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Dependence Structure between Bitcoin and Economic Policy Uncertainty: Evidence from Time–Frequency Quantile-Dependence Methods

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Abstract: In this study, the dependence between Bitcoin (BTC) and economic policy uncertainty (EPU) of USA and China is estimated by applying the latest methodology of quantile cross-spectral dependence. Daily data comprising a total of 1947 observations and covering the period of 1 October 2013 to 31 January 2019 are used in this study. The findings indicate that a positive return interdependence between BTC and EPU is high in the short term, and this dependence decreases as investment horizons increase from weekly to yearly. The information on the time-varying and time-frequency structure of interdependence is also extracted by applying wavelet coherence analysis. The estimated results of wavelet coherence suggest that the correlation between BTC and EPU is positive during a short-term investment horizon. Finally, the frequency domain Breitung and Candelon causality test is applied, and results show the evidence of insignificant causality between Bitcoin and EPU. Overall, the findings highlight the diversification benefits of Bitcoin during the period of uncertainty.

Keywords: Bitcoin; economic policy uncertainty; spillover; wavelet coherence analysis; quantile cross-spectral dependence

JEL Classification: C58; D80; G11



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1. Introduction

In the context of extreme uncertainty regarding economic policy measures and the loss of confidence in the existing international financial system, Nakamoto (2008) introduced a new digital currency, i.e., Bitcoin, a fully decentralized cryptocurrency without any control from a central authority. Since its introduction, the Bitcoin price has increased dramatically from USD 0.09 on 18 July 2010 to USD 48,767 on 23 August 2021. The dramatic change in the price of Bitcoin has motivated academicians and practitioners to explore the economic and financial factors which may affect the Bitcoin price (Demir et al. 2018), since the behavior of this digital currency seems to be independent of economic and financial development (Kristoufek 2015). Some studies argue that the attractiveness of Bitcoin increases during the period of financial distress and economic uncertainty (Bouri et al. 2017; Demir et al. 2018; Fang et al. 2019). With this backdrop, it is stated that Bitcoin offers significant diversification benefits to investors during the times of extreme economic uncertainty (Cheng and Yen 2020; Guesmi et al. 2019; Kang et al. 2020; Mokni et al. 2020; Paule-Vianez et al. 2020; Wang et al. 2019). However, there are several studies that criticized the role and suitability of Bitcoin in financial markets by analyzing its speculative nature (Corbet et al. 2018;

Eom et al. 2019), high price volatility (Aalborg et al. 2019; Shi et al. 2020; Elsayed et al. 2022), bubble formation tendencies (Baur et al. 2018; Eom et al. 2019; Bouri et al. 2019), legal regulations (Spaeth and Peráček 2022), and market efficiency (Al-Yahyaee et al. 2020; Choi et al. 2022; Mensi et al. 2019).

No doubt, government's economic policies, namely, fiscal and monetary policies, significantly impact the entire economy. Specifically, during the period of recession/distress, direct government intervention significantly impacts financial markets. Frequent interventions after global financial turmoil have aroused scholars' interest in such issues. In this regard, Baker et al. (2016) introduced the economic policy uncertainty (EPU) index to measure the uncertainties that arise due to government intervention and policies. Following that, recent studies have analyzed that such policy uncertainties have considerable impact on real economic systems and financial markets (Arreola Hernandez et al. 2022; Baker et al. 2016; Nguyen et al. 2020; Darsono et al. 2022; Mensi et al. 2021).

The interest in investigating the impact of EPU on the cryptocurrency market is fairly recent. Bouri et al. (2017), Bouri and Gupta (2019), Fang et al. (2020), and Colon et al. (2021) found that EPU is a significant predictor of volatility in the cryptocurrency market, especially in the Bitcoin market. Demir et al. (2018), Mokni et al. (2020), Mokni (2021), and Rubbaniy et al. (2021) reported that EPU significantly impacts Bitcoin returns and that Bitcoin acts as a potential hedging tool against economic uncertainty. On the contrary, Cheema et al. (2020) and Hasan et al. (2022) noted that cryptocurrencies do not act as a hedge or safe-haven during risky periods. Shaikh (2020) found that EPU in the US and Japan are negatively associated with the Bitcoin market whereas EPU in China is positively associated. Cheng and Yen (2020) found a positive correlation between Chinese EPU and the cryptocurrency market, while Yen and Cheng (2021) showed a negative correlation between Chinese EPU and the cryptocurrency market. Jiang et al. (2021) demonstrated that cryptocurrencies act as a hedge for higher EPU but not in moderate or low EPU. Furthermore, Haq et al. (2021) conducted a systematic review of empirical literature based on the cryptocurrency market and discovered the mixed connectedness pattern of cryptocurrency with all national EPU. This heterogeneous correlation patterns suggest future research avenues in the cryptocurrency market.

Accordingly, this study explores the linkage between Bitcoin returns and EPU indices of USA and China developed by Baker et al. (2016). More precisely, the dependence structure between Bitcoin and EPU is measured using the latest methodology of quantile cross-spectral (QS) analysis proposed by Baruník and Kley (2019). Our research has the following three contributions. First, prior studies (e.g., Demir et al. 2018; Wang et al. 2019; Shaikh 2020) have ignored the quantile interdependence across varied frequencies in describing the interrelationship between Bitcoin and EPU. Our study captures the interdependencies at various market conditions across and at different investment horizons. This is important because money market correlation increases during uncertain periods (Longin and Solnik 2001). Second, to enrich our results with respect to interdependence between Bitcoin and EPU across time frequencies, we have applied wavelet coherence analysis. Indeed, it is important to recognize the behavior of Bitcoin across various frequencies because the driving forces behind Bitcoin pricing are not constant since its inception in the global market (Maghyreh and Abdoh 2021). Third, Breitung and Candelón's (2006) Granger causality test is applied to investigate the causality between BTC and EPU at various frequency domains.

