Research in International Business and Finance 58 (2021) 101478

Contents lists available at ScienceDirect

Research in International Business and Finance

journal homepage: www.elsevier.com/locate/ribaf

Does economic policy uncertainty affect cryptocurrency markets? Evidence from Twitter-based uncertainty measures

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ARTICLE INFO

JEL classification:
G15
D81
C22

Keywords:
Cryptocurrencies
Economic policy uncertainty
Twitter-based uncertainty measures
Granger causality tests
Recursive evolving window approach
COVID-19 crisis

ABSTRACT

Using daily data from August 9, 2015, to July 7, 2020, this study examines the effects of economic policy uncertainty (EPU) on the returns of four cryptocurrencies: Bitcoin, Ethereum, Litecoin, and Ripple. To this end, two new measures of EPU (Twitter-based economic uncertainty and Twitter-based market uncertainty) are considered. A Granger causality test using the recursive evolving window approach shows a significant causality between the Twitter-based EPU measures and the BTC/USD exchange rate from October 2016 to July 2017. Moreover, a significant causality was noted from the EPU measures to the ETH/USD exchange rate from June 2019 to February 2020 and from the EPU measures to the XRP/USD exchange rate from January 2020 to February 2020. The Twitter-based EPU measures primarily positively affect the returns of the related cryptocurrencies during these periods. These results are robust to different measures of Twitter-based EPU and different econometric techniques. Potential implications, including the COVID-19 era, are also discussed.

1. Introduction

Bitcoin was proposed by Nakamoto (2008) as a digital currency (cryptocurrency) that uses an open-source payment system. Because Bitcoin was created, hundreds of digital coins have been introduced, and their market values have grown substantially. Data from CoinMarketCap (see http://www.coinmarketcap.com) show that as of April 23, 2021, the combined market capitalization of cryptocurrencies was $1.82 trillion, with Bitcoin worth $920 billion (50.5 % of the overall market cap), followed by Ethereum (14 %), Binance Coin (4.2 %), Tether (2.7 %), and Ripple (2.7 %).

Researchers have examined the factors that drive returns for cryptocurrencies because of significant increases in their prices and associated market caps. For example, Caporale et al. (2018) observed a significant persistence in returns for Bitcoin, Dash, Litecoin, and Ripple, thereby implying the presence of abnormal returns and market inefficiencies in those cryptocurrencies. Bariviera (2017); Nadarajah and Chu (2017); Tiwari et al. (2018), and Urquhart (2016) have further supported the "inefficient cryptocurrency markets" hypothesis. Several studies have analyzed cryptocurrencies' price volatility (Caporale and Zekokh, 2019; Elsayed et al., 2021; Katsiampa, 2017, 2019; Katsiampa et al., 2019; Shi et al., 2020), the factors driving attention toward cryptocurrencies (Dastgir et al.,

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https://doi.org/10.1016/j.ribaf.2021.101478
Received 29 July 2020; Received in revised form 5 June 2021; Accepted 10 June 2021
Available online 12 June 2021
0275-5319/

2019; Li et al., 2021; Urquhart, 2018), cryptocurrency speculative bubbles (Corbet et al., 2018), hedging and safe haven properties of cryptocurrencies (Beneki et al., 2019; Conlon et al., 2020; Klein et al., 2018; Liu et al., 2020; Urquhart and Zhang, 2019), and herding behavior regarding cryptocurrencies (Bouri et al., 2019). Corbet et al. (2019) provided an excellent recent review of studies examining different aspects of cryptocurrencies.

It is noteworthy that uncertainties related to economic policy can also affect cryptocurrency markets. Particularly during the Great Global Recession of 2008, uncertainty concerning central banks' monetary policy and government fiscal policy severely weakened the safe-haven properties of traditional assets, and Bitcoin was proposed as an alternative payment and investment tool at the time (Aysan et al., 2019). Given that cryptocurrencies use a decentralized payment system, they are intriguing investment candidates compared to central bank currencies and traditional assets, particularly during high EPU periods. The economic shocks related to the COVID-19 pandemic in early 2020 show that such uncertainties can significantly affect financial markets (Albulescu, 2021; Ashraf, 2020; Goodell, 2020). However, our knowledge of the effect of EPU on cryptocurrency markets during the COVID-19 era is limited (Conlon et al., 2020; Goodell and Goutte, 2021a).

This study examines the effects of changes in economic policy uncertainty (EPU) on cryptocurrency. We expect that fluctuations in an EPU index should significantly affect the returns of cryptocurrencies, thereby forming the study's central hypothesis. To evaluate this issue, we consider the returns of four cryptocurrencies (i.e., Bitcoin, Ethereum, Litecoin, and Ripple) and two new measures of EPU [Twitter-based economic uncertainty (TEU) and Twitter-based market uncertainty (TMU)]. We apply a new Granger causality test using the recursive evolving window approach in Shi et al. (2018). We then implement a wavelet coherence analysis (WCA) to understand the direction of the causal relationship. We further check the robustness of the primary findings from the Granger causality test based on Shi et al. (2018). As our sample covers August 9, 2015, to July 7, 2020, our analyses also capture the COVID-19 era.

To the best of our knowledge, this is the first study in the literature to examine the effects of these two new measures of Twitter-based EPU (i.e., TEU and TMU). Furthermore, this work is the first study in the cryptocurrency literature that uses the new Granger causality test in Shi et al. (2018), which can capture the effects of asymmetries and a neglected nonlinearity in causal relationships. We find a positive correlation between the returns of some cryptocurrencies and economic policy uncertainty shocks, indicating that Bitcoin, Ethereum, and Ripple can hedge against EPU shocks; however, this finding only holds during specific periods. Nevertheless, investors can diversify their portfolio risks by including Bitcoin, Ethereum, and Ripple during times of high EPU.

The remainder of this study is organized as follows. Section 2 reviews the literature on the relationship between EPU and cryptocurrency markets. Section 3 explains the details of the data, empirical models, and econometric procedures used in the study. Section 4 provides the preliminary empirical results with a discussion on the findings and checks the robustness of the primary findings. Section 5 offers concluding remarks.

2. Literature review

Previous studies have examined the effects of shocks (generally measured using the EPU index) on cryptocurrency markets. Bouri et al. (2017) were the first to analyze the causal relations between market shocks and Bitcoin returns by using the implied volatility (VIX) series for 14 equity markets in advanced and emerging economies. Their results indicate that Bitcoin can hedge uncertainty shocks as measured by the VIX. Demir et al. (2018) were the first to examine the effect of EPU shocks on Bitcoin. Using daily data for Bitcoin returns, the authors found that EPU has a significant predictive power for Bitcoin, which can be used as a hedging tool against uncertainty shocks measured using an EPU index for the United States (US). Gozgor et al. (2019) investigated the causal relationship between the trade policy uncertainty (TPU) index for the US and Bitcoin returns. Applying several Wavelet test procedures, they found a positive correlation between the TPU index and Bitcoin and concluded that Bitcoin could be an effective hedge against trade policy-related uncertainty shocks but only for specific periods.

