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Cryptocurrency returns and cryptocurrency uncertainty: a time–frequency analysis

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Abstract

This study investigates how the uncertainty surrounding cryptocurrency affects cryptocurrency returns (CR) by employing various wavelet techniques. We concentrate on the recently published cryptocurrency uncertainty index (UCRY) and the top eight cryptocurrencies by market capitalization from December 30, 2013, to June 30, 2023. Our results showed that the UCRY index strongly predicted CR. In particular, the UCRY index has a leading position at all frequencies for all cryptocurrencies in our sample. Additionally, when the impacts of economic policy uncertainty and the volatility index are eliminated, the significant comovement of UCRY-CR remains unchanged for the short-, medium-, and long-term investment horizons. Therefore, we conclude that the UCRY-CR relationship is both persistent and pervasive. Our study contributes toward the literature on the relationships between cryptocurrencies and market uncertainties, as well as toward investors who use uncertainty indices to design investment strategies for their portfolios.

Keywords: Cryptocurrency uncertainty index, Cryptocurrency, Bitcoin, Wavelet coherence analysis, Partial wavelet coherence

Introduction

Cryptocurrencies are a new class of assets that arose after the collapse of the global financial system amidst the 2008 financial crisis. Various academic and regulatory studies argue that cryptocurrencies should be recognized as independent asset classes (Bianchi 2020; Hairudin et al. 2020; Danielsson 2019; Bouri et al. 2017a). Bitcoin is the most well-known cryptocurrency because it was the first digital currency to be established. Following that, other cryptocurrencies, including Ethereum, Litecoin, and Ripple, were established and gained interest, especially after the "Bitcoin crash" in early 2018. Consequently, there has been a resurgence of interest in these assets, driving up their market value, and resulting in the total market capitalization of cryptocurrencies standing at $1.1 trillion in August 2022 (down from its all-time high of $3 trillion).

Cryptocurrency's speculative nature and ability to replace traditional currencies make a substantial contribution (Mokni and Ajmi 2021). Various studies have investigated the system of uncertainty effects in the cryptocurrency market (Fang et al. 2019; Wang et al. 2019; Akyldirim et al. 2020). The cryptocurrency market appeals to businesses and individuals from a wide range of cultures, backgrounds, and geographical areas.

Additionally, cryptocurrencies are appealing to investors since they are seen as a "safe haven" asset in comparison to uncertainty (Mokni et al. 2022; Wu et al. 2019) or other asset classes (Urquhart and Zhang 2019; Bouri et al. 2017b). However, the influence of the cryptocurrency uncertainty index on cryptocurrency returns (CR) is underexplored, which is one reason why this issue remains appealing. In this context, cryptocurrencies are recognized for their considerable volatility and unpredictability, making it essential for traders and investors to have instruments to optimize investment strategies, effectively manage risk, and provide investors with valuable insights that would enable them to make more educated investment decisions. Therefore, the cryptocurrency uncertainty index may serve as a valuable risk management instrument by providing insight into the degree of uncertainty in the cryptocurrency market. Furthermore, scholars specializing in financial economics and cryptocurrency are interested in understanding the complexity of the cryptocurrency market. By examining the relationship between returns and uncertainty, researchers can acquire valuable knowledge about the distinctive attributes of cryptocurrencies as an asset class of investments. Moreover, the cryptocurrency uncertainty index can be used as an indicator of market sentiment and the macroeconomic variables that affect cryptocurrencies. Analyzing the link between this index and returns may reveal how market sentiments influence cryptocurrency prices. Traders and investors who wish to integrate sentiment analysis into their decision making may find this information beneficial. Within this framework, a comprehensive understanding of the relationship between cryptocurrencies and market uncertainty remains to be achieved (Bouri et al. 2017c). As a result, there is a research gap in understanding the impact of the cryptocurrency uncertainty index on CR, as well as broader implications for risk management, market sentiment analysis, and investment strategies.

Our empirical study focuses on the top eight cryptocurrencies (of market capitalization). Studying the top eight cryptocurrencies is significant for many reasons: i) Top cryptocurrencies have a substantial market share and influence within the cryptocurrency ecosystem. By studying cryptocurrencies, researchers can gain insights into the behaviors and dynamics of the most traded and known digital assets. ii) The top eight cryptocurrencies are widely believed to represent the entire cryptocurrency industry. These include several cryptocurrencies with distinct properties, such as Bitcoin and Ethereum. Analyzing these cryptocurrencies may provide investors with a thorough understanding of the market's general trends and dynamics. iii) Top cryptocurrencies often have strong liquidity and trading volumes, suggesting active trading and several market participants. Bitcoin and Ethereum were among the most frequently traded coins on cryptocurrency exchanges in 2021. Increased liquidity allows for more rigorous data analysis and statistical modelling, enabling us to draw meaningful conclusions and make educated choices based on the findings. iv) The behavior of investors and market participants in the top cryptocurrencies may provide valuable information about market sentiment and investor behavior. Understanding how different cryptocurrencies react to a range of circumstances, including news events, regulatory changes, and market trends, may provide a better understanding of market dynamics and possible risks. v) In the cryptocurrency market, top cryptocurrencies typically play a critical role in price discovery and efficiency. vi) Many investors and financial institutions rely on top cryptocurrencies when making investment choices or managing cryptocurrency risks. Researchers can provide significant suggestions to market participants, investors, and risk managers regarding portfolio allocation, risk assessment, and risk reduction by studying the top cryptocurrencies.

Our study employs the cryptocurrency uncertainty index (UCRY) and various wavelet techniques to examine the dynamic lead-lag relationships and comovements between CR and major uncertainty indices (economic policy uncertainty (EPU) and volatility index (VIX)) across a spectrum of time and frequency domains. This method helps address important research questions regarding changes in these relationships over time and their influence on other uncertainty indices. It also offers consistent and comprehensive insights into the coherence between the top eight CR: UCRY, EPU, and VIX. Our findings enhance the existing body of literature by providing a thorough time-frequency domain analysis that is advantageous for investors optimizing diversification strategies and assessing portfolio risk over a range of time horizons. The rationale for using these indices in the analysis of comovement includes the following: Given the prominence of cryptocurrencies, there are two broad categories of predictor variables: market-based variables and macro-level influences. Technical indicators (Gerritsen et al. 2020), the three factors of the crypto-pricing model (Shen et al. 2020), and the stock market volatility index are examples of market-based factors (Bouri et al. 2017a). Macroeconomic variables include the activity of the world economy (Cheng and Yen 2020) and the unpredictability of economic policies (Demir et al. 2018; Cheng and Yen 2020). Therefore, we use VIX and EPU to capture both market-based variables and macro-level influences in our empirical investigation.

Although there is no solid theory examining the link between the cryptocurrency index and CR (De Pace and Rao 2023), the relationship between the cryptocurrency uncertainty index and CR can be examined through the lens of investor and market sentiments. The uncertainty index analyzes the amount of uncertainty in the cryptocurrency market by considering factors such as price changes, regulatory developments, and technological advancements. High levels of uncertainty may contribute to higher risk aversion and cautious investor behavior (Bouri et al. 2017a). Consequently, when the uncertainty index is high, CR may be lower, as investors take a more defensive approach and reduce their exposure to the market. Conversely, investors may display more risk tolerance and enthusiasm during low-uncertainty events, leading to larger CR (Cheah et al. 2018). However, this link is not absolute because other variables, such as market fundamentals and macroeconomic circumstances (Baur et al. 2018) have a substantial impact on predicting Bitcoin gains. Therefore, further research is required on the relationship between the cryptocurrency uncertainty index and CR.

Our findings indicate that the cryptocurrency uncertainty index (UCRY) index has a leading position for all cryptocurrencies in the sample at all frequencies. Thus, the UCRY index has strong and robust prediction power over the CR at all frequencies. Additionally, we show that after removing the effects of EPU and VIX for low-, medium-, and high-frequency horizons, the UCRY index still has a significant comovement with CR and that the UCRY-CR nexus does not change for all CRs. Our contribution to this field of study is the disclosure of robust and consistent results regarding the time-frequency relationship between the CR and the newly developed UCRY index. This includes determining the coherence between the UCRY index, EPU, VIX, and the top eight CR. To the best of our knowledge, our study is the first to expand the comovement analysis of the UCRY index, EPU, VIX, and CR from a time–frequency viewpoint. Our results are beneficial to both investors and market participants; it provides investors with a better understanding of active diversification strategies for cryptocurrency-driven portfolios (Cui and Maghyereh 2022; Stolfi et al. 2022). Investors can use our wavelet results to assess the portfolio riskiness of the UCRY index across different time horizons.

Literature review

Recent years have seen an increase in research on the relationships between different cryptocurrency price movements. Although there is increasing evidence of interconnectedness, the nature of the interconnectedness of CR remains understudied. The existing literature can be split into two groups: one dealing with the impact of policy uncertainty on cryptocurrencies and the other dealing with studies that investigate the connectedness between cryptos and/or other assets (mostly financial assets).

