation between FGI and ETHP. As shown, FGI and ETHP exhibit a negative correlation in the long term. At medium quantiles (1–256 days, 256–512 days) and high quantiles (1–256 days, 256–512 days), there is a positive correlation between FGI and ETHP. These results are consistent with the findings of the quantile correlation analysis between FGI and BTCP. Figure 3c also presents the quantile correlation between FGI and LTCP. At low quantiles (256–512 days), FGI and LTCP exhibit a positive correlation. This is because, during periods of market instability, increasing panic sentiment leads to a sharp decline in FGI, causing investors to sell high-risk assets such as Litecoin, resulting in a decrease in LTCP. For example, when market fears of the coronavirus intensify, investors seek to reduce risk exposure, leading to massive sell-offs of high-volatility and perceived high-risk assets such as Litecoin, resulting in a decline in LTCP. Furthermore, in May 2022, TerraUSD (UST) experienced a significant de-pegging event. This incident undermines investor confidence in the entire cryptocurrency market, spreads panic sentiment, and prompts investors to sell high-risk assets, including various cryptocurrencies such as Litecoin, thereby triggering a further decline in cryptocurrency prices.

Finally, we explore the indirect relationship between FGI and renewable energy stocks to enrich our understanding of its influence on the cryptocurrency market further. Figure 4 presents a comprehensive sample correlation analysis between FGI and renewable energy stocks. Specifically, Figure 4a describes the quantile correlation between FGI and ECO. The results show a negative correlation between FGI and ECO in the lower quantile (512–1024 days). This means that, in periods of market decline, the growing sentiment of fear decreases FGI and leads to investments in renewable energy stocks, which are characterized by stability and long-term growth potential (Song et al., 2019). This investment behavior helps investors diversify risks and achieve their goals of long-term return by supporting sustainable development. For instance, during the energy crisis caused by the Russia-Ukraine war, the U.S. government proposed the Clean Energy Plan to promote renewable energy development. Investors realize the long-term strategic value of renewable energy, and their funds are diverted into government-backed renewable energy stocks. FGI and ECO also show a positive correlation in the medium quantile period (257–512 days) and high quantile period (1–256 days). This is due to factors such as optimistic sentiment during market booms, policy support, and the herd effect among investors, collectively driving up ECO. Figure 4b describes the quantile correlation between FGI and ERIX. In the medium quantile (257–512 days) and high quantile (1–256 days, 257–512 days) periods, FGI and ERIX are positively correlated. These findings are consistent with the quantile correlation analysis between FGI and ECO. Figure 4c describes the quantile correlation between FGI and CNN. The results show a negative correlation between