Fang et al. (2019) observed that using the global EPU index improves the predictive power concerning Bitcoin's price volatility. However, the authors show that Bitcoin has a limited capacity as a hedge under specific conditions of economic uncertainty. The global EPU index increases correlations between Bitcoin and stocks and between Bitcoin and commodities; however, it negatively affects the correlation between Bitcoin and treasury bonds. Ji et al. (2019) investigated the connectedness among returns in six cryptocurrency markets and observed that Litecoin and Bitcoin are at the center of the connectedness. The spillover of negative returns is significantly larger than that of positive returns. Furthermore, a global EPU index and trading volumes are the primary determinants of connectedness among cryptocurrency returns. However, Wu et al. (2019) found that both gold and Bitcoin provide only weak hedging abilities versus global EPU across bearish, bullish, and normal market conditions and conclude that Bitcoin and gold should only be used for portfolio diversification purposes under normal market conditions. Using monthly data, Cheng and Yen (2020) showed that an EPU index for China could predict Bitcoin returns; however, it has an insignificant impact on other major cryptocurrencies. Furthermore, EPU indices for the US and other Asian countries have no significant effect on returns for Bitcoin or other major cryptocurrencies. Wang et al. (2020) extended Cheng and Yen's (2020) findings using the price of Bitcoin against both the British Pound (GBP) and the US Dollar (USD). Using the dynamic conditional correlation (DCC)-generalized autoregressive conditional heteroskedasticity (GARCH) model, they found the impact of EPU in the US on the BTC/USD exchange rate is significantly higher than the impact of EPU in the United Kingdom on the BTC/GBP exchange rate.

According to this review, several studies have investigated the effects of EPU indices on cryptocurrency returns by using various EPU indices (e.g., global EPU and EPU for China, the United Kingdom, and the US) based on various cryptocurrencies. Most studies still focus primarily on the Bitcoin market. This study contributes to the literature by using two new measures of EPU, namely the TEU and TMU indices, and the returns for four cryptocurrencies (i.e., Bitcoin, Ethereum, Litecoin, and Ripple). Social media (particularly Twitter data) has been used in the cryptocurrency literature. For example, using linear and nonlinear Granger causality test procedures, Shen et al. (2019) found that attention to Bitcoin, measured using Twitter data, is a significant driver of both the following day's trading volume and realized price volatility for Bitcoin.

We use the new Granger causality test that uses the evolving recursive window in Shi et al. (2018) to capture the effects of asymmetries and a neglected nonlinearity in causal relationships. The test results show that Bitcoin, Ethereum, and Ripple have a limited hedging capacity against EPU shocks as measured by the Twitter-based EPU indices. Nevertheless, traders must diversify their portfolio by including Bitcoin, Ethereum, and Ripple during times of high EPU. We found positive correlations between cryptocurrency returns and the EPU measures.

3. Data, models, and econometric procedures

3.1. Data and empirical models

In this study, we focus on the log-returns of four cryptocurrencies whose prices are quoted in USD, namely Bitcoin (BTC/USD), Ethereum (ETH/USD), Litecoin (LTC/USD), and Ripple (XRP/USD). We analyze the period from August 9, 2015, to July 7, 2020, using Yahoo! Finance data.

We use the TEU and TMU indices introduced by Baker et al. (2016) on their website.[1] The TEU and TMU indices are based on counts of the use of keywords related to "uncertainty in the economy" and "uncertainty in equity markets," respectively. The data, which are scaled to an average value of 100 over the period 2010–2015 to create the TEU and TMU indices, capture all English-language tweets. However, Baker et al. (2016) explained that US-based EPU heavily influences these indices because of the significant share of tweets originating from the US compared to the rest of the world. The starting date of the empirical analysis is based on data availability for the prices of the four cryptocurrencies. Overall, we have 1783 daily observations.

The empirical models are estimated as follows:

$$\Delta LogCryptocurrency\_Return_t = \alpha_0 + \alpha_1 \Delta LogTwitter\_Uncertainty_{t-k} + \mu_{t1} \tag{1}$$

$$\Delta LogTwitter\_Uncertainty_t = \beta_0 + \beta_1 \Delta LogCryptocurrency\_Return_{t-k} + \mu_{t2} \tag{2}$$

In Eqs. (1) and (2), *ΔLogCryptocurrency_Return* represents the log-returns of four cryptocurrencies (i.e., ΔLogBTC_USD, ΔLogETH_USD, ΔLogLTC_USD, and ΔLogXRP_USD) over the period from t to $t-k$. *ΔLogTwitter_Uncertainty* denotes the log changes of two measures of Twitter-based uncertainty (ΔLogTEU and ΔLogTMU) over the period from t to $t-k$. μ_{t1} and μ_{t2} are error terms.

3.2. Econometric procedures

In the econometrics literature, the Wald test of restrictions is explained by the null hypothesis that the dependent variable (*Y)* does not affect the explanatory variable (*X*) and vice versa (Gozgor, 2015). However, causal relationships can change over time because of factors, such as fluctuations in EPU. Traditional Granger causality analyses provide exogenous and static test statistics based on the complete sample, ignoring potential changes in the economic policy or the economy's structure. The Granger causality test introduced by Shi et al. (2018) allows the data to define a dynamic test procedure and the change points endogenously.

Shi et al. (2018) proposed a new test based on the supremum norm (also known as the Chebyshev norm) of a series of recursively evolving Wald test statistics. For each fractional observation (f), where ($f \in [f_0, 1]$), f_0 represents the minimum sample size in the regression. Wald test statistics are calculated for each subsample by using observations over $[f_1, f_2]$, and the sample size fraction (f_w) is $f_2 - f_1 \geq f_0$ is defined as $W_{f2}(f_1)$. The supremum Wald test statistic for all observations until the latest observation ($f = f_2$) can be written as follows (Shi et al., 2018: 969):

$$SW_f(f_0) = \sup\{W_{f2}(f_1)\}_{(f1f2)\in\tau0, f2=f} \tag{3}$$

In Eq. (3), $\tau_0 = \{(f_1, f_2): 0 < f_0 + f_1 \leq f_2 \leq 1, \text{ and } 0 \leq f_1 \leq 1 - f_0\}$ for minimum sample size (f_0) $\in$ (0,1) in the regressions. The approach in Eq. (3) is defined as the recursive evolving procedure.