From the first perspective, uncertainty is one of the most fundamental obstacles cryptocurrency investors should overcome. For this reason, the emergence of cryptocurrencies is linked to a decline in investors' trust in traditional currencies caused by excessive market uncertainty (Demir et al. 2018). Consequently, cryptocurrencies usually deviate from government or standard economic operations. In addition, cryptocurrency's lack of monetary control and its capacity to hold value allows it to establish itself as a powerful safe haven choice for individuals looking to secure their financial future (Hussain Shahzad et al. 2020). However, when there is a considerable amount of uncertainty in the markets, investors will utilize "wait-and-see" or other investment techniques (Lien et al. 2019). For instance, when investors notice an increase in EPU, particularly in China, where major Bitcoin mining pools are located (Ma et al. 2019), they may anticipate a decline in the Bitcoin market. Thus, they short Bitcoin and long other financial assets. Researchers have also examined the reciprocal effects of uncertainty on various market and industry configurations (Antonakakis et al. 2019; Walther et al. 2019). Goodell et al. (2020) and Pástor and Veronesi (2013) provide evidence of the impact of economic policy uncertainty on stock markets. They suggested that during times of heightened economic uncertainty, the likelihood of a Bitcoin crash is lower. This finding indicates that Bitcoin can serve as a diversification opportunity and safe haven asset during times of crisis and economic instability (Conlon et al. 2020; Conlon and McGee 2020; Goodell and Goutte 2021a, 2021b; Allen et al. 2021; Philippi et al. 2021).

Changes in social and economic situations may influence investors' expectations and aggravate financial instability, resulting in cryptocurrency market volatility (Wu et al. 2022). Additionally, uncertainty from various sources may have different implications and predictive powers in the Bitcoin market (Lucey et al. 2021). While growing uncertainty impacts cryptocurrency market dynamics, common indicators, such as economic policy uncertainty, contain multiple sectors of the economy and may incorrectly reflect special concerns related to the cryptocurrency domain. Given the importance of uncertainty in cryptocurrencies, a continual empirical study of the relationship between uncertainty and cryptocurrencies is required (Hasan et al. 2022a, b). Lucey et al. (2021)

introduced a new uncertainty index for cryptocurrencies, the UCRY[1] index, which is more relevant to cryptocurrency traders and has a more heterogeneous investment horizon than other uncertainty indices (Haq and Bouri 2022).

The second group of studies in the literature investigates the connectedness between cryptocurrency and other financial assets. Studies on the comovement of cryptocurrency with other financial assets offer multiple lines of evidence supporting its safe haven behavior (Dyhrberg 2016; Selmi et al. 2018; Corbet et al. 2020). Cryptocurrencies also act as hedges against the EPU index (Demir et al. 2018; Sifat 2021). In addition to the traditional EPU index, a recent study by Gozgor et al. (2019) report the hedging property of Bitcoin against uncertainty shocks using the United States Trade Policy Uncertainty Index. Colon et al. (2021) investigated the hedging property of cryptocurrencies against uncertainty indices. According to their results, cryptocurrencies have a strong hedging capacity against geopolitical risk in bear markets and show heterogeneous hedging ability against EPU and geopolitical risks during bull market periods.

The EPU index (both from a global perspective and at a country-specific level) has shown a significant relationship with CR. According to Fang et al. (2019), the global EPU index enhances portfolio hedging against bitcoin price volatilities. Additionally, Wu et al. (2019) show that when comparing the hedging ability of bitcoin and gold against EPU shocks, the former has a greater hedging characteristic. However, Wang et al. (2019) demonstrate that the risk spillover effect of EPU on Bitcoin price volatility is negligible. Moreover, Cheng and Yen (2020) provide evidence that the EPU index in China can accurately forecast the monthly returns of bitcoin. According to Yen and Cheng (2021), the EPU index in China has predictive power for Bitcoin's monthly price volatility, and the relationship is negative. Furthermore, there is a pool of evidence on the existence of a relationship between CR and various other uncertainty indices such as the volatility index (Akyldirim et al. 2020), news-implied volatility (Manela and Moreria 2017), geopolitical risk (Aysan et al. 2019), market liquidity (Hasan et al. 2022a, b) and sentiment index (Corbet et al. 2020) in finance literature.

Various methods have been used to investigate the relationship between cryptocurrencies and uncertainty indices. Bouri et al. (2017b) investigated the predictive power of the global uncertainty index over the CR using wavelet-based techniques. Their study showed that Bitcoin acts as a hedge against market uncertainty, especially over shorter periods. Additionally, Balli et al. (2019) employs a continuous wavelet transform technique to demonstrate the relationship between economic uncertainty and cryptocurrencies. Their results indicate that cryptocurrencies have the potential to be considered an alternative instrument for hedging against underlying uncertainty. Furthermore, Balcilar et al. (2017) examined the prediction of CR (Bitcoin) by employing a quantile-based model and found that trade volume has predictive power over CR, except for bear and bull market regimes. Finally, Demir et al. (2018), using the Bayesian Graphical Structural Vector Autoregressive model as well as Ordinary Least Squares and the Quantile-on-Quantile Regression estimations, demonstrate that the EPU index accurately predicts

[1] The UCRY index employs text-mining searches on the LexisNexis business platform, and it considers a variety of specialised terms pertaining to uncertainty, cryptocurrencies, central banks, governments, and regulators. The index is robust to various econometric techniques. For further information, please visit Lucey et al., (2021).

how the Bitcoin price moves and has a positive effect on Bitcoin returns. However, this is an old result that no longer holds, as shown by Sifat (2021).

The relationships among cryptocurrencies, including their comovements, interdependence, and dynamic linkages, are important for cryptocurrency portfolio optimization and risk management. To address this issue, Qiao et al. (2020) conducted a study to visualize the comovement of CR and volatility across different time frequencies. Their findings indicate a positive correlation between Bitcoin and other cryptocurrencies. Additionally, they report that Bitcoin has hedging effects on other cryptocurrencies. Qureshi et al. (2020) arrive at a similar conclusion, stating that the coherence between cryptocurrencies tends to vary at higher frequencies and remains notably stable at lower frequencies.

In a study conducted by Liu and Tsyvinski. (2021), it was discovered that the returns of Bitcoin, Ripple, and Ethereum have minimal sensitivity to traditional asset classes such as stocks, currencies, and commodities, as well as to common macroeconomic factors. Borri (2019) examines the conditional tail risk in cryptocurrencies, including Bitcoin, Ethereum, Ripple, and Litecoin. This study reveals that cryptocurrencies exhibit high correlations with one another, both unconditionally and conditionally, but demonstrate weak correlations with other global assets, including gold. Moreover, they suggest that cryptocurrencies can provide attractive returns and serve as effective hedging instruments. Yi et al. (2018) investigates the volatility connectedness among cryptocurrencies. Their findings indicate that cryptocurrencies with higher market capitalization have a greater influence on the transmission of volatility spillovers to other cryptocurrencies. Specifically, Bitcoin makes a significant contribution to volatility spillovers but does not dominate the entire market. Similarly, Ji et al. (2019) examines dynamic returns and volatility connectedness in cryptocurrency markets. Their results support the notion that Litecoin and Bitcoin play a central role in the return connectedness network, with Bitcoin being the primary transmitter for returns. This finding is consistent with the empirical results of Koutmos (2018).

Literature on the UCRY index's connections with cryptocurrencies is limited, and the discussion is still in its early phases. However, Elsayed et al. (2022) investigate the dynamic interdependence of volatility and return spillovers across the UCRY and gold. Their results show that the UCRY is the primary transmitter of return spillovers to other variables in bearish and bullish market situations. Hassan et al. (2021) employs the dynamic conditional correlation generalized autoregressive conditional heteroskedasticity model to investigate the hedging and safe haven characteristics of the UCRY. They conclude that the UCRY index acts as a hedge against gold, and that the DJ Islamic index, except for Bitcoin, returns over a range of quantiles.

Recent studies in the context of uncertainty, such as Aloui et al. (2020) and Sharif et al. (2020), investigate how the COVID-19 pandemic has influenced the interaction between multiple financial markets, including Bitcoin and commodities. Additionally, Conlon et al. (2020) and Conlon and McGee (2020) investigate the possibility of Bitcoin operating as a safe haven against other financial assets and commodities during crises. In this regard, the dynamic connections between cryptocurrencies have recently attracted considerable research attention. Yousaf and Ali (2020) investigate the interlinkages among major cryptocurrencies using high-frequency intraday data. They discover that during the COVID-19 pandemic, the dynamic linkages, hedging costs, and hedging effectiveness of cryptocurrencies were relatively high. Bouri et al. (2021) employed the dynamic equicorrelation generalized autoregressive conditional heteroskedasticity DECO- GARCH model to analyze market integration among prominent cryptocurrencies. They found strong market integration within the cryptocurrency market, with trading volume and uncertainty serving as the primary determining factors. Demiralay and Golitsis (2021) utilize a similar approach and determine that interlinkages among cryptocurrencies significantly increased following the outbreak of the COVID-19 pandemic. Although the pandemic has the potential to alter the market dynamics of financial assets, including cryptocurrencies (Goodell and Goutte 2021a), there is limited evidence on how the pandemic has affected the interconnectedness between CR and uncertainty indices, specifically the cryptocurrency uncertainty index.

The literature lacks evidence on the lead-lag relationship as well as the comovement of UCRY with CR. Moreover, empirical evidence related to the relationship between the UCRY and classic uncertainty indices, such as the EPU and VIX, is missing in the current finance literature. Analyzing the relationship characteristics (lead versus lag or comovements) of cryptocurrencies with one another or other indices facilitates an understanding of the events that lead to speculators' interest in these asset classes. Therefore, our study adds to the current knowledge on this subject. Furthermore, we use three uncertainty indices in our empirical investigation in the time and frequency domains.