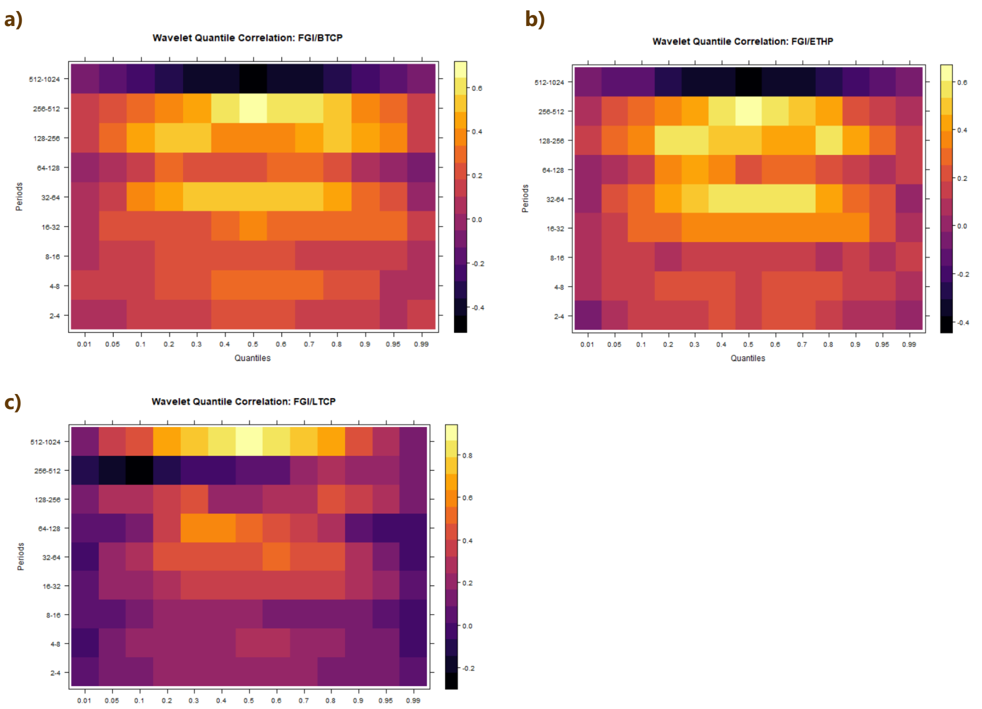


Figure 3. Wavelet correlation between investor sentiment and cryptocurrency

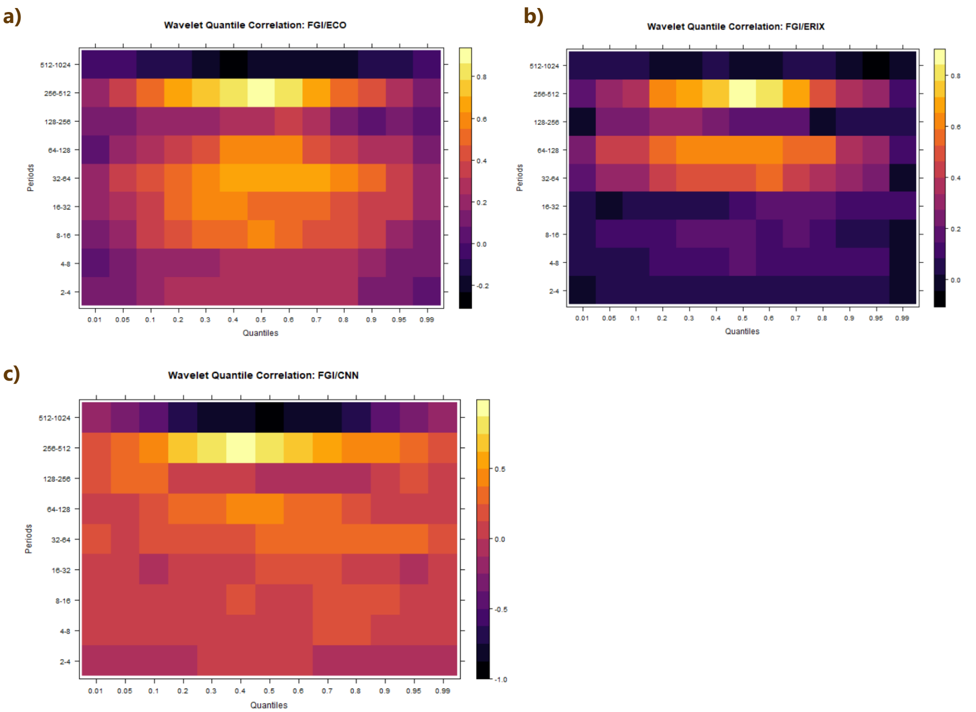


Figure 4. Wavelet correlation between investor sentiment and renewable energy stocks

FGI and CNN in the lower quantile (512–1024 days). In 2021, when the COVID-19 pandemic breaks out and rapidly spreads in China, extreme fear among investors leads to decreased FGI (Su et al., 2024c). However, the Chinese government continues to increase subsidies and support for photovoltaic and wind power projects to ensure that these critical sectors can maintain stable growth during economic uncertainty. For example, the stock prices of renewable energy companies like Longi Green Energy and Trina Solar quickly rebounded after initial fluctuations during the early stages of the pandemic. Additionally, FGI and CNN show a positive correlation in the high quantiles (1–256 days, 257–512 days) periods. For example, during the 2021 National People's Congress and the Chinese People's Political Consultative Conference, the Chinese government sets the goal of achieving carbon neutrality by 2060. It vigorously promotes renewable energy development during the 14th Five-Year Plan period. This initiative boosts market confidence, leading investors to significantly boost their investments in renewable energy stocks, thereby driving up CNN.