Let us assume that f_e and f_f represent the origination and termination points in the causality relationship, respectively. These points are estimated from the first observations whose test statistics exceed or are less than the critical value. At this stage, the recursive evolving test statistic and critical value can be written as follows (Shi et al., 2018: 969):

$$\widehat{f}_e = inf_{f\in[f_0,1]}\{f : SW_f(f_0) > scv\} \text{ and } \widehat{f}_f = inf_{f\in[\widehat{f}_e,1]}\{f : SW_f(f_0)\} < scv \tag{4}$$

In Eq. (4), *scv* is the critical value obtained from SW_f (the Supremum Wald statistic). The origination and termination points can experience multiple changes over the entire period; a given episode i represents the origination and termination points, and $i \geq 2$.

Furthermore, following Goodell and Goutte (2021a), we implement the WCA of Aguiar-Conraria et al. (2008) and phase analysis with different frequency bands. Therefore, we can detect the direction of causal relationships, whether uncertainty measures lead to cryptocurrency returns or vice versa at various points of their distributions with different lags. If the phase is between 0 and π/2 (an "in-phase condition"), the causal relationship has the same direction (a positive relationship), and EPU leads to cryptocurrency returns.

[1] See http://www.policyuncertainty.com for details of the new Twitter-based EPU indices.

Table 1
Descriptive Statistics and Preliminary Tests.

Variable	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque Bera	ADF	PP	KPSS	ZA	ARCH-LM(10)	Obs.
ΔLogBTC_USD	0.201	21.45	−31.59	4.092	−0.604*	9.087*	2861*	−12.47*	−43.63*	0.225	−13.23*	128.2*	1783
ΔLogETH_USD	0.312	43.27	−42.35	6.599	0.318*	9.491*	3160*	−11.79*	−42.23*	0.482	−12.36*	189.9*	1783
ΔLogLTC_USD	0.135	51.14	−44.90	5.554	0.778*	16.12*	12,972*	−12.06*	−42.38*	0.233	−12.74*	83.12*	1783
ΔLogXRP_USD	0.171	102.7	−61.62	6.723	2.919*	47.84*	151,943*	−10.87*	−43.33*	0.224	−11.50*	185.8*	1783
ΔLogTEU	0.333	2679	−2326	133.4	1.807*	147.5*	1,552,361*	−15.69*	−78.89*	0.007	−15.86*	608.2*	1783
ΔLogTMU	0.266	2954	−2648	172.7	1.766*	99.37*	690,891*	−17.16*	−79.25*	0.005	−17.47*	538.6*	1783

Note: * $p < 0.01$.

Table 2
Correlation Matrix.

Variable	ΔLogBTC_USD	ΔLogETH_USD	ΔLogLTC_USD	ΔLogXRP_USD	ΔLogTEU	ΔLogTMU
ΔLogBTC_USD	1.000	–	–	–	–	–
ΔLogETH_USD	0.472	1.000	–	–	–	–
ΔLogLTC_USD	0.075	0.016	1.000	–	–	–
ΔLogXRP_USD	0.007	0.073	0.431	1.000	–	–
ΔLogTEU	0.013	0.010	0.038	0.017	1.000	–
ΔLogTMU	0.007	0.007	0.041	0.021	0.703	1.000

Table 3
Normality Tests.

Variable	Bartels Test	Mann–Kendall Rank Test	Robust Jarque–Bera Test
ΔLogBTC_USD	2.177	−1.669	9459*
ΔLogETH_USD	1.217	−0.244	9577*
ΔLogLTC_USD	1.979	−0.673	53,698*
ΔLogXRP_USD	1.877	0.573	1,607,208*
ΔLogTEU	1.036	−0.457	17,329,713*
ΔLogTMU	−0.554	−0.921	9,856,434*

Note: * $p < 0.01$.

Table 4
Nonlinearity Tests.

Variable	Likelihood-Ratio Test	NN Test	Tsay Test
ΔLogBTC_USD	30.59*	58.74*	5.847*
ΔLogETH_USD	60.17*	20.68*	1.720*
ΔLogLTC_USD	36.60*	20.84*	2.662*
ΔLogXRP_USD	121.5*	119.9*	6.110*
ΔLogTEU	188.2*	262.8*	4.184*
ΔLogTMU	174.1*	244.3*	4.611*

Note: * $p < 0.01$.

If the phase is between $-\pi/2$ and 0 (an "in-phase" condition), the causal relationship is in the same direction (a positive relationship), and cryptocurrency returns lead to EPU. If the phase is between $\pi/2$ and π (the "out-of-phase condition"), the causal relationship is opposite (a negative relationship), and cryptocurrency returns lead to EPU. Finally, suppose the phase is between $-\pi$ and $-\pi/2$ (an "out-of-phase" condition). In that case, the causal relationship is in the opposite direction (a negative relationship), and EPU leads to cryptocurrency returns (Aguiar-Conraria and Soares, 2014).

4. Empirical findings

4.1. Preliminary findings

Table 1 presents descriptive statistics and preliminary findings for the variables used in the analyses. According to the findings, all cryptocurrencies experienced positive returns over the period. Furthermore, on average, the indicators of the EPU increased. The Jarque–Bera test results indicate that the returns of cryptocurrencies and changes in the EPU measures do not follow a normal distribution. Therefore, we should use a causality test to capture the non-normality (of the variables. Furthermore, standard unit root tests, such as the Augmented Dickey-Fuller (ADF), Phillips–Perron (PP), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Zivot–Andrews (ZA) tests show that the time series of log returns and changes in the EPU indices follow a stationary process. Furthermore, the autoregressive conditional heteroskedasticity-Lagrange multiplier (ARCH-LM) test shows no concern regarding autocorrelation in the series. Overall, the preliminary results indicate that the current structure of the variables can be used in a Granger causality analysis.

