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Does Uncertainty Indices Impact the Cryptocurrency Market?

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Abstract: Research Question: Does uncertainty indices have impact on cryptocurrency? **Motivation:** Most of the previous study investigate the impact of geopolitical risk and economic policy uncertainty on Bitcoin only and less research investigate the long run and short run relationship between the uncertainty indices and cryptocurrency. Hence, this study investigates whether the economic policy uncertainty, geopolitical risk and US equity market uncertainty have an impact on Bitcoin, Ethereum and Binance Coin by the multivariate VAR Granger non-causality. **Idea:** This study applied three different uncertainty indices (geopolitical risk, economic policy uncertainty and US equity market uncertainty) and top three ranking cryptocurrency (Bitcoin, Ethereum and Binance Coin) to investigate and compare the impact of uncertainty indices on cryptocurrency with different uncertainty conditions and applied top three ranking cryptocurrency in cryptocurrency market to reinforce the result. **Data:** This study applied monthly data with 42 observations which cover the period of December 2017 until May 2021 and data for cryptocurrency extracted from investing.com, while the uncertainty indices from policyuncertainty.com. **Method/Tools:** This study utilize multivariate VAR Granger non-causality to examine the cointegration relationship between the cryptocurrency and uncertainty indices. **Findings:** The results show that the economic policy uncertainty, geopolitical risk and US equity market uncertainty cointegrated with Bitcoin, while Binance Coin cointegrated with geopolitical risk only. Hence, the economic policy uncertainty, geopolitical risk and US equity market uncertainty plays a vital role in the Bitcoin prediction and geopolitical risk plays an important role to forecast the Binance Coin. **Contributions:** The Bitcoin investors may focus on the changes in economic policy uncertainty, geopolitical risk and US equity market uncertainty to predict the Bitcoin return, and Binance Coin investors focus on the geopolitical risk.

Keywords: Geopolitical risk, economic policy uncertainty, US equity market uncertainty, cryptocurrency.
JEL Classification: G1, G4

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1. Introduction

The blockchain system facilitates trusted transactions between untrusted participants through its cryptographic-based distributed ledger (Taylor *et al.*, 2020). As blockchain technology grows in popularity, a variety of applications are being used by businesses and private users. For businesses, blockchain is primarily applied to optimize the data storage, as well as data sharing, whereas cryptocurrency is its most popular use among private users (Teichmann and Falker, 2020). In November 2008, Satoshi Nakamoto proposed Bitcoin during the global financial crisis. His whitepaper, 'Bitcoin: A Peer-to-Peer Electronic Cash System', describes Bitcoins and its payment systems with technical details. This would enable consumers to manage their payments without involving any financial intermediaries (Nakamoto, 2008). Bitcoins launch and take advantage of a highly uncertain environment after the global financial crisis. Bitcoin is one of the cryptocurrencies, which is a form of electronic money. It is a digital currency decentralized fully without central authority and intermediaries required but from the Bitcoin blockchain network. The worsening economic conditions is believed can affect the Bitcoin volatility and infect the Bitcoin returns directly (Chaim and Laurini, 2018). In some cases, it can act as a safe-haven asset. Hence, with this property, the Bitcoin has received a significant amount of critical attention in the global economy as an investment strategy.

The network economics play a critical role to cryptocurrencies. Development of technology and innovation are closely related to network economics in cryptocurrency. Economic policy uncertainty and geopolitical risk can affect the pace of cryptocurrency innovation and application development. Startups and developers may be hesitant to pursue cryptocurrency-related projects due to uncertain regulatory environments and slow down the technological advancements. Furthermore, cryptocurrency relies on the network effects, as more participants join the cryptocurrency network, its value and utility increase. The adoption, acceptance and liquidity of cryptocurrency can be enhanced by effective network effect but it is possible to disrupt by the economic policy uncertainty and geopolitical risk, which negative events or regulatory actions can reduce confidence and impede the growth of networks.

Besides, the economic policy uncertainty and geopolitical risk have contingent spillover effect on cryptocurrency. Economic policy uncertainty and geopolitical risk could spread negative sentiment and market disturbance across different markets, including cryptocurrency. The volatility can be amplified and affect investor behaviour when crisis or shocks occur. The risk perception and investor behaviour in cryptocurrency market could affected by economic policy uncertainty and geopolitical risk. In exhibiting herd behaviour, investors can intensify market movements and volatile the prices. As a result of uncertain circumstances, the cryptocurrency may also perceive as riskier by risk-averse investors, which may increase the demand for traditional safe-haven assets and decreasing participation in cryptocurrency.