The general outcomes of the study estimated by applying quantile cross-spectral (QS) methodology indicate that EPU does not affect Bitcoin returns over long terms. Furthermore, the dependence between BTC and EPU decreases with the increase in frequency from weekly to yearly. Breitung and Candelón's (2006) Granger causality test shows evidence of an insignificant bidirectional causality between Bitcoin and USA-EPU at long-term frequencies. Moreover, the weak dependence and insignificant causality between Bitcoin and USA-EPU suggest the better diversification benefits of Bitcoin and USA-EPU.

The structure of the paper is as follows. In Section 2, we discuss data and methodological choices. Section 3 contains empirical results and their discussion. Section 4 explains the conclusion of the study.

2. Data and Empirical Analysis Methods

2.1. Data

The daily data comprising a total of 1947 observations and covering the period 1 October 2013 to 31 January 2019 was used for empirical investigation. The price data on Bitcoin (BTC) denominated in USD was gathered from the website: <https://bitcoincharts.com> (accessed on 3 March 2019). The data of the EPU index of USA (USA-EPU) and EPU index of China (CHN-EPU) was obtained from the website: <https://www.policyuncertainty.com> (accessed on 3 March 2019).

The statistical properties of BTC and EPU indices are reported in Table 1. It is shown from Table 1 that BTC has the highest mean value of 2491.518, followed by CHN-EPU with a value equal to 129.3. The standard deviation of BTC is the highest, whereas the standard deviation of USA-EPU is the lowest. All variables are skewed to the right as demonstrated by the positive value of skewness. Furthermore, the calculated values of kurtosis statistics are high, implying a wider distribution than normal distribution. The values of the Jarque–Bera test statistic suggest that the distribution of selected variables is not normal.

Table 1. Descriptive analysis.

	BTC_USD	CHN_EPU	USA_EPU
Mean	2491.518	129.3412	85.34069
Median	639.1537	117.6304	74.99000
Maximum	19,395.84	651.0512	586.5500
Minimum	100.8108	0.000000	3.320000
Standard deviation	3436.336	68.20854	48.13624
Skewness	1.867128	2.023943	2.116218
Kurtosis	6.328758	10.83213	12.60083
Jarque–Bera	2030.177	6305.661	8931.008
<i>p</i> -value	0.0000	0.0000	0.0000
Observation	1947	1947	1947

Note: BTC_USD = Bitcoin dominated in US dollar; CHN_EPU = Chinese economic policy uncertainty index; USA_EPU = USA economic policy uncertainty index.

2.2. Empirical Analysis Methods

In this study, the dependence structure between BTC and EPU is measured by applying quantile cross-spectral (QS) analysis. This method can capture the extreme period of interrelationship between variables in the frequency domain. This technique is independent of the conditional variances of the distribution in recognizing the co-movement of BTC and EPU at different quantiles. Thus, with the application of this technique, we can elucidate the interrelationship between BTC and EPU at varying frequencies as well as identify the dynamic correlation between these variables under changing market conditions.

In the next step, we have applied the wavelet coherence analysis to measure the strength of co-movement between time-series of BTC and EPU across frequencies and time scales. This technique has the ability to control for non-linearities, non-stationarity, structural breaks, and any seasonality in the linkage between time-series (Roueff and Sachs 2011). Cross-wavelet transformation is used to estimate wavelet coherence following the approach of Reboredo et al. (2017). Finally, Breitung and Candelon's (2006) Granger causality test is applied for further clarification of results.

2.2.1. QS Approach

Following Baruník and Kley (2019), $(\mathfrak{R}_t)_{t \in \mathbb{Z}}$ has two components and represents two strictly stationary processes of $\mathfrak{R}_t = (\mathfrak{R}_{t,j_1}, \mathfrak{R}_{t,j_2})$. Thus, the quantile coherency between these two processes $(\mathfrak{R}^{j_1,j_2})$ can be written as:

$$\mathfrak{R}^{j_1,j_2}(\omega; \eta_1, \eta_2) := \frac{f^{j_1,j_2}(\omega; \eta_1, \eta_2)}{(f^{j_1,j_1}(\omega; \eta_1, \eta_1) f^{j_2,j_2}(\omega; \eta_2, \eta_2))^{1/2}} \quad (1)$$

where $-\pi < \omega < \pi$ and $(\eta_1, \eta_2) \in [0, 1]$. QS density and quantile spectral densities of $\mathfrak{R}_{t,j_1}$ and $\mathfrak{R}_{t,j_2}$ are represented by f^{j_1,j_2} , f^{j_1,j_1} , and f^{j_2,j_2} , respectively. These densities can be obtained from the Fourier transform of the matrix of quantile-cross covariance kernels, $\Gamma(\eta_1, \eta_2) := (f(\omega; \eta_1, \eta_2))_{j_1 j_2}$:

$$\gamma_m^{j_1,j_2} := \text{Cov} \left(1 \left\{ X_{t+m,j_1} \leq q_{j_1(\eta_1)} \right\}, \left\{ X_{t+m,j_2} \leq q_{j_2(\eta_2)} \right\} \right), \quad (2)$$