The current paper is organized as follows: first, the data and methodology are presented; then, the results are presented, followed by a discussion; and finally, some concluding remarks are provided.

Data description and methodology

Data

The data for our investigation was gathered from several sources. We obtained the daily prices of Bitcoin (BTC), Cardano (ADA), Bitcoin Cash (BCH), Ethereum (ETH), Litecoin (LTC), Tether (USDT), Stellar (XLM), and Ripple (XRP) from the coin market website.[2]. Owing to the varying establishment dates of the cryptocurrencies in our study sample, the empirical investigation spans from their respective establishment dates until June 30, 2023. This period spans from December 2013 to June 30, 2023. Figure 1 shows the weekly closing price changes of cryptocurrencies from November 2018 to the end of June 2023.[3]. All cryptocurrencies are priced in US dollars.

Weekly cryptocurrency uncertainty index[4] data are gathered from a website hosted by Brian M. Lucey.[5]. Additionally, the EPU index, created by Baker et al. (2016) and measuring economic uncertainty in the US, was obtained from a webpage devoted to policy

[2] https://coinmarketcap.com.

[3] The data in Fig. 1 has been adjusted to highlight only the behaviour of cryptocurrency price movement and does not represent the whole sample of the research. The study's whole sample spans the period from December 2013 to the end of June 2023.

[4] The newly developed cryptocurrency uncertainty index (UCRY index) includes information on the Brexit vote, oil price shocks, the 2016 US presidential election, the BTC boom, China's restrictions on initial coin offerings (ICOs), and the COVID-19 outbreak (Lucey et al. 2021). Despite this, unlike previous uncertainty measures that rely on major newspapers (e.g., Baker et al. 2016; Carriero et al. 2018), the cryptocurrency uncertainty index is built on a diverse set of newspapers and newswire sources. Thus, we believe that investigation of the links between CR and the UCRY index is informative to cryptocurrency market participants.

[5] https://sites.google.com/view/cryptocurrency-indices/the-indices/crypto-uncertainty.

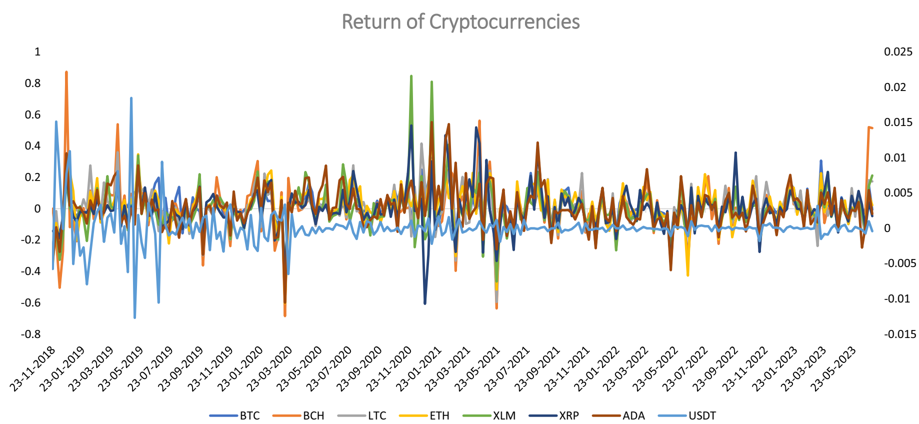


Fig. 1 Prices of cryptocurrencies. *Note* Fig. 1 reports the historical changes of weekly closing prices for each of the final samples of our investigation. All cryptocurrencies are priced in U.S. dollars

uncertainty.[6]. Finally, we obtain the standard and poor (S&P) 500 Volatility Index (often referred to as the VIX), which measures the degree of volatility represented by the prices of US stock index options, from Thomson Reuters DataStream. Figure 2 shows the plots of the weekly returns of the uncertainty indices used in our study. Given that the UCRY index data are only available as of December 30, 2013, Fig. 2 depicts the behavior of all uncertainty indices (EPU and VIX) from the UCRY index's inception.

To create our final dataset, we aggregated and blended various data frequencies that contained weekly prices from December 30, 2013, to June 30, 2023.

Methodology

Wavelet coherence analysis and cross-wavelet spectrum

We begin our investigation using wavelet coherence analysis (WTC).[7]. WTC is a method for studying periodic events in a time series, particularly in situations where there are sudden changes in frequency. The approach is comparable to the traditional bivariate correlation coefficient, and it assesses the degree and extent to which time-series variables (Y and X) move in conjunction with one another in the time–frequency domain. In WTC, "waves" or ψ_t are defined as follows:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

where $1/\sqrt{s}$ is a normalization factor to confirm that wavelet transforms are comparable across time-scale series. For each time series of x(t), the wavelet transformation specification with respect to the daughter wavelet or $\psi_{\tau,s}(t)$ is as follows:

$$W_x(\tau,s) = \int_{-\infty}^{+\infty} x(t)\psi^*_{\tau,s}(t)dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-\tau}{s}\right)dt \tag{2}$$

[6] https://www.policyuncertainty.com.

[7] We also investigate the linear relationship in addition to the time-frequency analysis. Please see empirical results in Sect. "Empirical results" for more details.

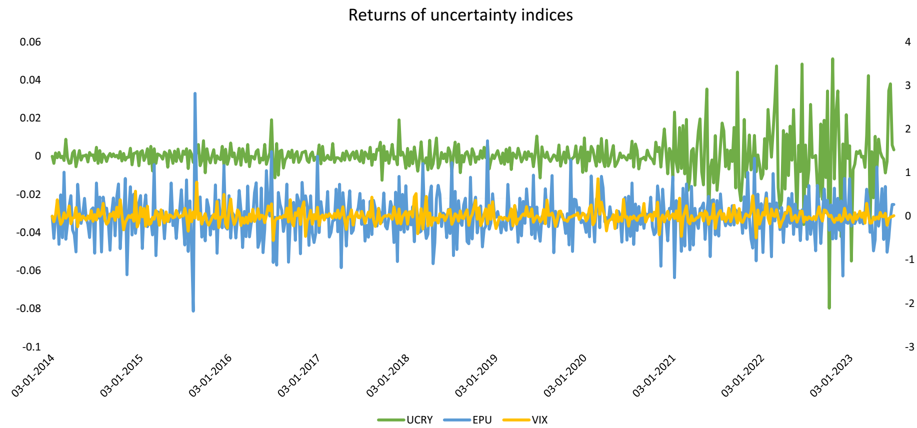


Fig. 2 Returns of uncertainty indices. *Note* Fig. 2 displays the historical changes of weekly prices for each uncertainty indices used in the empirical study. All prices are priced in U.S. Dollars

where * denotes the complex conjugate. Therefore, for a discrete time series x(t), $t=1, \ldots, N$, the continuous wavelet transform function has the following specification:

$$W_x(\tau,s) = \frac{1}{\sqrt{s}} \sum_{t=1}^{N} x(t)\psi^*\left(\frac{t-\tau}{s}\right) \tag{3}$$

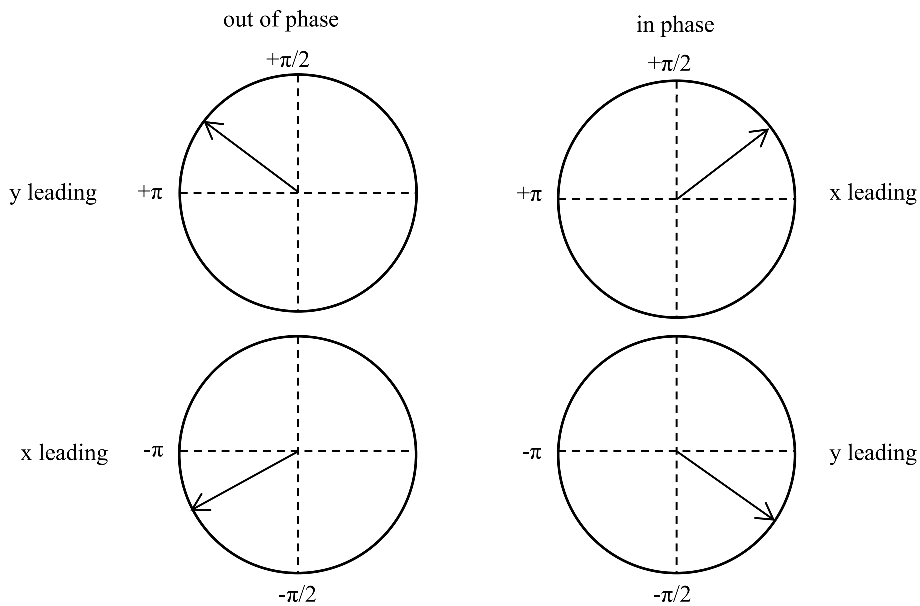
Given two time series of x(t) and y(t), with wavelet transforms $W_x(\tau,s)$ and $W_y(\tau,s)$ the cross-wavelet spectrum (XWT) is defined as follows:

$$W_{xy}(\tau,s) = W_x(\tau,s)W^*(\tau,s) \tag{4}$$

According to the WTC methodology, the arrows in the WTC spectrum represent a lead-lag relationship between two time series, where variable y is the respective CR and variable x is the UCRY index. In this respect, the arctangent of the wave is defined as follows:

$$\phi_{yx} = \arg\left[\psi\left(y,x\right)\right] = tan^{-1}\left[\frac{\psi\left(y,x\right)}{\psi\left(y,x\right)}\right] \tag{5}$$

where $\psi\left(y,x\right)$ represents the cross-wavelet power spectrum between y and x, as shown in Eq. 4. Following the methodology of Hu and Si (2021), $|\phi yx| < \pi/2$ indicates that two time series are cyclical or in-phase, while $|\phi yx| > \pi/2$ indicates that the time series are moving anti-phase (out of phase) in the time–frequency domain. Positive and negative arctangent values indicate the series in the leadership position. Below are the possible phase arrow difference outcomes and their respective lead-lag relationships.