Geopolitical risks can be defined as the risk of events such as wars, terrorist attacks, and political tensions threatening foreign relations' normal and peaceful nature (Caldara and Iacoviello, 2018).[1] Most previous studies investigate the impact of geopolitical risks on the stock markets and oil price. Kannadhasan and Das (2020), for instance, investigate the impacts of geopolitical risks and global economic policy uncertainty on the stock return. They find that both indicators have a negative impact on the stock return, with the impact of policy uncertainty is more substantial than geopolitical risk. Balcilar *et al.* (2017), on the other hand, find that geopolitical risk typically influences stock market volatility measures and not on

[1] The coronavirus disease (COVID-19) outbreak contains the potential to affect the geopolitical risk. Sharif *et al.* (2020), for example, find that the United States (US) geopolitical risk was more significant by the outbreak of COVID-19 than US economic uncertainty.

returns. The geopolitical risk also affects the oil price index. Antonakakis *et al.* (2017) discover that, in terms of average return and variability, the oil price index tends to be more strongly influenced negatively by the geopolitical tension index compared to the stock market.

Due to its characteristic as a highly volatile asset, Bitcoin becomes a major subject in the financial press and academia. Most of the study investigate the impact of geopolitical risk on stock or oil price. The geopolitical risk and economic policy uncertainty leads to weakening the investor's trust in the currencies or economy, especially the geopolitical risk in extreme times. Hence, we inspired to investigate whether different aspects of uncertainty indices have impact on cryptocurrency market. Apart from geopolitical risk and economic policy uncertainty, we decided to add an uncertainty index which is US equity market uncertainty to examine and compare the results in different aspects. For the cryptocurrency, we include the top 3 ranking cryptocurrency in cryptocurrency market which are Bitcoin, Ethereum and Binance Coin to reinforce the results. The market capitalization for BTC, ETH and BNB are $895.69 billion, $455.71 billion, and $88.64 billion respectively (according to the https://coinmarketcap.com/ and last search conducted on 2nd January 2022). Our findings suggest that portfolio managers who choose to invest Bitcoin should pay attention to economic policy uncertainty, geopolitical risk and US equity market uncertainty while Binance Coin investor recommend focus on the geopolitical risk trends. This study has been organized into five sections which are introduction, literature review, methodology, empirical finding, and conclusion.

2. Literature Review

2.1 Impact of Economic Policy Uncertainty on Bitcoin

EPU can be one of the determiners for dynamics of cryptocurrency (Koumba *et al.*, 2019). The EPU able to improve BTC prediction and influence long-term BTC volatility significantly (Fang *et al.*, 2019). Besides, the EPU has potential affect BTC (Hazgui *et al.*, 2022) with different frequencies (Al-Yahyaee *et al.*, 2019), especially in extreme market conditions (Mokni, 2021). Moreover, the economic uncertainty measure from internet-based index more predictive than the newspaper-based in BTC returns prediction (Bouri and Gupta, 2021). Before the BTC crash, the EPU have positive impact on BTC, but BTC affected negatively by EPU after the Bitcoin crash in December 2017 (Mokni et al, 2020). Qin *et al.* (2021) and Demir *et al.* (2018) found EPU have positive and negative effect on BTC. The BTC volatility and returns may increase when the uncertain times uprise (Paule-Vianez *et al.*, 2020; Singh *et al.*, 2022). The highest EPU days will generate greater BTC returns significantly compared to days of lowest EPU (Wang *et al.*, 2020). However, Kalyvas *et al.* (2020) and Hazgui *et al.* (2022) found EPU negatively related with BTC price crash risk which shown high EPU leads to low BTC crash risk.