7. Conclusions

The paper adopts the wavelet quantile correlation approach to investigate the correlations among renewable energy equities, FGI, and the cryptocurrency market over various time periods and quantiles. The analysis demonstrates that renewable energy stocks exhibit a predominantly negative correlation with cryptocurrencies in the medium to short term during extremely adverse market situations. This implies that investors tend to transfer their funds from cryptocurrencies with high levels of risk to renewable energy equities that are comparatively more stable to safeguard the value of their investment portfolio under such market conditions. During market stability or growth periods, renewable energy stocks and cryptocurrencies are positively correlated. This means that investors can diversify their portfolios by investing in high-risk cryptocurrencies and renewable energy stocks that have the potential for long-term growth. The FGI also correlates positively with cryptocurrencies in the long term, which means investors reduce their exposure to high-risk assets like cryptocurrencies for better risk management in long-term investments. Under economic downturn conditions, FGI is found to be mainly positively related to cryptocurrencies. It means that investors have pessimistic sentiments during the market downturn and sell off the high-risk cryptocurrency on a large scale. We also verify that under different market states, FGI has both positive and negative impacts on renewable energy stocks, which further reinforces the relationship between renewable energy stocks and cryptocurrencies.

These analytical results are of tremendous importance for both investors and policy makers, as these provide essential information. First, investors can include renewable energy stocks in their portfolio due to the strong linkage between the market of cryptocurrency and the market of renewable energy stocks. Employing this approach will not only help to economically diversify the portfolio but also contribute to achieving the goals of sustainable development. Furthermore, through profound comprehension of market information, investors can make better judgments regarding market sentiment so that necessary portfolio adjustments can be made during different economic scenarios to avoid unexpected risks. At the same time, the regulatory authorities should ensure transparency in the cryptocurrency market and enhance supervision over trading activities and market liquidity. The strictest disclosure requirement, through decreasing information asymmetry, will enable investors to make a choice that accords with reason and, furthermore, reduce fears resulting from changed market sentiment effectively. With the highly volatile nature and systemic risks observed in the cryptocurrency market, timely interventions by regulators with price limits or trade halts amidst wild swings of investor sentiment will provide stability in the market and balm to shaken confidence. Ultimately, policymakers must adopt proactive risk prevention and an early warning mechanism. In-depth research on the relationships between the cryptocurrency market and other economic indicators will help policy makers more precisely identify possible risks in the markets and make timely and effective macro-economic adjustments to better protect investors' interests and long-term market stability.

Several limitations of the present study provide avenues for future research. First, the results' generalisability may be impacted by limitations pertaining to the sample period and geographic scope. To validate the results of this research, future research could broaden the data sources to include more nations, regions, and a more extended period of time. The fear and greed index might not adequately capture the subtleties of attitude shifts, and measuring sentiment is difficult. More market data, sophisticated prediction models, and qualitative analysis techniques might all be used in future studies to examine the linkage between shifting sentiment and the cryptocurrency marketplace.

Acknowledgements

This work was supported by a grant from the Romanian Ministry of Research, Innovation and Digitalization, the project with the title "Economics and Policy Options for Climate Change Risk and Global Environmental Governance" (CF 193/28.11.2022, Funding Contract

No. 760078/23.05.2023), within Romania's National Recovery and Resilience Plan (PNRR) – Pillar III, Component C9, Investment I8 (PNRR/2022/C9/MCID/I8) – Development of a program to attract highly specialised human resources from abroad in research, development and innovation activities. This article was also supported by the National Natural Science Foundation of China (24AGJ009).

Author contributions

Chi Wei Su was responsible for the conceptualization of the study and contributed to writing–review and editing. Xin Yue Song prepared the original draft of the manuscript. Meng Qin acquired the funding and conducted the investigation. Oana-Ramona Lobonţ developed the methodology and administered the project. Muhammad Umar provided supervision and was responsible for validation.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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