Table 2 shows the correlation matrix for the variables in the analyses. The correlations between the log-returns of the four cryptocurrencies are positive. Interestingly, the correlation between BTC/USD and ETH/USD and between LTC/USD and XRP/USD returns is 0.472 and 0.431, respectively. This evidence suggests that the Bitcoin and Ethereum markets are connected and that the Litecoin and Ripple markets tend to move together more than the3 other cryptocurrency markets. The correlations between the log-returns of the four cryptocurrencies and Twitter-based EPU indices are also positive; however, the correlation coefficients are substantially smaller, ranging from 0.007 to 0.041. The correlation between the two Twitter-based EPU indices (i.e., the TMU and TEU) is 0.703, thereby showing that these indices move together. However, the TMU and TEU indices measure different things because the correlation

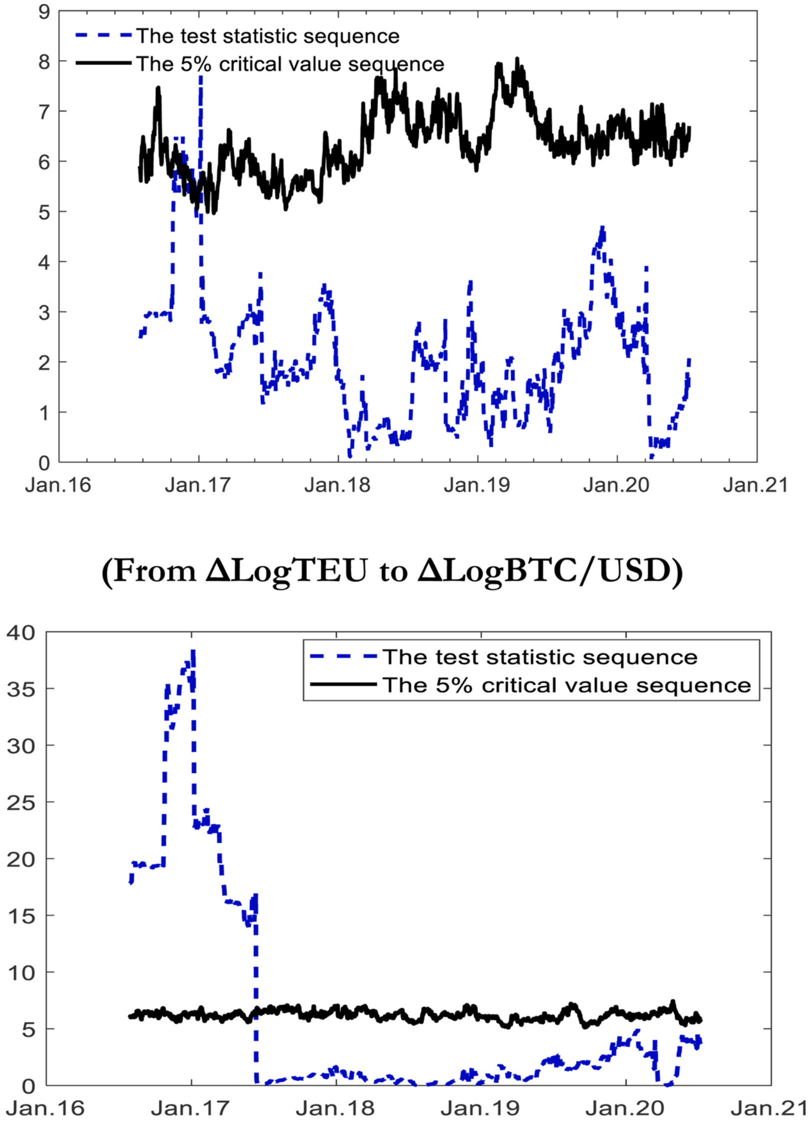


Fig. 1. Results of Causality Analysis of Shi et al. (2018) for Bitcoin Market and TEU.

between them is less than 0.80.

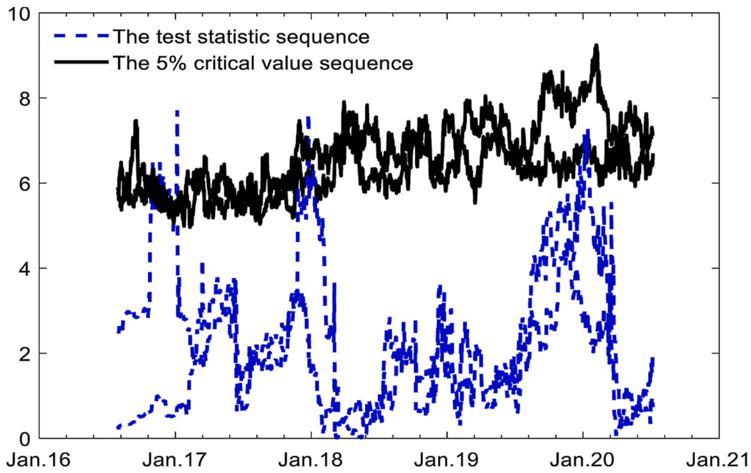
Table 3 provides the results of additional tests of normality. Normality tests can be relevant before conducting a causality analysis because we must capture asymmetries in the time series. Here, the results of three normality tests (i.e., Bartels, Mann–Kendall Rank, and Robust Jarque–Bera) discussed in Gel and Gastwirth (2008) are reported. The null hypothesis of the Bartels and Mann–Kendall Rank tests is that the time series follows a non-normal distribution, and that of the Robust Jarque–Bera test is a normal distribution. Therefore, the results show that these time series do not follow a normal distribution, and the causality test that captures the asymmetric effects in the causality analysis must be considered.

Table 4 reports the findings of three test statistics for neglected nonlinearity. First, we consider the likelihood-ratio test used in Chan (1991), where the null hypothesis is that the series follows a linear autoregressive (AR) process. Second, we consider the Neural Network (NN) test in Terasvirta et al. (1993), where the null hypothesis indicates "linearity in the mean." Third, we run the nonlinearity test used in Tsay (1986), where the null hypothesis states that the model follows an AR process. All three tests indicate that all-time series have neglected nonlinearity; therefore, we must use a causality test that captures the nonlinear effects in the analysis.

We then provide the results of the Granger causality test used in Shi et al. (2018), which captures asymmetric effects and nonlinearity in the causal relationships.

4.2. Primary findings: causality between changes in TEU and cryptocurrencies returns

We provide the Granger Causality test results in Shi et al. (2018), introducing the recursive evolving window approach to analyze



(From ΔLogTEU to ΔLogETH/USD)

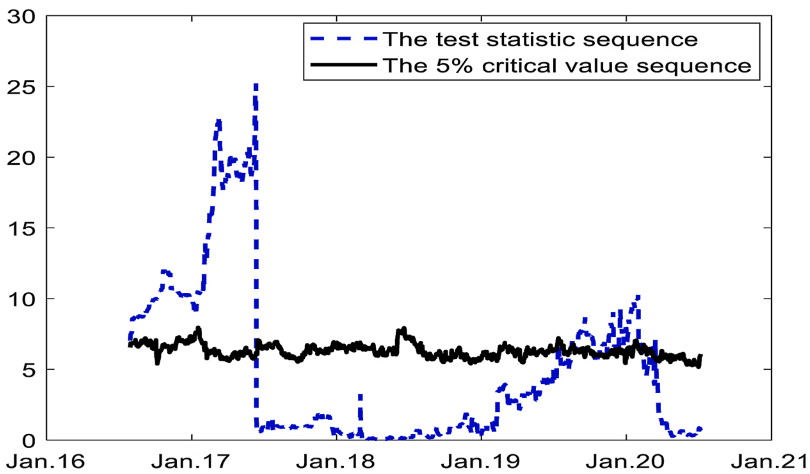


Fig. 2. Results of Causality Analysis of Shi et al. (2018) for Ethereum Market and TEU.