When the unfavorable economic conditions, the global EPU and US EPU have greater effect on BTC (Al Mamun *et al.*, 2020). The returns of BTC in US, China and Japan are more responsive to EPU (Shaikh, 2020) but Cheng and Yen (2020) shown the EPU of US and other Asian countries have no predictive power. Besides, there has significant causal effect exists between the BTC and US EPU (Ben and Ben, 2023), as well the nonlinearity is one of the critical factors to examine the causal effect of US EPU and BTC shown by BDS test (Fasanya *et al.*,2021). The BTC/USD is more affected by the US EPU than BTC/GBP by the UK EPU (Wang *et al.*, 2020). The US EPU have both positive and negative effect on BTC (Umar *et al.*, 2021). Panagiotidis *et al.* (2019) found BTC have positive reaction to the changes of US EPU. The US EPU raise the BTC volatility and trading volume after the spike days of EPU (Wang *et al.*,2020). The US EPU also have negative effect on BTC which the US EPU shocks will reduce the volatility of BTC (Shaikh, 2020; Matkovskyy *et al.*, 2020). Furthermore, Cheng and Yen (2020) and Ben and Ben (2023) found China EPU able to predict the BTC returns but the results from Panagiotidis *et al.* (2019) is not significant. After China regulates the crypto trading, Cheng and Yen (2020) found the China EPU able to enhance its predictive power on BTC returns while Bouri and Gupta (2021) shown the China EPU might not have impact on the cryptocurrency volatility. Furthermore, Shaikh (2020) and Chen *et al.* (2021) found China EPU have positive impact on BTC. However, Yen and Cheng (2021) found the China EPU associated negatively with BTC volatility. The Japan EPU also have negative effect on BTC that the reduction of volatility of BTC market in Japan caused by the raising of Japan EPU (Matkovskyy *et al.*, 2020). The raising of European EPU also will leads to the BTC returns increase (Panagiotidids *et al.*, 2019).

Risk premiums are obtained by global EPU during the distress market conditions (Al Mamum *et al.*, 2020). The BTC have strong hedge against the EPU in average conditions (Wu *et al.*, 2019). BTC have a potential act as a hedging instrument against the risk of global EPU (Ali *et al.*, 2023; Demir *et al.*, 2018), US EPU (Matkovskyy *et al.*, 2020), and China EPU (Yen and Cheng, 2021; Chen *et al.*, 2021). The BTC able to hedge the EPU (Kalyvas *et al.*, 2020) and not limit to internet-based or newspaper-based measure of economic uncertainty (Bouri and Gupta, 2021). On the other side, Qin *et al.* (2021) found EPU cannot always hedge by BTC. The cryptocurrency market has a weak hedge against the EPU during the bull market conditions (Colon *et al.*, 2021; Wu *et al.*, 2019). Fasanya *et al.* (2021) also shown the US EPU cannot hedge by BTC. Furthermore, BTC behave more as a safe haven rather than speculative assets (Paule-Vianez *et al.*, 2020). BTC generally immune from EPU risk spillover effect indicate by MVQM-CAViaR approach while the result from Granger causality risk test is insignificant (Wang *et al.* 2019). When the EPU is high, BTC able act as a safe haven (Zhou, 2021) but the relationship tends to change from the short run to long run (Umar *et al.*, 2021). The BTC can be a safe haven under average market conditions (Wu *et al.*, 2019). However, BTC serve as a weak safe haven when the market is extremely bearish and bullish (Wu *et al.*, 2019; Colon *et al.*, 2021). Moreover, the BTC able function as a safe haven if the EPU have positive impact on BTC, but it cannot be sustained when the negative effect exists (Qin *et al.*, 2021). The BTC cannot serve as a safe haven against the US EPU (Fasanya *et al.*, 2021).

2.2 Impact of Geopolitical Risk on Bitcoin

The GPR have a potential forecast the BTC volatility and returns (Al-Yahyaee *et al.*, 2019; Aysan *et al.*, 2019; Bouri *et al.*, 2022; Singh *et al.*, 2022). The BTC able influence by GPR at different frequencies (Al-Yahyaee *et al.*, 2019). The GPR has greater impact on BTC volatility and risk premia compared to global EPU and US EPU (Al Mamun *et al.*, 2020). The impact of GPR on BTC more significant during the unfavorable economic conditions (Al Mamun *et al.*, 2020; Kyriazis, 2020). A positive and negative influence can be observed on BTC from GPR (Su *et al.*, 2020). The GPR have positive impact on BTC price volatility and influence BTC returns negatively (Aysan *et al.*, 2019). The BTC affect positively by GPR (Su *et al.*, 2020) at higher quantiles (Aysan *et al.*, 2019). However, Kyriazis (2020) found BTC affected by GPR negatively. The BTC seen as a valuable asset to immune from GPR when existing the positive effect while this view is invalid on the negative effect (Su *et al.*, 2020). The GPR acquired a risk premium during the distressed market conditions (Al Mamun *et al.*, 2020). The BTC can be served as a hedging tool against the GPR (Aysan *et al.*, 2019). GPR's extreme upsides can be hedged by BTC (Al-Yahyaee *et al.*, 2019). Although the cryptocurrency market provides a strong hedge against the GPR but in most of the cases it unable act as a safe haven (Colon *et al.*, 2021) but Kyriazis (2020) found BTC can serve as a safe haven against the GPR.