where $j_1, j_2 \in \{1, \dots, d\}$, $m \in \mathbb{Z}$, $\eta_1, \eta_2 \in [0, 1]$, and $1\{A\}$ is the indicator function of event A . The information about the serial dependence is denoted by the m value. Further information about cross-section dependence can be obtained by choosing $j_1 \neq j_2$. In the frequency domain, this yields the matrix of QS density kernels, $f(\omega; \eta_1, \eta_2) := (f(\omega; \eta_1, \eta_2))_{j_1 j_2}$:

$$f(\omega; \eta_1, \eta_2) := (2\pi)^{-1} \sum_{m=-\infty}^{\infty} \gamma_m^{j_1,j_2}(\eta_1, \eta_2) e^{-im\omega}. \quad (3)$$

Then, quantile coherency can be estimated by the smoothed quantile cross-periodograms as

$$\hat{G}_{n,\mathfrak{R}}^{j_1,j_2}(\omega; \eta_1, \eta_2) := \frac{2\pi}{n} \sum_{s=1}^{n-1} w_n \left(\omega - \frac{2\pi s}{n} \right) I_{n,R}^{j_1,j_2} \left(\frac{2\pi s}{n}, \eta_1, \eta_2 \right), \quad (4)$$

where $I_{n,R}^{j_1,j_2}$ shows the rank-based copula cross-periodograms matrix and W_n describes the sequence of weight functions. Then, the estimators for the quantile coherency can be computed by

$$\hat{\mathfrak{R}}_{n,\mathfrak{R}}^{j_1,j_2}(\omega; \eta_1, \eta_2) := \frac{\hat{G}_{n,\mathfrak{R}}^{j_1,j_2}(\omega; \eta_1, \eta_2)}{\left(\hat{G}_{n,\mathfrak{R}}^{j_1,j_1}(\omega; \eta_1, \eta_1) \hat{G}_{n,\mathfrak{R}}^{j_2,j_2}(\omega; \eta_2, \eta_2) \right)^{1/2}}. \quad (5)$$

The coherency matrix for three quantiles (lower 0.05, medium 0.5, and upper 0.95) and the combination of quantile levels of joint distribution (0.05 | 0.05, 0.5 | 0.5, and 0.95 | 0.95) are estimated in this paper.

2.2.2. Wavelet Coherence

The cross-wavelet of two time-series $y(t)$ and $z(t)$ is written as:

$$W_{y,z}(v, s) = W_y(v, s) W_z^*(v, s),$$

where v represents the position index and s denotes the scale.

According to Torrence and Webster (1999), the co-movement between $y(t)$ and $z(t)$ over time and across frequencies can be estimated using wavelet coherence, which can be written as:

$$R^2(v, s) = \frac{|S(s^{-1} W_{yz}(v, s))|^2}{S(s^{-1} |W_y(v, s)|^2 s^{-1} |W_z(v, s)|^2)}. \quad (6)$$

In the above equation, $R^2(v, s)$ is the squared wavelet coherence coefficient and S is the smoothing operator in both time and frequency. The value of $R^2(v, s)$ lies between '0' and '1' in the time–frequency space. The value of $R^2(v, s)$ close to zero indicates weak correlation between time-series and a value close to 1 indicates a strong correlation. Monte Carlo simulations with statistical significance at 5% is used to examine statistical significance of coherence (Torrence and Compo 1998).

2.2.3. Granger Causality Test

The dependence structure between Bitcoin and EPU is further explored by applying Breitung and Candelon's (2006) Granger causality test in the frequency domain. This test is based on the fact that causality between two stationary time-series can vary along the time-scale as well as over different frequencies.

Breitung and Candelon (2006) used the bivariate vector autoregressive (VAR) model to show the relationship between y_t and z_t variables. The model takes the following form:

$$y_t = \alpha_1 y_{t-1} + \dots + \alpha_p y_{t-p} + \beta_1 z_{t-1} + \dots + \beta_p z_{t-p} + \mu_t, \quad (7)$$

where α_p and β_p are coefficients and μ_t is the error term. The null hypothesis of Granger causality from z_t to y_t at frequency (ω) is tested by $M_{z \rightarrow y}(\omega) = 0$, which is equivalent to the null linear restriction:

$$H_0 = R(\omega)\beta = 0, \quad (8)$$

where $\beta = [\beta_1, \dots, \beta_p]'$ is the vector of the coefficients z_t and

$$R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \dots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \dots & \sin(p\omega) \end{bmatrix}. \quad (9)$$

F-statistics are used to test the null hypothesis in the frequency interval, $\omega \in (0, \pi)$.

3. Results of Empirical Analysis

3.1. Results of Quantile Coherency Estimation

The quantile coherency results estimated by applying the QS approach are displayed in Figure 1. The plots show the real and unreal parts of the quantile coherency estimates across various frequencies and different quantiles (lower 0.05 | 0.05, middle 0.5 | 0.5, upper 0.95 | 0.95) in their joint distribution. The lower label of the horizontal axis shows the daily cycles, while the upper label illustrates the frequency cycles. The vertical axis displays the interdependence between BTC and EPU. The visual inspection of plots shows that return quantiles of BTC and USA-EPU, and BTC and CHN-EPU are strongly connected in short-term frequency as compared to long-term frequency. Indeed, a strong dependence between BTC and EPU indices is shown in the case of the short-term horizon, i.e., weekly frequency. Moreover, the dependence between BTC and EPU decreases with the increase in frequency from weekly to yearly. Overall, the estimates indicate that the irregularity in the interdependence structure between BTC and EPU depends upon market conditions and investment time horizons.

