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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 latest methodology of quantile cross-spectral dependence. The findings indicate a positive return interdependence between BTC and EPU is high in short-term, and this dependence decreases as investment horizons increase from weekly to yearly. The information on above interdependence is also extracted by applying wavelet coherence analysis and the estimation results suggest that correlation between BTC and EPU is positive during short-term investment horizon. Furthermore, more diversification benefits of BTC can be obtained during USA-EPU as compared to China-EPU.

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

JEL Classification: C58; D80; G11

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 of central authority. Since its introduction, the Bitcoin price has increased dramatically from $0.09 on 18 July 2010 to $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). 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). In 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; Mokni et al., 2020; Paule-Vianez et al., 2020; Wang et al., 2019).

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 by using the latest methodology of quantile cross-spectral (QS) analysis proposed by Barunik and Kley (2019). Prior studies have ignored the quantile interdependence across varied frequencies in describing the interrelationship between Bitcoin and EPU. In other words, the current study captures the interdependencies at various market conditions across and at different investment horizons. This is important because money market correlation increases during uncertain period (Longin and Solnik, 2001). For further clarification of results with respect to interdependence between Bitcoin and EPU across time frequencies, we have applied wavelet coherence analysis. Finally, Breitung and Candelon's (2006) Granger causality test is applied to investigate the causality between BTC and EPU in frequency domain. The general outcomes of the study indicate that EPU do not affect Bitcoin returns over long terms. Moreover, the weak dependence and insignificant causality between Bitcoin and USA-EPU suggest the better diversification benefits of Bitcoin during USA-EPU.

2. Data and Empirical Analysis Methods

The daily data comprising a total of 1,947 observations and covering the period 01/10/2013 to 31/01/2019 is used for empirical investigation. The price data on Bitcoin (BTC) denominated in US$ is gathered from the website: https://bitcoincharts.com. The data of EPU index of USA (USA-EPU) and EPU index of China (CHN-EPU) is obtained from the website: https://www.policy uncertainty.com.

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 2491.5, followed by CHN-EPU with a value equal to 129.3. The standard deviation of BTC is highest whereas the standard deviation of USA- EPU is 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 Jarque–Bera test statistic suggest that the distribution of selected variables is not normal.

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 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 are able to 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 comovement between time-series of BTC and EPU across frequencies and time scales. This technique has the ability to control for non-linearities, non-stationary, structural breaks, and any seasonality in the linkage between time-series (Roueff and Von Sachs, 2011). Cross-wavelet transformation is used to estimate wavelet coherence following the approach of Reboredo et al. (2017).

3. Results of Empirical Analysis

3.1. Results of Quantile Coherency Estimation

The quantile coherency results estimated by applying 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 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; 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 case of the short-term horizon, i.e., weekly frequency. Moreover, the dependence between BTC and EPU decreases with the decrease in frequency from weekly to yearly. Overall, the estimates indicate that the irregularity in interdependence structure between BTC and EPU depends upon market conditions and investment time horizons.

With respect to weekly frequency, it can be noted that the dependence of 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

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with the study of Cheng and Yen (2020) that CHN-EPU can better predict the BTC monthly returns than USA-EPU.

By using 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 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 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 mean of exchange.

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 vertical axis measures the frequencies. Higher frequencies relate to short-term investment horizon, whereas lowest frequencies relate to 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. Upward direction of arrow indicates that BTC returns leading during economic uncertainty whereas downward direction of arrow indicates that BTC returns 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 short-term investment horizon i.e., 280-512 days frequency band with Bitcoin returns leading during the period of economic uncertainty. Some evidence of relatively strong and significant coherence is also observed during 2013-2014 period and 64-128-days frequency band with leading Bitcoin returns. The evidence of weak and negative coherence is observed at long-term investment horizon and 2-6 days frequency cycle throughout the sample period where Bitcoin returns are lagging during uncertainty. These outcomes support the short-run effectiveness of hedge/diversification benefits of Bitcoin future during uncertainty such as 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 16-512 days frequency cycle during mid 2016-2019 period. At long-investment horizon, the co-movement between BTC and CHN-EPU become weak and insignificant. The evidence of strong coherence from mid-2016-2019 support the conclusion of Cheng and Yen (2020) that the trade ban announced by the Chinese government in 2017 increased the predictive ability of 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 increases during uncertainty that justify the role of Bitcoin as hedging instrument during crisis period.

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 frequency domain. The advantage of this test is that it explains causality between two stationary time-series at various time-scale and across varying frequencies by imposing linear restriction on the autoregressive parameters in a VAR model.

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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 Granger causality test and does not depend on stationary properties of time-series. The outcomes show clear evidence of unidirectional causal relationship from CHN-EPU to BTC. In contrast, we cannot find evidence to prove causality either bidirectional or unidirectional between USA-EPU and BTC. Unfortunately, Toda-Yamamoto causality cannot identify the evidence of causality across different frequency bands, that's why we have 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 Granger cause CHN-EPU at any frequency level. Granger causality from USA-EPU to BTC is significant at 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.

4. Conclusion

This study investigates the dependence structure between BTC and EPU indices of USA and China by applying latest QS dependence approach and wavelet coherence analysis. The findings estimated by using daily data covering the period of 01/10/2013 to 31/01/2019 demonstrate that (i) positive return quantile of BTC and EPU is higher in short term rather in 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 2013-2015 period and short-term investment horizon i.e., 280-512 days frequency cycle. (iv) frequency domain causality test shows the evidence of significant causal relationship running from CHN-EPU to BTC at short-term frequencies. Overall, the results suggest that prevalence of EPU over long-run do not affect BTC returns and BTC provide more diversification benefits during USA-EPU due to its weak dependence and insignificant causality with BTC.

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