2.3 Short Summary

Most of the previous study applied quantile regression approach (eg: Umar *et al.*, 2021; Chen *et al.*, 2021; Colon *et al.*, 2021; Shaikh, 2020; Paule-Vianez *et al.*, 2020; Wu *et al.*, 2019; Demir *et al.*, 2018; Wang *et al.*, 2019) and GARCH-based approach (eg: Zhou, 2021; Malladi and Dheeriya, 2021; Bouri and Gupta, 2021; Mokni *et al.*, 2020; Wang *et al.*, 2020, Al Mamun *et al.*, 2020, Wu *et al.*, 2019, Fang *et al.*, 2019; Kyriazis, 2020) to examine the influence of EPU or GPR on BTC. Earlier studies utilize quantile regression model to investigate effectiveness of BTC as a hedging tool, diversifier etc. For instance, Umar *et al.* (2021) modelled quantile regression approach to identify the time changing effect of the uncertainty on BTC. Moreover, Wang *et al.* (2019) evaluated the U.S. EPU index risk spillover effect to BTC by employed the multivariate quantile model. Similarly, Wu *et al.* (2019) applied both quantile regression and GARCH model to analyze and compared the Bitcoin and gold when perform as the hedging tools or safe haven against the EPU. Furthermore, most of the previous study applied GARCH-based models used to examine the conditional variance of Bitcoin. Malladi and Dheeriya (2021) applied EGARCH model to analyze the BTC returns to the EPU which it provides a better fit to the data than other GARCH models, according to standard goodness-of-fit measures. Moreover, Fang *et al.* (2019) examine the BTC long run volatility in response to EPU by GARCH-MIDAS model. Wang *et al.* (2020) and Mokni *et al.* (2020) applied dynamic conditional correlation (DCC)-GARCH and DCC-EGARCH to examine the dynamic correlation and time-varying correlation between BTC and EPU. In this study, we ascertain the cointegration between the uncertainty indices and cryptocurrency based on multivariate VAR Granger non-causality.

In this study, we adopt the top three ranking of cryptocurrency in the cryptocurrency market which are Bitcoin, Ethereum, and Binance Coin (based on the https://coinmarketcap.com/ and the searches conducted on 2nd January 2022) to denote the cryptocurrency instead of Bitcoin only to compare and examine whether the current result still valid. Besides, we expand the research by adding uncertainty indices in this study which is US equity market volatility to compare and reinforce the results in this study. Therefore, there have three uncertainty indices in different aspects included in this study which are economic policy uncertainty, geopolitical risk, and US equity market volatility. In summary, this study investigates the impact of economic policy uncertainty, geopolitical risk, and US equity market volatility on the Bitcoin, Ethereum, and Binance Coin by multivariate VAR Granger non-causality with monthly data.

3. Methodology

This empirical research investigates the impact of uncertainty risk on the cryptocurrency. Hence, this study adopted three cryptocurrency and uncertainty indices which Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB) and uncertainty indices as independent variables which are Economic Policy Uncertainty (EPU), Geopolitical risk (GPR) and US equity market uncertainty (USEMV). The hypothesized functional relationship between the cryptocurrency and the uncertainty indices shown in Equation (1), Equation (2) and Equation (3). The Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) exhibits the BTC, ETH and BNB as the dependent variable and shown in Equation (1), Equation (2) and Equation (3) respectively. The usual log-linear equation for estimation is obtained by taking natural logarithms on both sides.

Model 1 (BTC):

$$LBTC_t = \beta_0 + \beta_1 LEPU_t + \beta_2 LGPR_t + \beta_3 LUSEMV_t + v_t \tag{1}$$

Model 2 (ETH):

$$LETH_t = \beta_0 + \beta_1 LEPU_t + \beta_2 LGPR_t + \beta_3 LUSEMV_t + v_t \tag{2}$$

Model 3 (BNB):

$$LBNB_t = \beta_0 + \beta_1 LEPU_t + \beta_2 LGPR_t + \beta_3 LUSEMV_t + v_t \tag{3}$$

where β_0 indicates constant and the error term, v_t should be independent and normally distributed.