Partial wavelet coherence

The partial wavelet coherence (PWC) is similar to the traditional partial correlation coefficient in that it calculates the wavelet coherence between two time series Y and X_1 after removing the influence of third time series X_2. To estimate the PWC, we utilized the methodology introduced by Torrence and Webster (1999) and the normalized smoothed wavelet power spectrum, which equals the absolute value squared of the smoothed cross-wavelet spectrum based on the following specification:

$$R^2(\tau, s) = \frac{\left|S\left(s^{-1}W_{xy}(\tau, s)\right)\right|^2}{S\left(s^{-1}|W_x(\tau, s)|^2\right)S\left(s^{-1}\left|W_y(\tau, s)\right|^2\right)} \tag{6}$$

where S(.) denotes smoothing in time and scale. We used a weighted running average for smoothing in both time and scale aspects. In this regard, we used a filter for periodic smoothing that computed the absolute value of the wavelet function at each scale and normalized it to a total weight of one. We also used a boxcar filter corresponding to the scale-decorrelation length to facilitate scale smoothing. Employing various filter widths and shapes yields either smoother (and bigger) coherency or noisier (smaller) coherency while preserving the same qualitative outcomes. The expressions of the PWC approach for the identification of the relationships between x_1 after eliminating the effect of x_2 are as follows:

$$RP^2\left(y, x_1, x_2\right) = \frac{\left|R\left(y, x_1\right) - R\left(y, x_2\right).R\left(y, x_1\right)*\right|^2}{\left[1 - R\left(y, x_2\right)\right]^2\left[1 - R(x_2, x_1)\right]^2} \tag{7}$$

In our estimations, x_1 takes its value from the UCRY policy index, and x_2 is calculated using EPU and VIX, whereas Y is the respective CR. The PWC ranges from 0 to 1 at different times and frequencies, and the theory that the PWC is very close to 0 suggests that the time series x_2 does not have any other significant effects on Y, in addition to those caused by the time series x_1. However, values that are closer to 1 indicate strong comovements in the time series (Mihanovi´c et al. 2009). To estimate the PWC, a smoothing operator with the desired time–frequency resolution (similar to Fourier analysis) is required; otherwise, the squared coherency would always be one.[8]

Table 1 presents the descriptive statistics for the CRs and uncertainty indices of the samples in our study. The descriptive statistics include measurements of central tendency (mean and median) as well as measures of variability (maximum and minimum, standard deviation, skewness, and kurtosis). Throughout our research, we observe that the USDT has remained steady in comparison to other cryptocurrencies of interest. Additionally, XLM has the highest variability (following a high standard deviation) among all cryptocurrencies, reaching 0.1893. However, UCRY is the uncertainty index that exhibited the lowest level of volatility during our study period. In addition, the distributions of all three uncertainty indices are not normal because they are skewed to the right, except for UCRY, and they contain an excessive amount of kurtosis (see the results of the Jarque–Bera test). The fact that our samples re not normally distributed validates Mandelbrot's (1967) fractal geometry model and challenges the traditional assumption that price changes follow a normal distribution. In this respect, the cryptocurrencies in our study exhibit self-similarity and long-range dependence. In other words, patterns repeat at various scales, and the influence of prior events can extend over extended periods. This is especially pertinent to the study of cryptocurrency prices because it suggests that markets are influenced by complex and nonlinear processes that traditional models cannot capture. Table 1 also supports the findings of Rodriguez and Miramontes (2022), that returns on the cryptocurrency market are not normal, demonstrating the diversification and risk management of cryptocurrency investments.

Every time series has a high Jarque–Bera coefficient and a low p-value. The null hypothesis of normal distribution is rejected because the p-values are below the standard significance threshold of 0.05. Given the rejection of the null hypothesis, we conclude that the sample data used in this study are not normally distributed. Additionally, given its fundamental concerns about data distribution, it is noteworthy that it offers insights into the dynamics of price shifts and the behavior of market participants. Having observed the right skew in our data, it refers to a type of random walk where the step lengths follow a probability distribution with heavy tails or Lévy walks. Introduced by Mantegna (1991), this indicates that there is a greater likelihood of larger step lengths compared to a normal distribution, which is commonly referred to as "jumps" or "fat tails." Understanding Lévy walks is important for risk management because these properties may alter the accuracy of the models used for pricing derivatives, assessing portfolio risk, and making investment choices. The fact that the distributions of CRs and uncertainty indices are not normal lends even more credibility to the choice of the wavelet approach. In this regard, in addition to the benefits offered by wavelet approaches

[8] The smoothing procedure is described in detail in Torrence and Webster., (1999).

Table 1 Summary statistics

	BTC	ADA	BCH	ETH	LTC	USDT	XLM	XRP	UCRY	VIX	EPU
Mean	0.0071	−0.0043	0.0015	0.0133	0.0093	−2.1E-05	0.0121	0.0076	0.0001	−2.5E-05	−0.0003
Median	0.0084	−0.0126	−0.0012	0.0049	0.0056	0.0000	−0.0031	−0.0118	−0.0002	−0.0160	−0.0012
Maximum	1.6375	0.5522	0.8728	0.8449	0.8567	0.0406	1.3430	1.1494	0.0511	0.8537	2.8178
Minimum	−1.3435	−0.5990	−0.6846	−0.6030	−0.5941	−0.0556	−0.4642	−0.6063	−0.0796	0.5562	−2.1783
Std. Dev	0.1383	0.1473	0.1591	0.1443	0.1468	0.0061	0.1893	0.1789	0.0108	0.1626	0.5249
Skewness	1.2256	0.2225	0.4387	0.3718	0.6205	−1.1721	1.9983	1.9180	−0.2699	0.8285	0.2872
Kurtosis	56.7377	2.1834	7.0548	4.0185	5.2470	29.8119	10.4466	8.8727	11.7832	3.3142	1.8939
Jarque–Bera	66,653.7	59.1710	505.4153	265.1435	432.4476	12,072.37	1725.416	1713.0768	2875.4646	283.7505	80.9510
Observations	496	286	240	381	357	324	331	440	496	496	496

This table shows the descriptive statistics for eight cryptos of interest and three uncertainty indices. Returns are in natural log in the wavelet domain, they have several theoretically appealing properties. These include the ability to accurately deconstruct and reconstruct finite, non-periodic, and non-required stationary variables as well as the ability to accurately represent functions that have discontinuities and extreme values (Rua and Nunes 2009). Wavelet analysis has emerged as a crucial approach in signal processing and time–frequency analysis because of the following characteristics: wavelets' multiresolution signal decomposition (Mallat 1989) makes them particularly effective for analyzing signals with varying frequency content at different scales, allowing signal decomposition into different frequency components, and making them well-suited for capturing both high- and low-frequency details. In addition, wavelets may adapt to the local features of a signal (Meyer 1993). This flexibility is particularly useful when dealing with signals that are nonstationary or that change over time. Moreover, wavelets may represent both rapid shifts and steady trends in a signal owing to their capacity to collect features of diverse sizes. Furthermore, wavelet transformations often produce sparse representations (Donoho 1995), indicating that a small number of wavelet coefficients can capture critical information about the signal. This may be useful for data compression as well as for efficiently describing and processing data.

Table 2 lists the advantages and disadvantages of other time–frequency techniques. These properties are of utmost significance for our study of the cryptocurrency market, in which individuals have different ideas, use different strategies, and act with very different timeframes (Kurov 2010).

Empirical results

Before presenting the empirical investigation using wavelet analysis, it is important to note that we examine the linear relationship between CR and UCRY based on the following equation:

$$\Delta ln(CR_i)_t = \beta_0 + \beta_1 \Delta ln\left(Uncertainty\, Index_i\right)_t + \varepsilon_t \tag{8}$$

where the uncertainty index i takes the value from the UCRY, EPU, and VIX indices and represents the logarithmic return of the UCRY index, EPU, and VIX. The dependent variable in the simple regression in Eq. 8, $\Delta ln(CR_i)_t$ is the logarithmic return of the respective cryptocurrency and ε_t is the error term. The linear regression model exhibits a negative correlation between CR and UCRY, except for USDT. The same results hold true for the CR and other uncertainty indices in our study. The model in Eq. 8 satisfies the assumption of heteroskedasticity and multicollinearity in the linear model, in addition to the stationarity test for Granger causality. The outcomes are presented in separate tables in the Appendix.[9] Although the linear model passes important diagnostic tests, it fails to adequately capture the comovement of assets, particularly in the case of extreme values. Moreover, a linear model lacks the ability to accurately capture the time and frequency aspects of the connections between variables, which is the primary focus of this study. Hence, to save space, the findings of the linear model are omitted from the discussion, although they can be found in the Appendix.