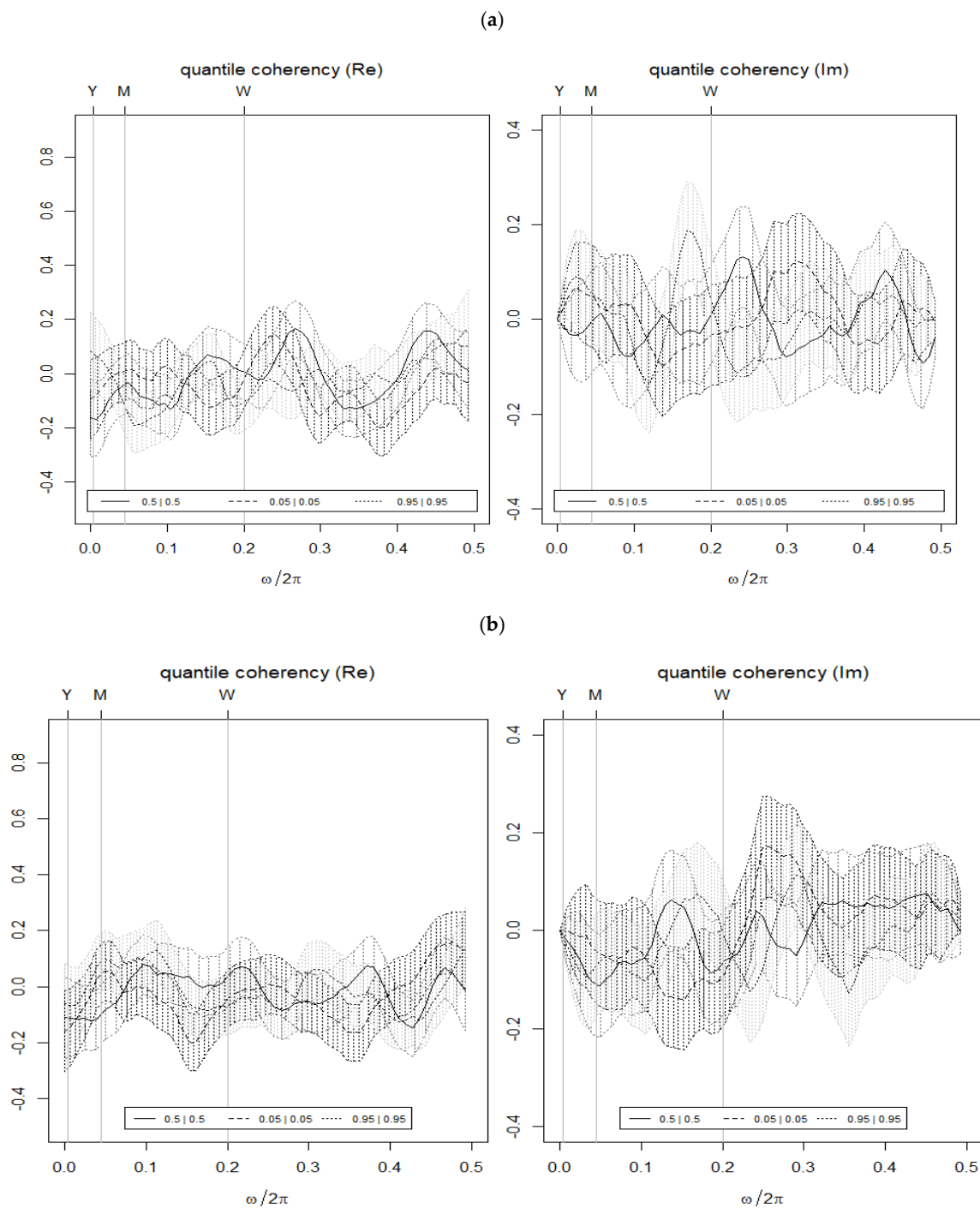


Figure 1. Quantile coherence estimates. (a) BTC vs. USA-EPU. (b) BTC vs. CHN-EPU. Notes: (i) BTC = Bitcoin; CHN_EPU = Chinese economic policy uncertainty index; USA_EPU = USA economic policy uncertainty index. (ii) The plots report the real (left) and unreal (right) parts of the quantile coherence estimates for the different lower, middle, and upper quantiles (0.05|0.05, 0.5|0.5, and 0.95|0.95) of the joint distribution across the different frequencies. The daily cycles over the intervals [0, 0.5] are shown on the horizontal axis, whereas the vertical axis measures the co-dependence of two time series. The frequency cycles in the upper label of the horizontal axis show how yearly (Y), monthly (M), and weekly (W) frequencies are connected across the joint-distribution quantiles.

With respect to weekly frequency, it can be noted that the dependence of the BTC high return quantile on CHN-EPU is slightly highest with a value of 0.25 as compared to USA-EPU with a value of 0.20. Overall, the findings indicate that short-term fluctuation

can explain well the positive return portfolio of BTC and EPU. The findings are consistent with the study of [Cheng and Yen \(2020\)](#) that CHN-EPU can better predict the BTC monthly returns than USA-EPU.