the relationship between the TEU index and returns for the four cryptocurrencies. Following Shi et al. (2018), we set the initial date as October 27, 2016.[2]

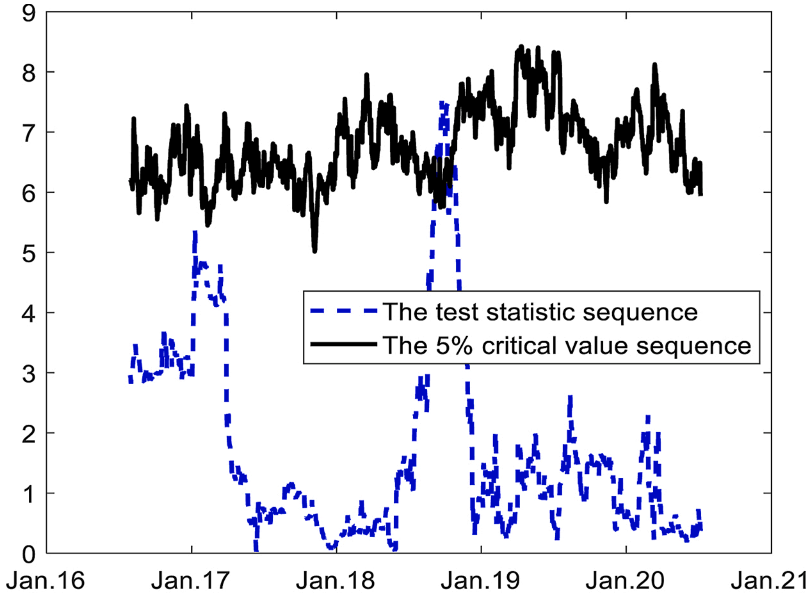
Fig. 1 shows the results of the time-varying causal relationship between BTC/USD returns and the TEU index. According to the findings, a significant causality (at the 5% level) is observed from the BTC/USD returns to changes in the TEU but only from October 2016 to January 2017. Changes in the TEU significantly result in BTC/USD returns from October 2016 to July 2017.

Fig. 2 reports the findings of a time-varying causality between ETH/USD returns and changes in the TEU index. The results show a significant causality (at the 5% level) from the ETH/USD returns to changes in the TEU from October 2016 to January 2017. Changes in the TEU significantly yield ETH/USD returns from October 2016 to July 2017 and from October 2019 to February 2020.

Fig. 3 illustrates the time-varying causal relationship between LTC/USD returns and changes in the TEU. The findings show a significant causality (at the 5% level) from LTC/USD returns to changes in the TEU index for a brief period from November 2018 to December 2018. Changes in the TEU index significantly caused LTC/USD returns from October 2016 to July 2017.

Fig. 4 represents the findings of a time-varying causality between XRP/USD returns and changes in the TEU index. The results show no significant causality from XRP/USD returns to changes in the TEU. However, changes in the TEU significantly cause XRP/USD returns in two months from October 2019 to November 2019 and January 2020 to February 2020.

[2] According to Shi et al. (2018), Starting Observation = Total Observation/4. Because we have 1783 observations, the starting observation is 446, which is October 27, 2016.



(From ΔLogTEU to ΔLogLTC/USD)

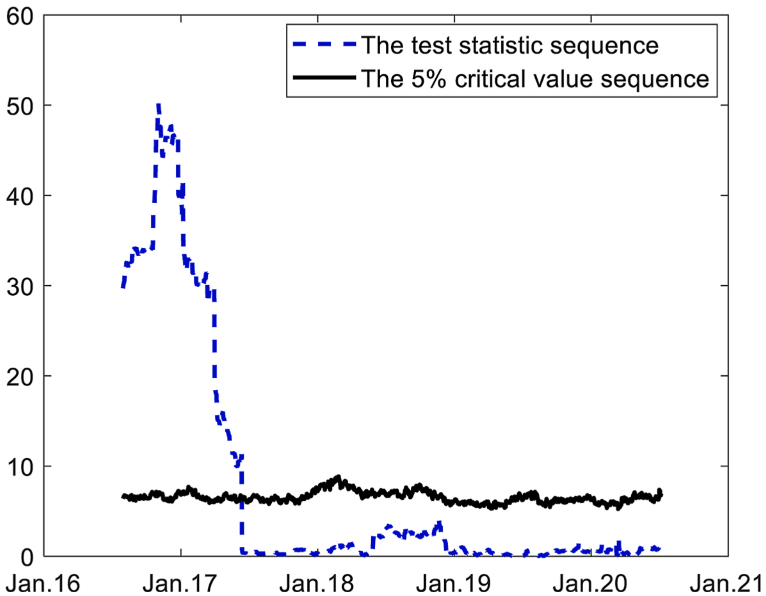


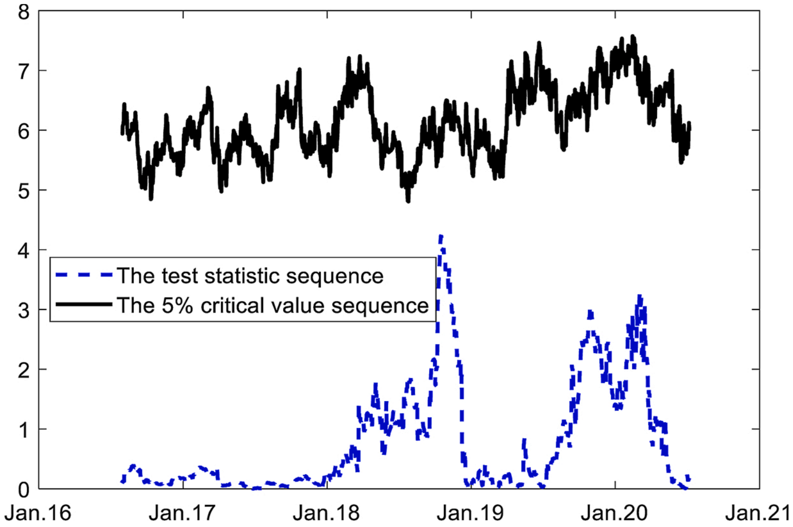
Fig. 3. Results of Causality Analysis of Shi et al. (2018) for Litecoin Market and TEU.