[9] Further evidence pertaining to the diagnostic exams could be provided upon request.

Table 2 Comparative comparison of various methodologies for wavelet analysis

#	Method	Advantage	Limitation
1	Fourier transform	Provides a representation of a signal in the frequency domain	Do not provide time good time localization
		Computationally efficient	Less suitable for analysing with time-varying characteristics
		Widely used for analysing stationary signals	
2	Short time fourier transform (STFT)	Overcomes the time localization of Fourier Transform	Non-stationary signals may not be handled well
		Provides signal components over short time intervals	It assumes a constant frequency within each time interval
3	Time–frequency representations (TFRs)	Provides time frequency representation of a signal over a spectrogram	Time–frequency resolution is fixed
			No suitable for signals with varying characteristics
4	Empirical mode decompositions (EMD)	Decomposes a signal into intrinsic mode functions	The decomposition process can be sensitive to noise
		Captures signal components with different frequencies	Number of components is not predetermined
5	Principal component analysis (PCA)	Used for dimensionality reduction and feature extraction	May not be well-suited for time–frequency analysis or capturing non-linear relationships in the data
		Identifies the principal components that capture the most significant variations in the data	
6	Hilbert-huang transform (HHT)	Combines empirical mode decomposition with the Hilbert transform to provide time–frequency information	Sensitive to noise
			The decomposition process may not be unique

However, these findings indicate a mixed causal relationship between the UCRY index and CR. The Granger causality effect, indicating the existence of implied volatility, implies greater uncertainty, which can result in increased risk aversion and greater required returns. Changes in market sentiment may affect the implied volatility, which also plays a role in trading strategies. Overall, the connection between implied volatility and asset returns is sophisticated and depends on market conditions, asset classes, and investor behavior. Owing to the fact that this topic is outside the scope of the present study, we do not discuss this effect. These experiments support the subsequent time–frequency analysis.[10]

We begin our empirical investigation by discussing the WTC results. Panel A of Fig. 3 displays the WTC results for the UCRY index and eight CRs under investigation in wavelet space. The horizontal axis represents the time domain, whereas the vertical axis represents the frequency domain of each spectrum. Our study considered three frequency cycles: 1–8, 8–16, and > 16-day bands. The first cycle reflects short-term (high-frequency) bands, the second captures the medium-term, and the third represents long-term or low-frequency domains. The selection of these time–frequency bands relies on the distinctive dynamics of cryptocurrency markets, which undergo rapid, high-frequency changes coupled with intermediate variations and long-term trends. The short-term band captures quick reactions to news and speculative trading; the medium-term reveals market adaptations to macroeconomic or regulatory changes; and the

[10] Details of the tests are available from the corresponding author upon valid request.

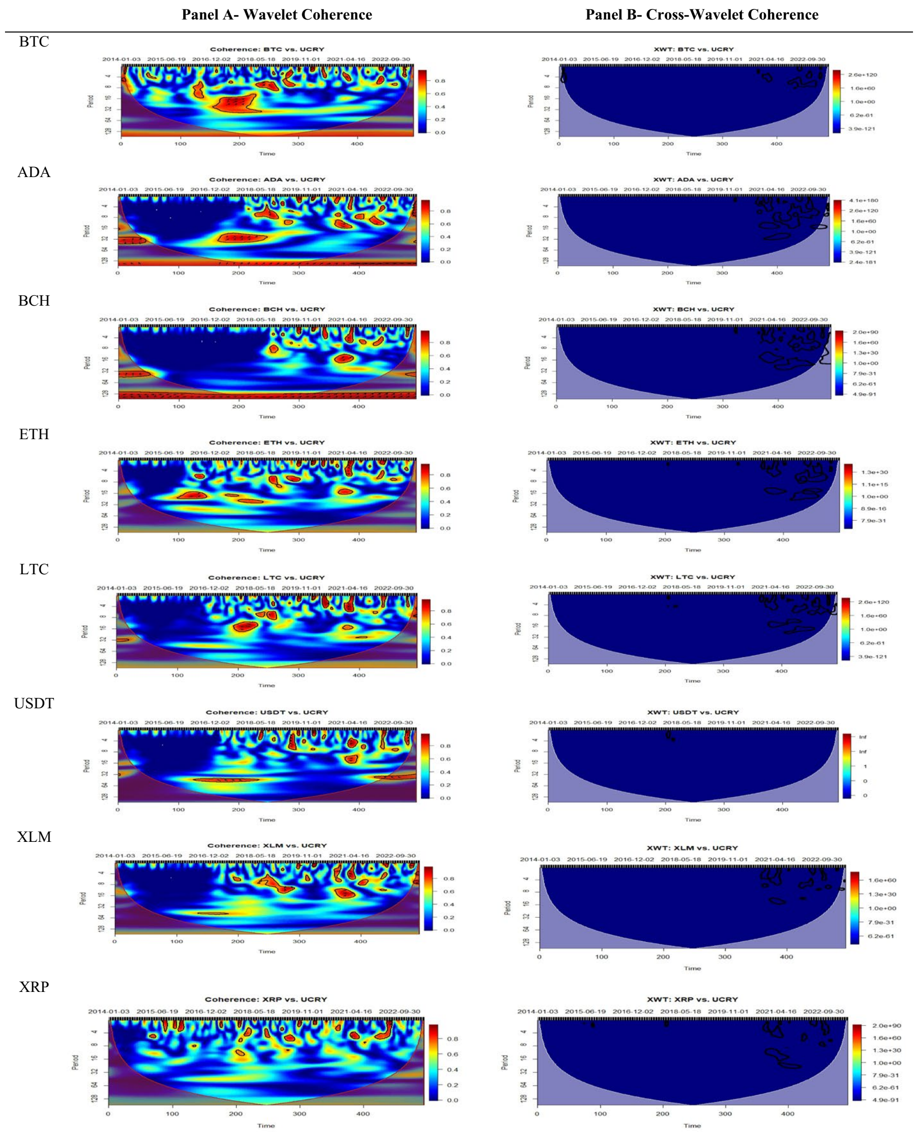


Fig. 3 Wavelet coherence transforms and cross-wavelet coherence

long-term displays overall trends influenced by fundamental variables. These bands are crucial for differentiating between transitory volatility and systemic patterns, providing vital insights into the complex behavior of cryptocurrency markets across various timeframes.

We obtain significance values from a Monte Carlo simulation at a 5% significance level. In this regard, we performed 1,000 simulations to get significant values, a conventional method that ensures an accurate equilibrium between computing efficiency and the accuracy of p-value calculation. We aimed to preserve the fundamental characteristics of the original data, such as its temporal and spectral features, to ensure the evaluation of the null hypothesis against appropriately randomised surrogates. This careful procedure ensures the validity of our significance tests and improves the reliability of the observed patterns. In addition, as indicated by the color codes on the right side of each spectrum, the power ranges from low coherence (blue) to high coherence (red).

As previously noted, the dynamics of price leadership can be analyzed by observing the phase directions of the arrows. A phase difference of 0 indicates that the CR and UCRY move in synchronization. Arrows pointing to the right indicate in-phase, and arrows pointing to the left indicate anti-phase (out-of-phase). In addition, the arrows pointing to the north-east and south-west suggest that UCRY leads to CR. In contrast, the north-west and south-east arrows imply that CR is the leading UCRY index. Finally, the statistically significant points are in the part of the spectrum that is shaded like a funnel.

According to our WTC results, in the short term (high-frequency data of one to eight days), the UCRY policy index leads the CRs for all cryptocurrencies, except for LTC. Thus, the in-phase movement of BTC suggests that BTC returns and UCRY move in the same direction. Additionally, for the high-frequency interval (one–eight days), the north-east direction of the arrows indicates that UCRY is in a leading position over BTC. Furthermore, the UCRY's lead over BTC has become increasingly pronounced since 2018. For ADA, BCH, ETH, XLM, and XRP, our WTC results in the high-frequency interval also demonstrate that the UCRY index leads to a better CR. This leadership position was shaky throughout 2018 and at the beginning of 2019. However, the lead position for these coins strengthened considerably from the beginning of 2020 and began to increase at the start of 2021. For the LTC and USDT in the short term, as shown by the dominant blue color in the spectrum, there is evidence of substantial joint movement (xero-phase) of the CR and UCRY. However, in terms of the lead-lag relationship, our WTC result for these two coins indicates that CR was leading UCRY for a short period (at the end of 2019 for USDT and the beginning of 2021 for LTC), but this short-run leading position vanished by the end of 2022 for both coins.

In the medium-term (8–16 days), our WTC results indicate that BTC returns and the UCRY index move in phase, indicating that the UCRY index leads to BTC returns over this period. In this respect, the color coding of our WTC spectrum demonstrates that the substantial leadership position expanded from 2016 to 2019 (yellow and red regions) and subsequently decreased. Our WTC results for ADA, BCH, ETH, XRP, and LTC indicate a joint movement (xero-phase), skewed toward the out-phase within the 16-day timeframe from 2018 to 2019. However, this changed after 2019, and the respective coins and UCRY index have been moving together since then. The WTC results of USDT and XLM are identical in the medium-run interval. There is an in-phase relationship between the returns of these coins and the UCRY index, indicating that the UCRY index leads to the returns of the respective cryptos. However, the UCRY index's large lead over both cryptocurrencies has grown substantially since 2020 (see the red color code for this period), and this trend continues until the end of our sample.