By using the QS approach, the dependence of the joint distribution between 0.05 | 0.95 quantiles can also be measured. In particular, we can examine the positive return of BTC (0.95 quantile) and a negative effect of EPU (0.05 quantile) by using the QS approach. The plots of Figure 2 show that the extreme return quantiles are weak for BTC with respect to USA-EPU and dependence displays the lowest level at a monthly frequency. However, the extreme return quantiles are strong for BTC and CHN-EPU. This result explains that greater uncertainty in the economic policies of China leads to asymmetric information in the market and, in turn, leads to asymmetric investors' expectations ([Akerlof 1970](#)). This evidence supports the conclusion of [Fang et al. \(2019\)](#) and [Paule-Vianez et al. \(2020\)](#) that Bitcoin is an investment asset like gold and not just a means of exchange.

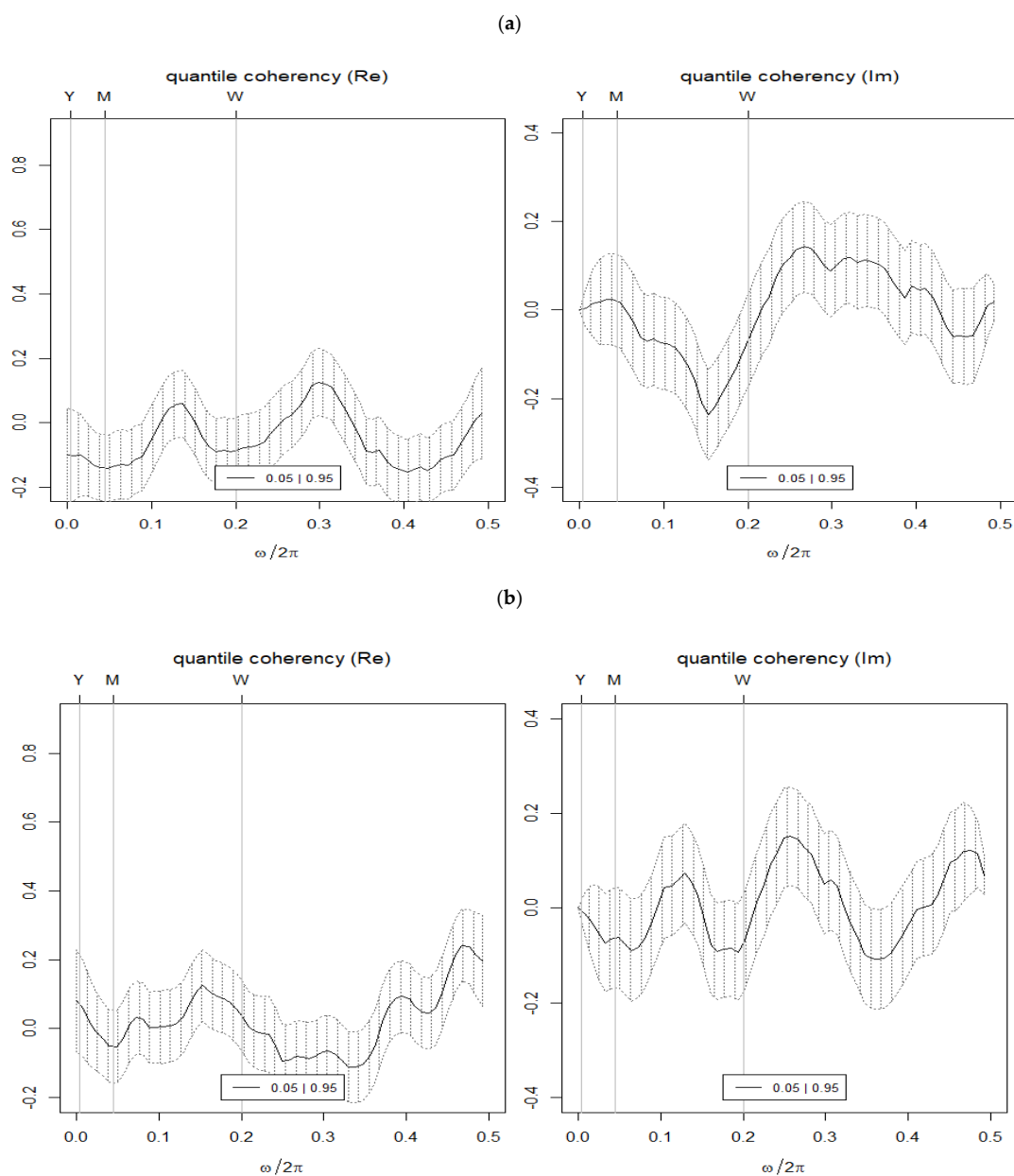


Figure 2. Interdependence between the 0.05 | 0.95 quantiles of joint distribution. (a) BTC vs. USA-EPU. (b) BTC vs. CHN-EPU. Note: (i) BTC = Bitcoin; CHN_EPU = Chinese economic policy uncertainty index;

USA_EPU = USA economic policy uncertainty index. (ii) The plots measure the interdependence between the 0.05 | 0.95 quantiles of joint distribution. The daily cycles over the intervals $[0, 0.5]$ are shown on the horizontal axis, whereas the vertical axis measures the co-dependence of two time series. The frequency cycles in the upper label of the horizontal axis show how yearly (Y), monthly (M), and weekly (W) frequencies are connected across the joint-distribution quantiles.