4.3. *Robustness checks*

4.3.1. *Findings from the TMU Index*

We then report findings from the Granger causality test in Shi et al. (2018) for the relationship between the TMU index and the returns of the four cryptocurrencies. As in the previous section, the recursive evolving window approach is used, and the initial date is October 27, 2016.

Fig. 5 shows the time-varying causal relationship between BTC/USD returns and changes in the TMU. A significant causality (at the 5% level) is observed from BTC/USD returns to changes in the TMU for two months, from January 2019 to February 2019 and from January 2020 to February 2020. Moreover, changes in the TMU significantly cause BTC/USD returns for long periods from October 2016 to July 2017 and from June 2019 to October 2019. Overall, only the causality from Twitter-based indices to BTC/USD returns



(From ΔLogTEU to ΔLogXRP/USD)

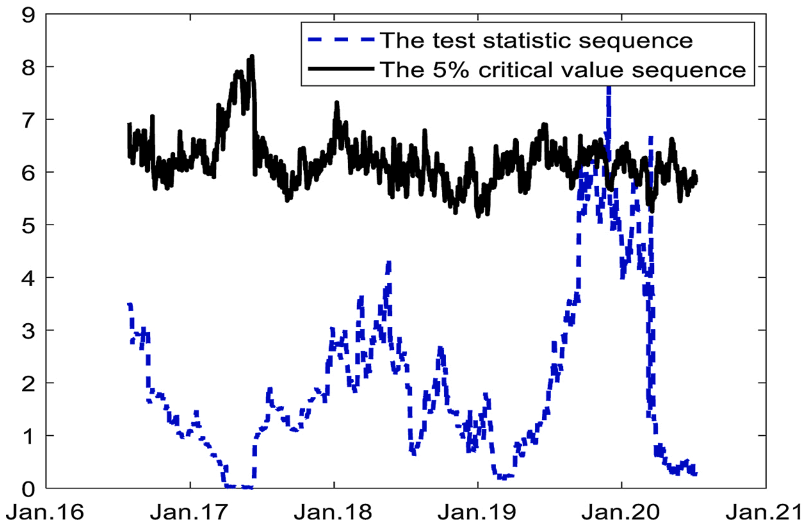


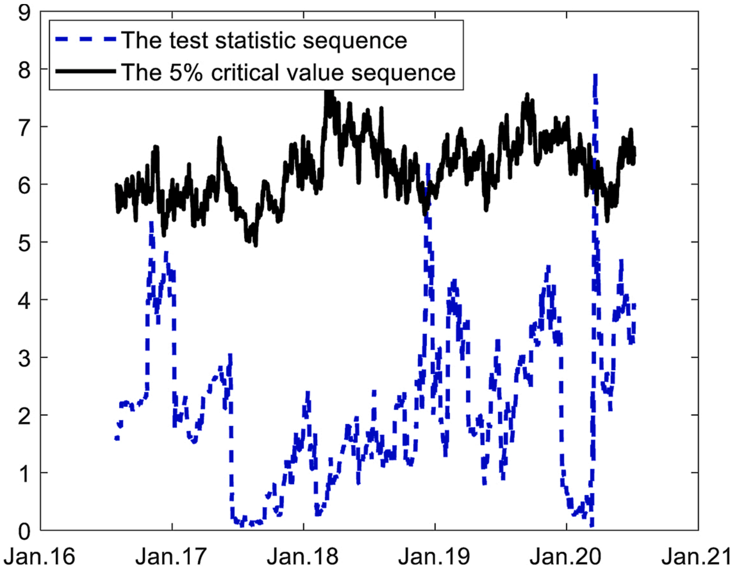
Fig. 4. Results of Causality Analysis of Shi et al. (2018) for Ripple Market and TEU.

during the period from October 2016 to July 2017 is robust to using different measures of Twitter-based EPU.

Fig. 6 reports the time-varying causality between ETH/USD returns and changes in the TMU index. The results indicate a significant causality (at the 5% level) from ETH/USD returns to changes in the TMU index from October 2018 to January 2019 and February 2020 to March 2020. Furthermore, changes in the TMU index significantly cause the ETH/USD returns from October 2016 to July 2017 and from June 2019 to February 2020. In summary, the only causality from changes in the Twitter-based uncertainty indices to ETH/USD returns during the periods from October 2016 to July 2017 and from June 2019 to February 2020 is robust to using different Twitter-based uncertainty measures.

Fig. 7 illustrates the results of analyzing the time-varying causal relationship between LTC/USD returns and changes in the TMU. The findings indicate no significant causality between LTC/USD returns and changes in the TMU; however, changes in the TMU significantly cause LTC/USD returns for the one month from February 2020 to March 2020.

Fig. 8 presents the time-varying causality between XRP/USD returns and changes in the TMU index. The results show no significant causality between XRP/USD returns and changes in the TMU; however, changes in the TMU significantly cause XRP/USD returns from June 2019 to February 2020.



(From ΔLogTMU to ΔLogBTC/USD)