In the long run (> 16-day band), our WTC results exhibit an in-phase trend for BCH and ADA, indicating that the UCRY index leads to the respective CR. Given the red color in our spectrum, the leading position of these cryptocurrencies is rather solid, beginning in the middle of 2016. Considering the rest of the coins in our sample, there is a substantial xero-phase direction between the UCRY index and the CR, indicating that both series move together in low-frequency intervals (as shown by the blue, dark blue, and yellow colors in the WTC spectrum).

We now turn our attention to the XWT analysis. Panel B of Fig. 3 presents the XWT results. Our XWT spectrum, similar to the WTC spectrum, displays time on the x axis and frequency on the y axis, with a color code on the right-hand side of each spectrum indicating the strength of the link. The XWT analysis identifies regions in the time and frequency spaces where the two series of studies (UCRY index and CR) share areas of common energy. These results are consistent with our previous results obtained using the WTC method. The color coding of the XWT graphs demonstrate this, showing a lighter shade of blue during low-frequency (long-run) periods and a darker shade of blue during high-frequency (short-run) periods. Our XWT findings also reveal that, throughout the time the coins in our research have a lead-lag relationship with the UCRY index, all coins share common energy (shown by the islands in the dark circles inside the significant area). Therefore, our earlier discovery of a positive and strongly significant association between UCRY and CR at all frequencies is validated using XWT.

To conclude our empirical analysis, we investigate whether other uncertainty indices influence the comovement of CRs and UCRY over different time and frequency intervals. We use the PWC technique by operationalizing two widely used global uncertainty indices: EPU and VIX. EPU is the uncertainty surrounding the government and regulatory bodies and is influenced by changes in political and economic decisions. This implies that EPU influences macroeconomic factors such as consumption and employment, as well as future investment (Demir et al. 2018; Yen and Cheng 2021). The VIX is a major market risk indicator that reflects market sentiment and is widely used in risk management strategies by market participants (Demir et al. 2018).

Figure 4 shows the outcomes of the PWC analysis. Panel A of Fig. 4 shows the PWC after eliminating the impact of EPU, whereas Panel B depicts the PWC after removing the influence of the VIX for each cryptocurrency in the time and frequency domains. In both panels of Fig. 4, time is displayed on the x axis and frequency on the y axis; the color code on the right side of each panel indicates the degree of comovements between the two series (blue indicates weak comovements and red indicates strong comovements).

The PWC results for the high-frequency period (one–eight days) for BTC, ADA, XLM, XRP, LTC, and ETH reveal strong coherence between the CR and UCRY indices after removing the influence of EPU and VIX. This coherence began in the middle and later parts of 2016 and continued until recently. However, 2018 marked the beginning of a new era in which the BTC and UCRY indices moved together, a trend that continued until the end of our sample. In the medium-run, from 2016 to the end of our sample period, BTC and the UCRY index showed higher comovements, which persisted throughout a low-frequency period (the long run).

As for the results of currency-backed cryptocurrencies in our sample (ETH, USDT, XRP), as well as BCH and LTC, our PWC results demonstrate a similar pattern of considerable coherence between CR and the UCRY index after removing the influence of EPU and VIX. In this regard, for high-frequency (one–eight days) and medium-run intervals (8–16 days), the significant comovement between the UCRY

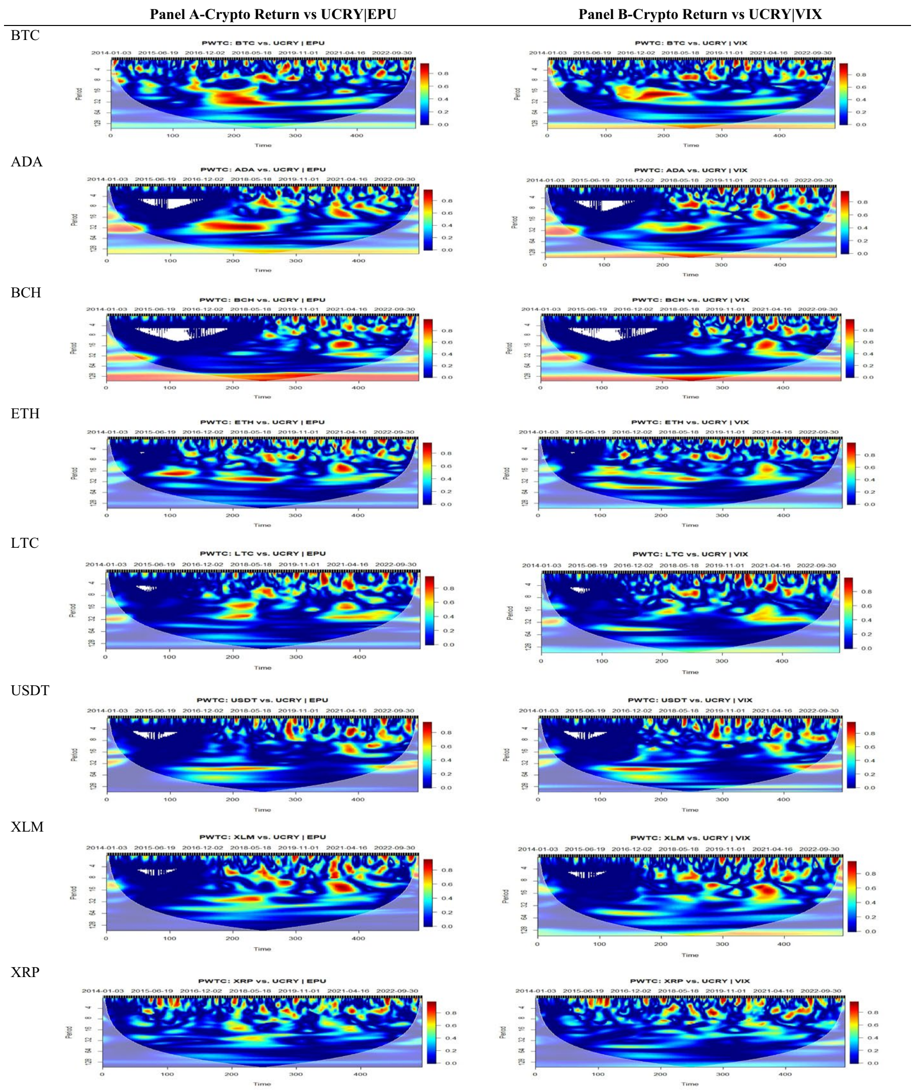


Fig. 4 Partial wavelet coherence

index and the respective cryptocurrency began in 2018 (for ETH, it started in 2017), and these comovements have been reinforced in recent years, from 2020 until the end of our study sample for this group of coins. However, the magnitude of these comovements has decreased. Nonetheless, the coherence is still substantial, as indicated by the significant blue areas in the low-frequency interval regions of the spectra.

Our PWC results support our earlier findings regarding the presence of a strong, robust, and statistically significant link between CR and the UCRY index at all frequencies. Therefore, we conclude that the UCRY index holds a leading position over CR, and that the UCRY-CR nexus is unaffected by EPU and VIX at low, medium, and high frequencies. To further support our findings, we conduct a correlation analysis[11] between the uncertainty indices and cryptocurrencies used in our study. Figure 5 shows the

[11] This test is in addition to what we have presented in Appendix A.