3.2. Results of Wavelet Coherence Analysis

Next, we have applied wavelet coherence and phase difference to investigate the correlation and causality between BTC and EPU over time and frequency domains. Figure 3 shows the outcomes of wavelet coherence and phase difference for pairs of BTC and EPU from 2 days to 512 days (approximately two years). The horizontal axis displays the time-scale, whereas the vertical axis measures the frequencies. Higher frequencies relate to a short-term investment horizon, whereas the lowest frequencies relate to a long-term investment horizon. The direction of arrows signifies the phase differences between BTC and EPU. Arrows pointing right and left indicate that both time-series are in phase and out of phase, respectively. An upward direction of an arrow indicates that BTC returns were leading during economic uncertainty, whereas a downward direction of an arrow indicates that BTC returns were lagging during uncertainty.

The panel (a) of Figure 3 demonstrates the significant and strong interdependence between BTC and USA-EPU for the 2013–2015 period during a short-term investment horizon, i.e., a 280–512 day frequency band, with Bitcoin returns leading during the period of economic uncertainty. Some evidence of relatively strong and significant coherence is also observed during the 2013–2014 period and a 64–128 day frequency band with leading Bitcoin returns. The evidence of weak and negative coherence is observed at a long-term investment horizon and a 2–6 day frequency cycle throughout the sample period where Bitcoin returns are lagging during uncertainty. These outcomes support the short-run effectiveness of the hedge/diversification benefits of Bitcoin during uncertainty such as the European Sovereign debt. Our findings corroborate the conclusion of [Cheng and Yen \(2020\)](#), [Mokni et al. \(2020\)](#), and [Paule-Vianez et al. \(2020\)](#).

The panel (b) of Figure 3 explains that the strong coherence between BTC and CHN-EPU is observed from a 16–512 day frequency cycle during the mid-2016–2019 period. At the long-term investment horizon, the co-movement between BTC and CHN-EPU becomes weak and insignificant. The evidence of strong coherence from mid-2016–2019 supports the conclusion of [Cheng and Yen \(2020\)](#) that the trade ban announced by the Chinese government in 2017 increased the predictive ability of the CHN-EPU index for BTC returns.

Overall, the findings of this section support the previous analysis that coherence between BTC and EPU is strong during short-term and medium-term scales and future returns of Bitcoin increase during uncertainty that justify the role of Bitcoin as a hedging instrument during crisis periods.