This study aims to investigate the relationship and causal dynamics among cryptocurrency and uncertainty risk by multivariate Vector Autoregression (VAR) framework, specifically examining the non-causality between the variables. Non-causality analysis is essential for understanding the interdependencies and direction of influence among cryptocurrency and uncertainty risk, which can provide valuable insights for policymakers and researchers.

We employed a multivariate VAR model of order *p* to capture the dynamic relationships among the variables. The order of the VAR model was determined based on the VAR lag order selection criteria to indicate the optimal lag length which are sequential modified LR test statistic (LR), Final prediction error (FPE), Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ). To investigate the non-causality between the variables, the Granger causality test adopted to examines whether past values of one variable improve the forecast of another variable, thus indicating causal effect between the variables. The granger causality test tested based on the following hypothesis:

H_0: The variables absence causal relationship.
H_1: The variables presence causal relationship.

The causal relationship exists between the variables if the null hypothesis rejected. In addition, to ensure the reliability of our results, we assessed the statistical properties of the VAR model, including the presence of heteroscedasticity and autocorrelation. Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) passed the diagnostic test to ensure the robustness of the results.

Furthermore, the impulse response function (IRF) analysis adopted to examine the dynamic effects of uncertainty risk on cryptocurrency. In order to estimate the impulse response functions, we followed the Cholesky identification approach which identified structural shocks and provides robust standard errors to account for the uncertainty in the estimates. The estimated VAR coefficients used to compute the IRFs for each variable in response to a one-standard-deviation shock in each of the variables. It examines the impact of exogenous shocks on the system and understand the response patterns over time. In addition to IRFs, the variance decomposition analysis conducted to understand the relative contributions of each shock to the variability of the variables. The variance decomposition analysis was performed within the framework of a Vector Autoregression (VAR) model. This analysis provides insights into the proportion of forecast error variance attributed to each shock at different horizons.

3.1 Data

The monthly data of Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), geopolitical risk (GPR), economic policy uncertainty (EPU) and US equity market uncertainty (USEMV) cover the period of December 2017 until May 2021 comprising of 42 observations in total. The BTC, ETH and BNB are extracted from investing.com, while the GPR, EPU and USEMV are from policyuncertainty.com. The cryptocurrencies and uncertainty indices act as the dependent variable and independent variable, respectively. All data are transformed to natural logarithm to decrease the data variability. Model 1 (BTC), Model 2 (ETH), and Model 3

(BNB) indicates the BTC, ETH and BNB acts as the dependent variables in each models respectively.

Table 1: Descriptive statistics, 2017M12 - 2021M05

	BTC	ETH	BNB	EPU	GPR	USEMV
Observations	42	42	42	42	42	42
Mean	9.217	5.842	3.068	5.476	4.968	3.113
Median	9.121	5.616	2.836	5.508	4.897	3.052
Maximum	10.981	7.928	6.435	6.064	5.942	4.149
Minimum	8.142	4.670	1.633	4.818	4.181	2.514
Standard Deviation	0.700	0.878	1.039	0.282	0.367	0.344
Skewness	1.024	0.804	1.770	-0.163	0.286	0.667
Kurtosis	3.697	2.768	5.974	2.495	2.894	3.461
Jarque-Bera	8.195	4.622	37.396	0.631	0.594	3.484
Sum	387.118	245.367	128.839	229.986	208.649	130.77
Sum of Squared Deviation	20.064	31.597	44.248	3.257	5.509	4.853
Probability	0.017**	0.099*	0.000***	0.729	0.743	0.175

Notes: *, ** and *** denotes that H_0 is rejected at the 10%, 5% and 1% significance levels, respectively.

4. Empirical Findings

The optimal lag order needs to be determined before proceeding to the granger causality test. Table 2 shown the results of the criteria for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB). The table reveals final prediction error (FPE), Schwarz information criterion (SC) and Hannan-Quinn information criterion (HQ) suggests Model 1 (BTC) and Model 2 (ETH) indicates 1 lag. However, sequential modified LR test statistic (LR) and Akaike information criterion (AIC) reveals 4 lags and 5 lags respectively. For Model 3 (BNB), all criteria signify 1 lag only.