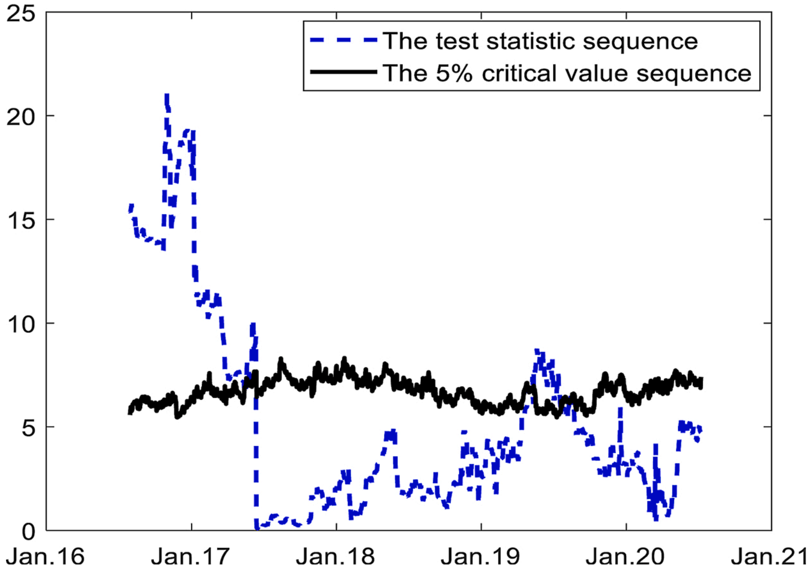


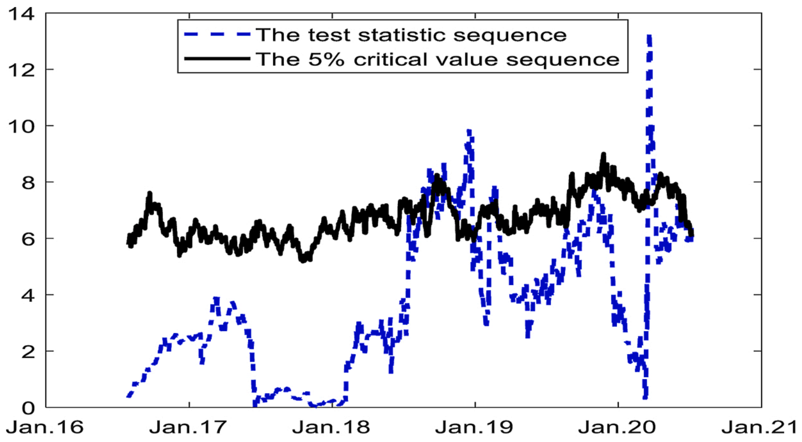
Fig. 5. Results of Causality Analysis of Shi et al. (2018) for Bitcoin Market and TMU.

4.3.2. Findings from the wavelet coherence analysis

In the Appendix, Figures I–VIII show the findings from the WCA. Figures I and V in the Appendix confirm a significant causality from changes in the Twitter-based EPU indices to BTC/USD returns from October 2016 to July 2017. Figures II and VI in the Appendix also show a significant causality from the TEU indices to ETH/USD returns from June 2019 to February 2020. Finally, Figures IV and VIII in the Appendix indicate a significant causality from the TEU indices to XRP/USD returns from January 2019 to February 2020. The relationships between the related variables are positive because most of the phase differences for different bands range from 0–π/2.

4.4. Discussion and potential implications

Our results, including various robustness checks, show a significant causality from the Twitter-based EPU indices to BTC/USD returns from October 2016 to July 2017. A significant causality is also observed from the Twitter-based EPU measures to ETH/USD



(From ΔLogTMU to ΔLogETH/USD)

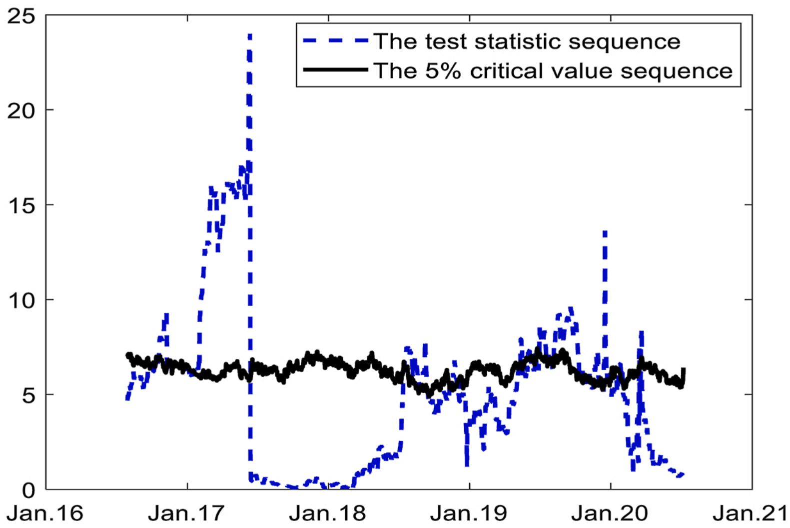


Fig. 6. Results of Causality Analysis of Shi et al. (2018) for Ethereum Market and TMU.

returns from June 2019 to February 2020. Finally, we found a significant causality from the Twitter-based EPU indices to XRP/USD returns from January 2020 to February 2020. The TEU indicators positively affect returns for the relevant cryptocurrencies during these periods. The results are robust to using different measures of TEU and different econometric techniques. These findings are consistent with Fang et al. (2019) and Gozgor et al. (2019), who revealed that Bitcoin has a limited hedging capacity against EPU shocks. This study expands their findings to three cryptocurrencies, namely, Bitcoin, Ethereum, and Ripple.

Our results indicate that an increase in EPU causes higher returns for Bitcoin, Ethereum, and Ripple. Therefore, we suggest that these cryptocurrencies can be considered as hedges against changes in EPU. However, the effect is temporary; therefore, dynamic portfolio risk management with efficient diversification would be required. Market participants in related cryptocurrency markets can also benefit from our findings. For example, investors and traders should follow Twitter, particularly tweets from the US, when holding and modifying positions in these cryptocurrencies.

Finally, we did not observe a significant causal relationship between the Twitter-based EPU indices and the returns for the four cryptocurrencies during the COVID-19 era. Therefore, we conclude that although cryptocurrencies have some hedging capacity against changes in EPU, this feature is valid only in specific periods and does not include the COVID-19 era. Other forces have also impacted the cryptocurrency "ecosystem," and thus, relationships between the EPU and Bitcoin. that existed a few years ago are no longer apparent. It is difficult to know whether the COVID-19 is affected or not (Goodell and Goutte, 2021b). Therefore, future research must update our data for the COVID-19 era to include newer data.