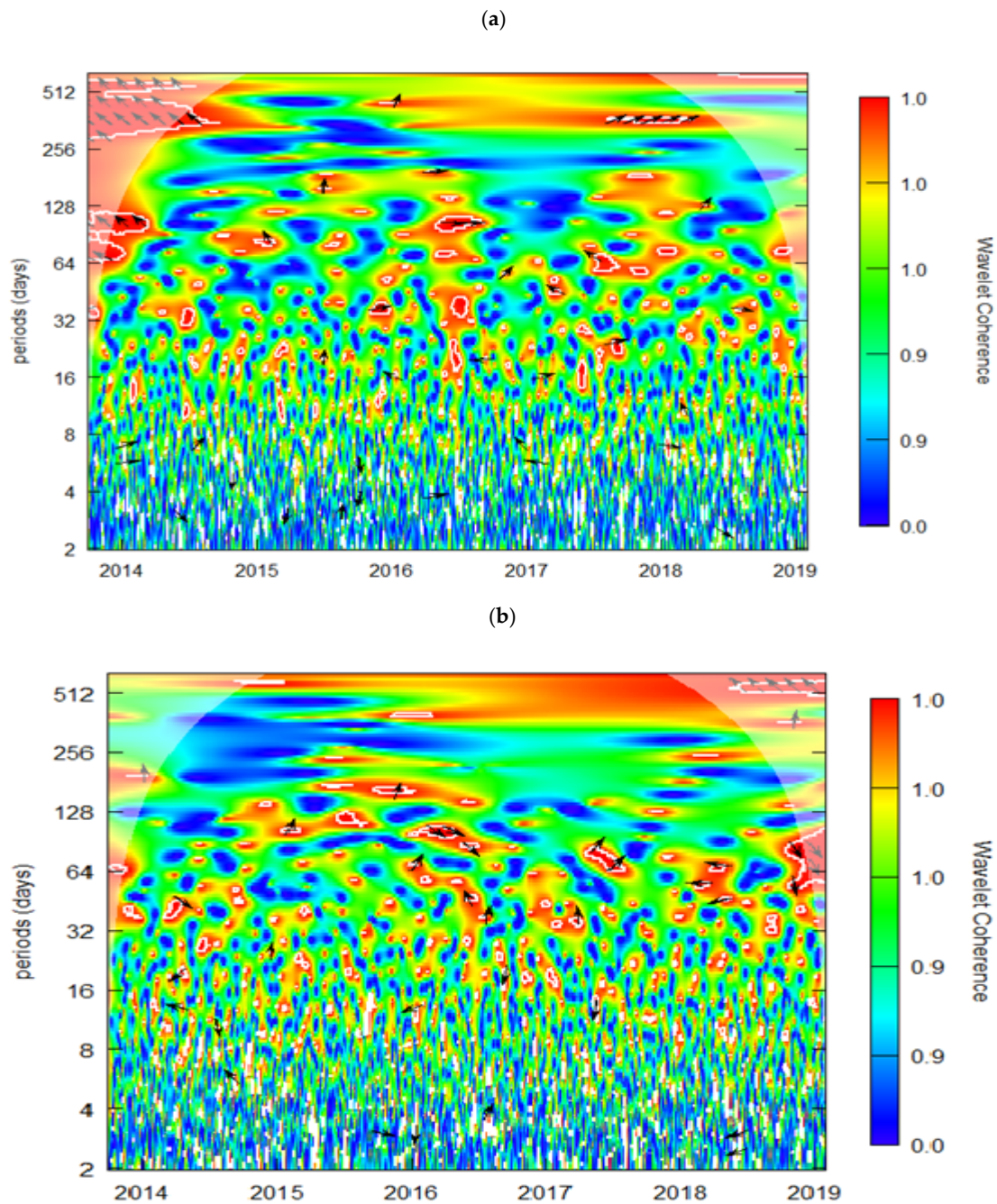


Figure 3. Wavelet coherence. (a) BTC vs. USA-EPU. (b) BTC vs. CHN-EPU. Notes: (i) BTC = Bitcoin; CHN_EPU = Chinese economic policy uncertainty index; USA_EPU = USA economic policy uncertainty index. (ii) The plots show the estimated wavelet coherence for pairs of Bitcoin and the EPU. Lower scales are associated with the long-term investment horizon, whereas higher scales are associated with the short-term investment horizon. The horizontal axis shows the time; the leftmost reflects the start of the data interval and the rightmost reflects the end of the data interval. Warm colors such as red represent high coherence (or correlation) and cold colors such as blue represent low coherence. A thick black line represents statistically significant areas of coherence. The direction of the black arrows displays two things: the sign of correlation and the lead–lag phase relations between the two series.

3.3. Result of Additional Test

We have applied the [Breitung and Candelon's \(2006\)](#) Granger causality test to further investigate the interdependence structure between BTC and EPU in the frequency domain. The advantage of this test is that it explains causality between two stationary time-series at various time-scales and across varying frequencies by imposing linear restriction on the autoregressive parameters in a VAR model.

However, prior to the application of [Breitung and Candelon's \(2006\)](#) Granger causality test, we have applied the Toda–Yamamoto (TY) causality test, as shown in Table 2. This test is a modified version of the Granger causality test and does not depend on stationary properties of a time-series. The outcomes show clear evidence of a unidirectional causal relationship from CHN-EPU to BTC. In contrast, we cannot find evidence to prove causality either bidirectionally or unidirectionally between USA-EPU and BTC. This evidence indicates that Bitcoin returns are independent of the changes of EPU and can be used as a safe-haven or a diversifier in conditions of extreme EPU shocks. In other words, Bitcoin can be a safe-haven, like gold, and allows investors to consider this cryptocurrency as a tool to protect their savings in times of economic uncertainty. The role played by Bitcoin in uncertainty is found to be relevant in the formation of investment portfolios, because this cryptocurrency can contribute to the construction of better diversified portfolios. This result supports the findings of [Wang et al. \(2019\)](#).

Table 2. TY Granger causality test.

	GC from USA-EPU to BTC	GC from BTC to USA-EPU	GC from CHN-EPU to BTC	GC from BTC to CHN-EPU
Test	3.937	11.791	2.493	32.584
<i>p</i> -value	0.787	0.107	0.972	0.000

Note: GC = Granger causality; BTC = Bitcoin; CHN_EPU = Chinese economic policy uncertainty index; USA_EPU = USA economic policy uncertainty index.

Unfortunately, Toda–Yamamoto causality cannot identify the evidence of causality across different frequency bands, and that was why we applied [Breitung and Candelon's \(2006\)](#) Granger causality approach. Figure 4 illustrates that CHN-EPU Granger cause BTC at short-term frequencies, whereas BTC does not show Granger causality with CHN-EPU at any frequency level. Granger causality from USA-EPU to BTC is significant at an intermediate level of frequency; however, we cannot find evidence of causality from BTC to USA-EPU. Finally, the causality from CHN-EPU to BTC is more significant than USA-EPU to BTC.