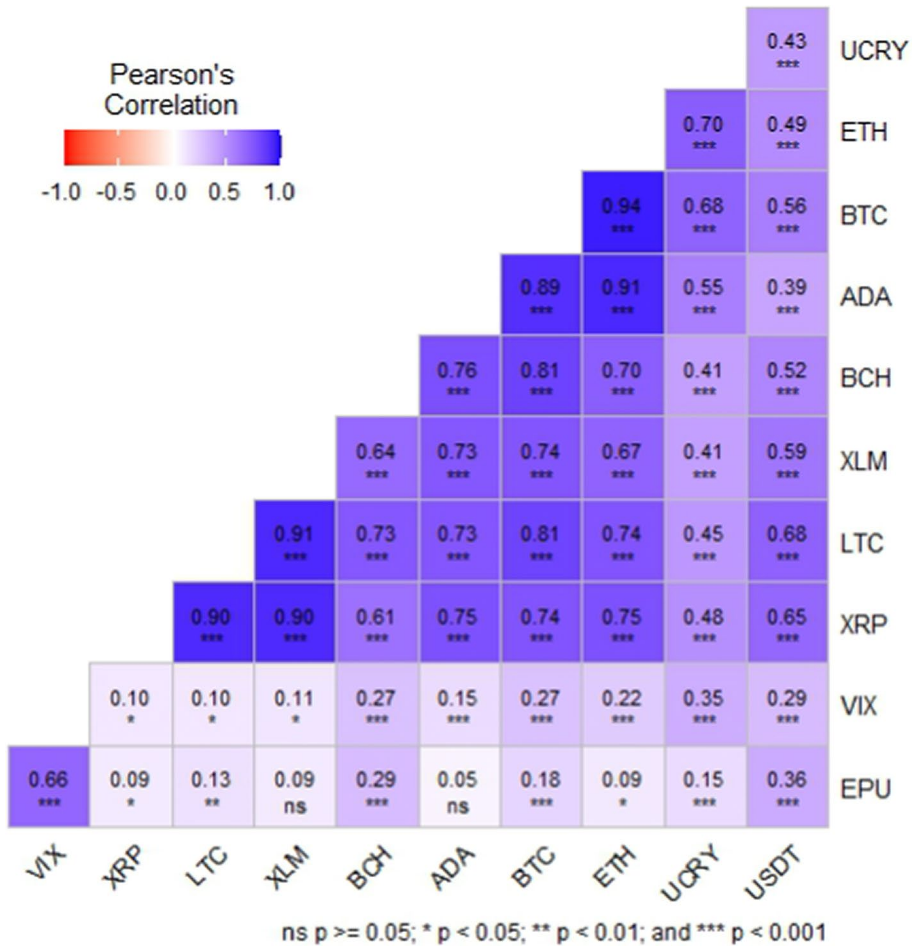


Fig. 5 Correlation heatmap

correlation test results. Based on the correlation heatmap, there is a positive and significant association between the UCRY index and all cryptocurrencies in this study, except ADA and XLM. Based on the correlation principle, this implies that the UCRY and CR generally move in the same direction.[12] However, CR behavior can differ based on various factors, including market capitalization, technology, market sentiment, investor behavior, and the regulatory environment. Large-cap cryptocurrencies with established track records may provide greater stability, whereas small- and mid-cap cryptocurrencies may have higher growth potential but greater volatility. The adoption and success of the underlying technologies can impact CR. Additionally, market sentiment, investor behavior, and regulatory decisions can impact returns. When investing in various kinds of cryptocurrencies, it is critical to conduct extensive research, assess risk tolerance, and diversify portfolios.

[12] The outcome of the correlation table may reveal the UCRY index's hedging and safe-haven features. However, this issue is outside the scope of our investigation.

Discussion

The empirical results of the present study reveal that the UCRY index has predictive power for all cryptocurrencies in our sample because of its leading position over CR. This trend remained until the latest day in our sample data, which is consistent with the results of Hasan et al. (2022a, b). Additionally, different uncertainty indices have no influence on the UCRY-CR nexus, which supports Sifat's (2021) results, demonstrating that CR are uncoupled from global economic sentiments. The author uses this to justify the treatment of cryptocurrencies as independent asset classes. These comovements are consistent across all frequencies, further supporting the presence of a strong link between the UCRY index and CR. Our findings echo those of Cui and Maghrereh (2022) that comovements among cryptocurrencies are both time- and frequency-dependent.

It is important to mention that the price of Bitcoin (the biggest cryptocurrency in terms of market capitalization) increased from around USD 700 to over USD 40,000 between July 2016 and February 2021. During the same period, the S&P 500 returned an average of 15%, The Financial Times Stock Exchange 100 Index (FTSE 100) returned 2%, and The Shanghai Stock Exchange (SSE) composite returned 4% on average. This comparison reveals Bitcoin's overwhelming growth, outperforming all other asset classes (Lahiani et al. 2021). Additionally, from our empirical results, it is evident that the UCRY index mirrored Bitcoin's features (along with many other cryptocurrency-related properties, such as news wire feeds and media transcripts), which enabled it to outperform CR at different times during the same period. These results acknowledge the *"social"* aspect[13] of UCRY index (Lucey et al. 2021).

By contrast, COVID-19 has had a considerable impact on EPU (Matuka 2020). Compared to previous crises, the evaluation of variable coherence during the COVID-19 era showed unexpected data fluctuations (Chowdhury et al. 2021). Our results complement wavelet coherence and cross-wavelet transform studies on the EPU and VIX indices, demonstrating long-term consistency in the coherence between cryptocurrency and the EPU and VIX indices. We believe that the presence of out-of-phase comovements at low frequencies, as well as the fact that the comovement between the UCRY and CR is always unaffected by standard fear indices, is the basis of the significant and strong connection between the UCRY and CR. Our findings are consistent with those of Hasan et al. (2022a, b) regarding the strong connection between UCRY and CR.

The results of this study offer investors strategic insights and a portfolio assessment of the UCRY and UCRY-CR nexuses. Our WTC results are important for short- and medium-term traders, including speculators and portfolio managers, when identifying portfolio risk. Additionally, our wavelet analysis highlights the complexities of both the CRs and the UCRY index. Furthermore, our results will benefit investors who use uncertainty indices to develop their own investment strategies and select the best portfolios. In this regard, cryptocurrency traders should take advantage of the price leadership between the UCRY uncertainty index in short-, medium-, and long-term investment intervals to make a profit, particularly a quick profit in high-frequency investment intervals. Traders may also use this index in conjunction with other fundamental and technical indicators to analyze market sentiment and make informed trading choices.

[13] Please see Lucey et al. (2021) for a discussion of social and general media.

High levels of uncertainty often result in increased volatility, which traders can exploit by employing volatility-based trading strategies or timing their transactions based on the degree of uncertainty. Additionally, staying updated about forthcoming events and their possible influence on the uncertainty index and cryptocurrency markets may help traders position themselves for potential price movements. It is essential to remember, however, that the relationship between uncertainty indices and CR may not always be consistent, and speculators should undertake extensive research and utilize appropriate risk management. From this perspective, Kou et al. (2024a) note that in the analysis process, multi-criteria decision-making procedures may be used for risk management, performance testing, and cost evaluation.

This study contributes to the existing literature on the UCRY price index by addressing several gaps using a novel approach. Here are the key characteristics of this study: 1) Relationship between the UCRY price index and CR: The study focuses on analyzing the relationship between the UCRY index and CR. By conducting a detailed analysis, this study aims to provide insights into the connection between these two factors. 2) Lag connection and comovements: We investigate the lag connection and comovements between the UCRY index and the top eight cryptocurrencies. This analysis aims to understand the dynamics and interactions between these variables and how they influence each other over time. 3) Time and frequency perspectives: Unlike previous studies, this study explores the relationship between the UCRY index and the CR from different time and frequency perspectives. By considering different timeframes and frequencies, this study aims to provide a more comprehensive understanding of the dynamics between these variables. 4) Impact of macroeconomic uncertainty indexes: Our study goes a step further by examining the comovements between the UCRY index and CR after removing the impacts of the two macroeconomic uncertainty indexes (EPU and VIX). By isolating these effects, we delve deeper into the link between the UCRY index and cryptocurrencies. 5) Standard linear modelling: Our study employs standard linear modelling techniques to offer statistical evidence of the link between the CR and UCRY indices. This approach provides a quantitative framework for analyzing relationships and drawing meaningful conclusions based on the data. To conserve space, the linear modelling findings are not discussed but are supplied in the Appendix.

Regarding the relevance of our results, it is essential to note that the UCRY index has distinct advantages in comparison to other uncertainty indices. First, the UCRY depicts the volatility and unpredictability of the cryptocurrency market, revealing the level of uncertainty surrounding cryptocurrencies. Given the distinctive characteristics of cryptocurrencies, such as their decentralized nature and vulnerability to regulatory changes, this is crucial. Additionally, the UCRY index incorporates a sentiment analysis from social media platforms, enabling a comprehensive understanding of market sentiment and its influence on uncertainty (Lucey et al. 2021). However, traditional uncertainty indices, such as the EPU index and the global policy uncertainty index, concentrate on macroeconomic factors and policy-related uncertainties (Baker et al. 2016), whereas UCRY focuses on the unique dynamics of the cryptocurrency ecosystem. Hence, the UCRY index provides a specialized measure of uncertainty that complements existing indices by incorporating these factors. Despite being a comparatively new index,[14] the empirical results of this study demonstrate a significant relationship between the UCRY index and CR for various investment horizons. Despite being relatively new, the UCRY index has demonstrated the capacity to capture and reflect uncertainties in the cryptocurrency market. The significant findings from the wavelet analysis emphasize the validity and reliability of the relationship between the UCRY index and CR, indicating its potential as a useful instrument for investors and researchers to evaluate the impact of uncertainty on cryptocurrency market dynamics. Moreover, Lucey et al. (2021) note that the UCRY index passed multiple econometric tests, further validating its robustness and dependability. These analyses evaluate the significance and stability of the relationship between the UCRY index and the CR using statistical techniques. Thus, our findings significantly enhance the understanding of the relationship between cryptocurrencies and market uncertainty. Furthermore, our findings suggest incorporating the UCRY index into investment decisions for risk management purposes, which is consistent with the perspective of Kou et al. (2023) who assert that taking the most important risks provides financial stability.

Conclusions

This study examines the lead-lag relationship and comovements of the UCRY over the weekly returns of eight cryptocurrencies between December 30, 2013, and June 30, 2023. Using the WTC, XWT, and PWC techniques, we demonstrate that UCRY has significant predictive power, with UCRY in the leading position, for all CR series throughout the short, medium, and long terms. Furthermore, we investigate whether other uncertainty indices, such as EPU and VIX, influence the UCRY-CR nexus. According to our PWC results, the strong and significant relationship between the UCRY index and CR is unaffected by EPU and VIX, and this holds true across all frequencies.