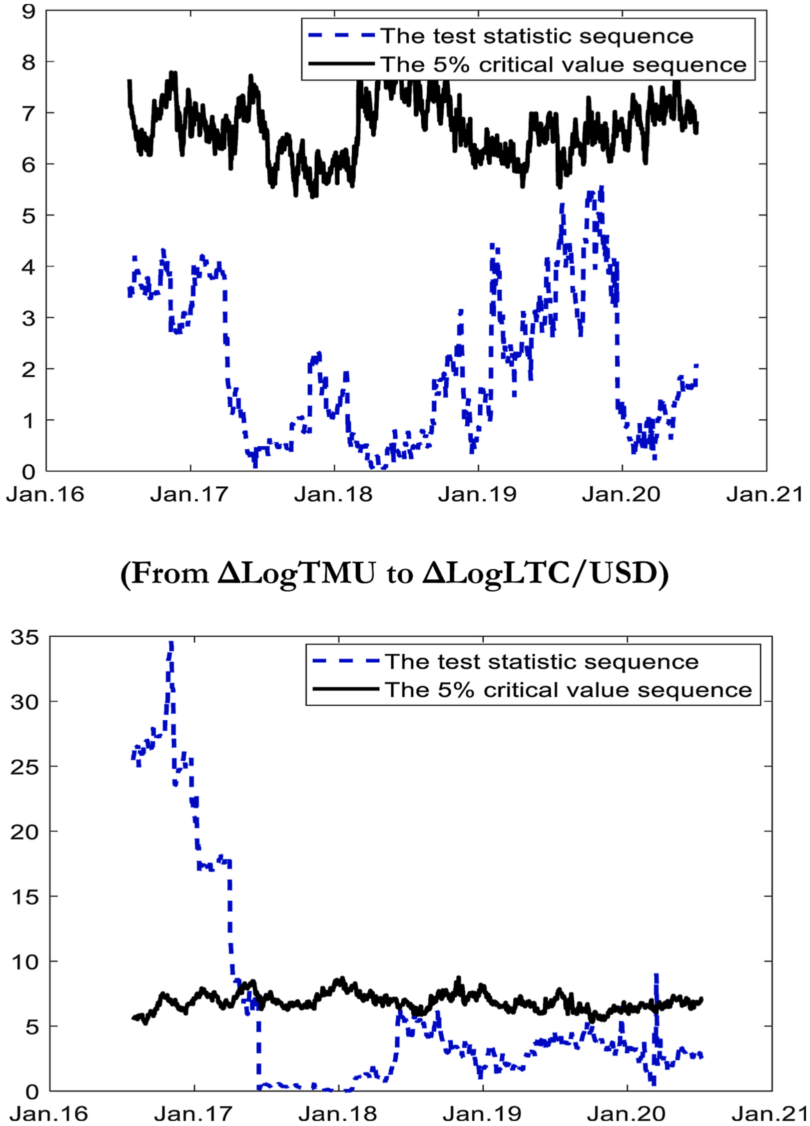
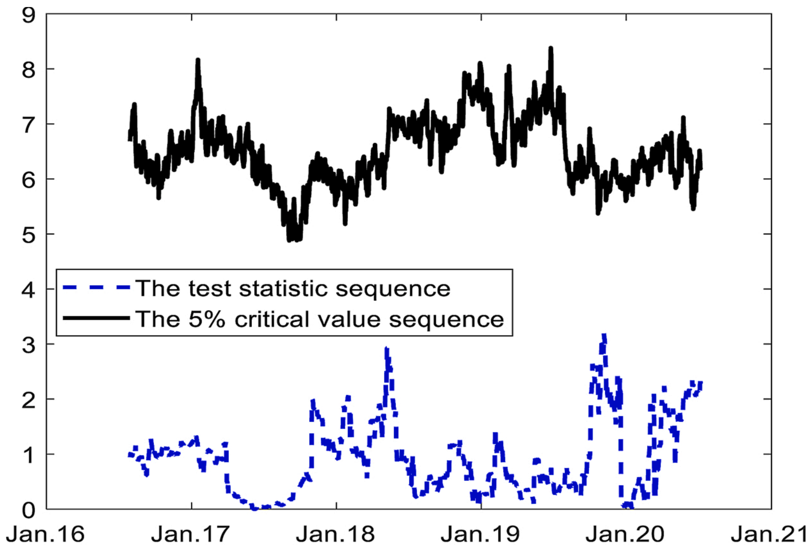


Fig. 7. Results of Causality Analysis of Shi et al. (2018) for Litecoin Market and TMU.

5. Concluding remarks

This study analyzes the effects of EPU measures on the returns for four cryptocurrencies, namely, Bitcoin, Ethereum, Litecoin, and Ripple, from August 9, 2015, to July 7, 2020. The EPU was measured using new EPU indices, the TEU and TMU indices. We applied the Granger causality test with the recursive evolving window approach and the WCA analyses to the data. The results indicate a significant causality from changes in the EPU indices to BTC/USD returns from July 2016 to July 2017, from changes in the EPU measures to ETH/USD returns from June 2019 to January 2020, and from changes in the EPU measures to XRP/USD returns from January 2020 to February 2020. Notably, changes in the Twitter-based EPU indices are positively related to the returns for these cryptocurrencies during these periods. We did not find a significant causal relationship between changes in the EPU indices and cryptocurrency returns during the COVID-19 era.

These results indicate that three cryptocurrencies (i.e., Bitcoin, Ethereum, and Ripple) have a limited hedging capacity against changes in EPU in specific periods, which does not include the COVID-19 era. However, the results suggest that Bitcoin, Ethereum, and Ripple could be used for portfolio diversification purposes. Future studies could implement different econometric techniques to investigate the effects of EPU on cryptocurrencies. Notably, as stated in Goodell (2020), our knowledge of the determinants of cryptocurrencies' returns and volatility levels during the COVID-19 era must be enhanced.



(From ΔLogTMU to ΔLogXRP/USD

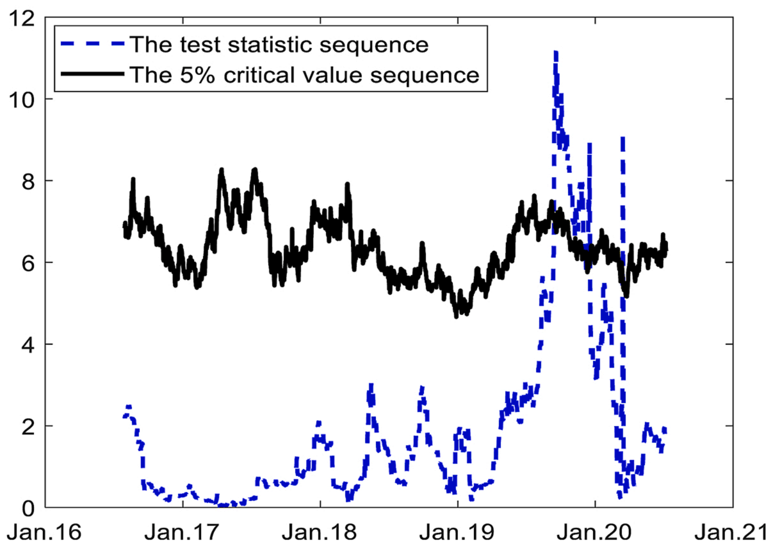


Fig. 8. Results of Causality Analysis of Shi et al. (2018) for Ripple Market and TMU.

CRediT authorship contribution statement

Wanshan Wu: Investigation, Validation, Visualization, Writing - original draft. **Aviral Kumar Tiwari:** Formal analysis, Methodology, Software, Writing - review & editing. **Giray Gozgor:** Conceptualization, Data curation, Supervision, Writing - original draft. **Huang Leping:** Visualization, Writing - review & editing.

Acknowledgments

We acknowledge the National Social Science Fund of China (16BJY052); the Fundamental Research Funds for the Provincial Universities of Zhejiang (GB201902002 & GB202002003); the Major Humanities and Social Sciences Research Projects in Zhejiang Province (2021QN050); the Humanities and Social Sciences Pre-Research Fund of the Zhejiang University of Technology, and Guangdong Philosophy and Social Science Planning Project (GD19CJY22).

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ribaf.2021.101478.

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