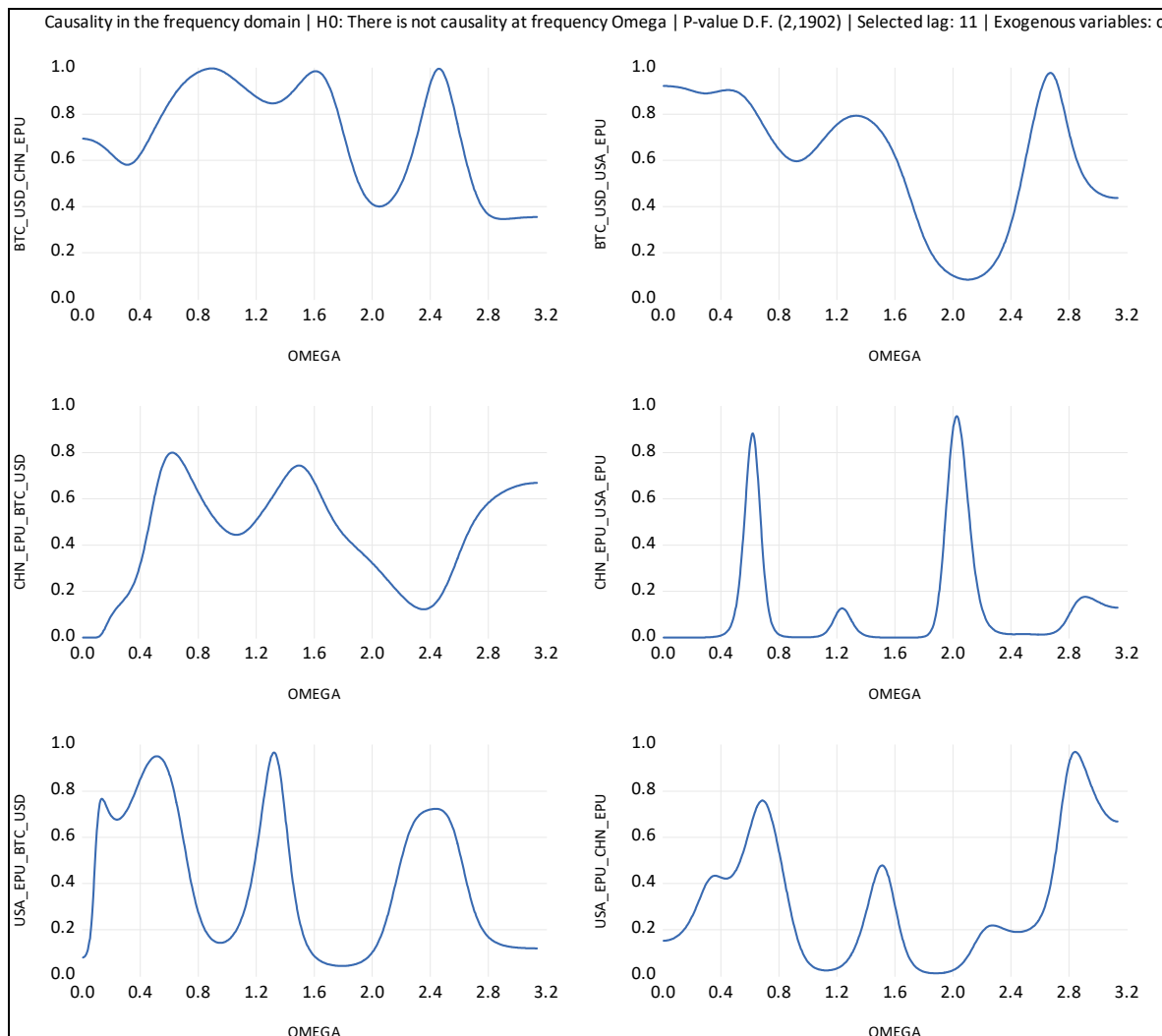


Figure 4. Breitung and Candelon's (2006) Granger causality test. Notes: (i) BTC = Bitcoin; CHN_EPU = Chinese economic policy uncertainty index; USA_EPU = USA economic policy uncertainty index. (ii) Breitung and Candelon's (2006) Granger causality test measures the causality in the frequency domain.

4. Conclusions

This study investigates the dependence structure between BTC and EPU indices of USA and China by applying the latest QS dependence approach and wavelet coherence analysis. The findings estimated using daily data covering the period of 1 October 2013 to 31 January 2019 demonstrate that (i) the positive return quantile of BTC and EPU is higher in the short term rather than in the long term, (ii) a strong dependence between BTC and EPU indices is observed during the short-term horizon, i.e., weekly frequency, (iii) the correlation between BTC and EPU is found to be significant and strong during the 2013–2015 period and the short-term investment horizon, i.e., 280–512 day frequency cycle, (iv) the frequency domain causality test shows the evidence of a significant causal relationship running from CHN-EPU to BTC at short-term frequencies. Overall, the results suggest that prevalence of EPU over the long run do not affect BTC returns and BTC provides more diversification benefits during USA-EPU due to its weak dependence and insignificant causality with BTC.

From a policy perspective, our findings are useful to researchers and Bitcoin market participants to understand the diversification benefit of Bitcoin and in making better risk management decisions in terms of portfolio optimization since uncertainty is an important

factor driving investor behavior in financial markets. Furthermore, the announcement of the ban on crypto-trading by the Chinese government to curtail financial losses and prevent economic instability is not the right solution because the ban on crypto-trading has no significant impact on the predictive power of the CHN-EPU for the volatility of Bitcoin. The need of the hour is to develop a more comprehensive regulatory framework for Bitcoin exchange that will protect investors and firms alike. The security risks and financial losses call for risk management approaches and insurance of the individual users of cryptocurrencies. Finally, the hedging quality and diversification benefits of Bitcoin demand the acceleration and prioritization of the development of Blockchain technology (see also Čajková and Čajka (2021) on the sustainability of China's socio-economic development).

Although the findings of this study are relevant to the literature on the role played by Bitcoin in the face of uncertainty, it is not without limitations. In this study, for the measurement of economic policy uncertainty, we used the daily CHN-EPU and US-EPU indices developed by Baker et al. (2016), and the prices of Bitcoin are dominated by USD. In the future, our research can be extended to examine whether our results are sensitive to the use of other uncertainty measures and Bitcoin data dominated in other currencies.

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Data Availability Statement: The price data on Bitcoin (BTC) denominated in USD, that supports the findings of this study, are openly available on the website: <https://bitcoincharts.com> (accessed on 3 March 2019). And the data of the EPU index of USA (USA-EPU) and EPU index of China (CHN-EPU) that support the findings of this study are openly available on the website: <https://www.policyuncertainty.com> (accessed on 3 March 2019).

Conflicts of Interest: The authors declare that they have no conflict of interest.

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