This study has several implications for both academic research and practical implementation in the digital cryptocurrency industry. First, the UCRY's significant predictive capacity in a leadership position for weekly returns across many time horizons improves our understanding of the lead-lag connection in the cryptocurrency market. This discovery implies that investors and market players can use the UCRY as a valuable indicator to make more knowledgeable decisions about cryptocurrency investments. Furthermore, the ability of the UCRY-CR relationship to withstand the influence of other well-established measures of uncertainty, such as the EPU and VIX, emphasizes the distinct and autonomous nature of cryptocurrency uncertainty. The fact that UCRY exhibits independence indicates that it captures the forms of uncertainty unique to the cryptocurrency market. This further strengthens its importance as a focused measure to evaluate market sentiment and possible returns. These observations have practical consequences for investors and portfolio managers who may use UCRY as a beneficial tool to build investment strategies for their cryptocurrency portfolios. By acknowledging the long-term and widespread nature of the connection between UCRY and CR, those involved in the cryptocurrency market can navigate its continually evolving and unpredictable environment more effectively. Furthermore, this study adds to the existing body of knowledge on the relationship between cryptocurrencies and uncertainty. It also sets the stage for future investigations into the variables that impact market behavior and

Table 3 Comparison of UCRY, EPU and VIX indices

	Cryptocurrency uncertainty index	Economic policy uncertainty	Volatility index
Purpose	To quantify the level of uncertainty surrounding cryptocurrencies	To quantify the level of uncertainty surrounding economic policy decisions. It considers factors such as changes in government policies, regulatory actions, and geopolitical events that may impact economic conditions	To measure the market's expectation of near-term volatility for a specific asset class, typically the stock market. It indicates the anticipated fluctuations in prices over a defined period
Measurement	Text-mining searches and it considers a variety of specialised terms pertaining to uncertainty, cryptocurrencies, central banks, governments, and regulators	Calculated based on textual analysis of news articles and other relevant sources to gauge the frequency and tone of policy-related uncertainty	The VIX is calculated based on options prices for a particular market, specifically the S&P 500 index options. It reflects the implied volatility derived from the prices of these options
Focus	Cryptocurrency only	It provides insights into the impact of economic policy uncertainty on economic indicators such as investment, consumer behaviour, and business decisions	It provides an indication of market sentiment and the expected magnitude of price swings within the given asset class
Application	Institutional and individual participants in cryptocurrency market as well as policy makers	The Economic Policy Uncertainty Index is often used by policymakers, economists, and investors to assess the potential effects of policy uncertainty on financial markets and the broader economy	The VIX is primarily used by traders, investors, and risk managers to assess market volatility levels, manage portfolio risk, and inform trading strategies
Focus	Uncertainty shrouded in cryptocurrency market	Uncertainty related to economic policy decisions	Measures the expected volatility of prices in a particular market
Data source	Textual Analysis	Textual Analysis of news articles	Derived from option prices
Asset class	Cryptocurrency only	Not limited to any specific asset class and can apply to the broader economy	Pertains to the stock market
Indicators of risk	Reflects the uncertainty surrounding cryptocurrencies only	Reflects the risk associated with uncertain policy environments	Represents the perceived risk of price fluctuations
Market sentiment	Yes	Yes	Yes
Informing decisions	Assists in managing short- and long-term market risk	Guides long-term investment strategies	Assists in managing short-term market risk

the changing correlations between uncertainty indices and CR. In this vein, Kou et al. (2024b) introduced a unique decision-making model that combines quantum theory and the image fuzzy rough set approach, which is based on a causal link between indicators, and may be utilized to establish a causal relationship between UCRY and CR.

Although our analysis sheds light on the useful predictive power of UCRY with respect to CR, certain limitations must be acknowledged. First, our study is limited to the top eight cryptocurrencies by market capitalization and ignores smaller or developing cryptocurrencies that may display distinct trends. Furthermore, although we take economic policy uncertainty and the volatility index when isolating the UCRY-CR link, other undiscovered elements and exogenous events might alter the dynamics of cryptocurrency uncertainty and returns. Moreover, the characteristics of the cryptocurrencies studied may limit the generalizability of our findings and render them less directly applicable to a wide variety of digital assets. Finally, the inherent volatility of cryptocurrency markets may create a degree of uncertainty that is difficult to evaluate adequately. Future studies could overcome these limitations by considering a wider range of cryptocurrencies and investigating other variables that may influence the link between cryptocurrency uncertainty and returns.

Appendix

The OLS estimation is conducted based on the following linear regression $\Delta ln(CR)_t = \beta_0 + \beta_1 \Delta ln\left(\text{Uncertainty Index}_i\right)_t + \varepsilon_t$.

	UCRY	EPU	VIX	Obs
BTC	−0.2006 (−0.3481)	−0.0229** (−1.9409)	−0.0871** (−2.2879)	496
ADA	−0.4543 (−0.7189)	−0.0065 (−0.3687)	−0.2357*** (−4.4355)	285
BCH	−1.0423 (1.5188)	−0.0303 (−1.4262)	−0.1682** (−2.5209)	240
ETH	−1.1927 (−1.9714)	−0.0232 (−0.1586)	−0.1802*** (−3.9237)	381
LTC	−1.2404** (−1.9996)	−0.0121 (−0.7695)	−0.1669*** (−3.4334)	356
USDT	0.0066 (0.2527)	0.0028** (0.4008)	0.0011 (−0.5352)	324
XLM	−0.4391 (−0.5859)	−0.0075 (−0.3507)	−0.2180*** (−3.3107)	331
XRP	−1.3488* (−1.8087)	−0.0099 (−0.6135)	0.1131** (−2.1608)	440

Linear regression on the relationship between CR and uncertainty indices are presented. Numbers in parentheses are t-statistics. *, **, and *** indicate significance at the 10%, 5% and 1% statistical levels, respectively.

The diagnostic tests for the linear regressions are shown below. In this regard, heteroskedasticity and serial correlation tests are performed, and the results are shown in the subsequent tables. In addition, ADF and Granger causality tests are provided to further support the time–frequency analysis.

Heteroskedasticity test: Breusch-Pagan-Godfrey			
	UCRY	**EPU**	**VIX**
BTC	0.2499	0.7205	0.8244
ADA	0.0067	0.8179	0.8701
BCH	0.0072	0.1516	0.0147
ETH	0.0066	0.5918	0.6963
LTC	0.0188	0.1955	0.9774
USDT	0.9135	0.7319	0.8254
XLM	0.0340	0.4541	0.7721
XRP	0.7535	0.2918	0.8139

Null hypothesis: Homoskedasticity. Numbers are presenting the probability of Chi-Square (1) on Obs*R-squared based on ordinary covariance method. Heteroskedasticity and autocorrelation consistent (HAC) standard error & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000) test is applied for the probabilities below 5% to rectify the issue of heteroskedasticity. These results are available upon request.

The linear model in Eq. 8 satisfies the assumption of heteroskedasticity in the study samples, as the probability of Chi-Square (1) on observed R-squared is greater than 5%, as shown in the table above. Additionally, the LM autocorrelation test is used to identify multicollinearity in the linear model in addition to the stationarity test. To reinforce our time–frequency analysis, we additionally present the Granger causality test. The outcomes are presented in the tables below. These results show that the assumptions of multicollinearity for linear regression and stationarity of the data for Granger causality are correct. Further evidence pertaining to the diagnostic exams could be provided upon request.

Breusch-Godfrey serial correlation LM test			
	UCRY	**EPU**	**VIX**
BTC	0.4538	0.5908	0.5458
ADA	0.0070	0.0077	0.0197
BCH	0.4849	0.3514	0.3416
ETH	0.0152	0.0207	0.0253
LTC	0.4336	0.5709	0.6374
USDT	0.0001	0.0001	0.0001
XLM	0.0008	0.0009	0.0020
XRP	0.0053	0.0092	0.0109

Null hypothesis: No serial correlation at up to 2 lags. Numbers are presenting the probability of F-statistic based on ordinary covariance method. Heteroskedasticity and autocorrelation consistent (HAC) standard error & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000) test is applied for the probabilities below 5% to rectify the issue of autocorrelation. These results are available upon request.

Augmented Dickey-Fuller		
	t-statistics	**Prob**
UCRY	− 6.3627	0.0000
EPU	− 13.1177	0.0000

Augmented Dickey-Fuller		
	t-statistics	Prob
VIX	− 11.7407	0.0000
BTC	− 24.4242	0.0000
ADA	− 12.7652	0.0000
BCH	− 21.7997	0.0000
ETH	− 13.3896	0.0000
LTC	− 21.3845	0.0000
USDT	− 10.0770	0.0000
XLM	− 7.7919	0.0000
XRP	− 13.6021	0.0000

For ADT test the Akaike information criterion is selected as an estimator of prediction error.

Granger Causality		
	UCRY → CR	CR → UCRY
BTC	N	N
ADA	N	N
BCH	N	Y
ETH	N	N
LTC	N	N
USDT	N	N
XLM	N	N
XRP	N	N

Abbreviations

ADA	Cardano
BCH	Bitcoin cash
BTC	Bitcoin
COVID	Corona virous disease
CR	Cryptocurrency return
DJ	Dow Jones
DECO- GARCH	Dynamic equi-correlation generalized autoregressive conditional heteroskedasticity
EPU	Economic policy uncertainty
ETH	Ethereum
ICO	Initial coin offering
JB	Jarque Bera
LN	Natural logarithm
LTC	Litecoin
OLS	Ordinary least square
PWC	Partial wavelet coherent
S&P	Standard and Poor
SSE	Shanghai stock exchange
UCRY	Cryptocurrency uncertainty index
USD	United States Dollar
USDT	Tether
VIX	Volatility index
WTC	Wavelet coherent transform
XLM	Stellar
XRP	Ripple
XWT	Cross-wavelet coherent

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Declarations

Competing interests
The author declare that they have no competing interests.'

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