Table 2: VAR lag order selection criteria

Lag	LR	FPE	AIC	SC	HQ
Model 1 (BTC, EPU, GPR, USEMV)					
0	NA	0.00022	2.92285	3.09700	2.98425
1	129.5814	9.11e-06*	-0.26171	0.60906*	0.04528*
2	10.14227	1.56e-05	0.24093	1.80831	0.79351
3	9.93778	2.66e-05	0.69172	2.95572	1.48989
4	27.15721*	1.93e-05	0.19873	3.15934	1.24248
5	25.45041	1.28e-05	-0.52706*	3.13016	0.76228
Model 2 (ETH, EPU, GPR, USEMV)					
0	NA	0.00028	3.18387	3.35802	3.24527
1	120.9542	1.55e-05*	0.26892	1.13969*	0.57591*
2	13.40392	2.35e-05	0.65507	2.22245	1.20765
3	8.82865	4.21e-05	1.15208	3.41607	1.95024
4	29.50103*	2.72e-05	0.54189	3.50250	1.58564
5	21.37689	2.32e-05	0.07070*	3.72792	1.36004
Model 3 (BNB, EPU, GPR, USEMV)					
0	NA	0.00045	3.64485	3.81900	3.70625
1	111.8923*	3.26e-05*	1.01308*	1.88385*	1.32007*
2	10.47834	5.50e-05	1.50372	3.07110	2.05630
3	13.24388	8.19e-05	1.81676	4.08075	2.61492
4	20.47806	8.30e-05	1.65772	4.61833	2.70147
5	18.52520	8.47e-05	1.36476	5.02198	2.65410

Notes: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion.

Table 3: Results of Granger causality test

Dependent Variable	Independent Variable			
Model 1 (BTC)				
	BTC	EPU	GPR	USEMV
BTC	-	7.0584***	4.7194**	2.8031*
EPU	2.1184	-	1.0322	0.0371
GPR	2.4438*	1.2108	-	0.2672
USEMV	0.1036	1.4195	1.6164	-
Model 2 (ETH)				
	ETH	EPU	GPR	USEMV
ETH	-	1.5321	1.2068	3.52e-06
EPU	5.4310**	-	1.8883	0.0259
GPR	2.9333*	2.8143*	-	0.2394
USEMV	0.5172	0.7364	2.0538	-
Model 3 (BNB)				
	BNB	EPU	GPR	USEMV
BNB	-	0.0270	3.1069*	0.0275
EPU	0.4537	-	0.4404	0.0852
GPR	1.0057	1.0533	-	0.1875
USEMV	0.1655	1.4775	1.7173	-

Notes: The statistics are chi-squares of Wald tests. *, ** and *** denote that H_0 is rejected at the 10%, 5% and 1% significance levels, respectively. The optimal lag length selected is 1.

The Wald statistics of granger causality test for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) exhibits in Table 3. There is bi-directional granger causality between BTC and GPR in Model 1 (BTC), and unidirectional granger causality running from EPU to BTC and from USEMV to BTC. For Model 2 (ETH), there is unidirectional granger causality from ETH to both EPU and GPR, as well as from EPU to GPR. Moreover, only GPR have granger causes on BNB for Model 3 (BNB).

Table 4: Decomposition of variance

	Period									
	1	2	3	4	5	6	7	8	9	10
Model 1 (BTC)										
Variance decomposition of BTC										
BTC	100.00	91.99	84.64	77.62	71.07	65.18	60.04	55.64	51.90	48.77
EPU	0.00	1.47	5.19	10.05	15.16	20.04	24.45	28.31	31.64	34.47
GPR	0.00	3.33	5.49	7.16	8.56	9.74	10.73	11.54	12.20	12.74
USEMV	0.00	3.21	4.68	5.18	5.21	5.03	4.78	4.51	4.25	4.02
Variance decomposition of EPU										
BTC	1.31	2.91	4.52	6.10	7.62	9.06	10.40	11.60	12.64	13.52
EPU	98.69	94.84	91.66	89.18	87.16	85.45	83.97	82.67	81.53	80.56
GPR	0.00	2.20	3.56	4.22	4.46	4.50	4.44	4.37	4.31	4.29
USEMV	0.00	0.05	0.25	0.51	0.76	0.99	1.19	1.37	1.51	1.63
Variance decomposition of GPR										
BTC	0.62	0.59	0.78	1.01	1.19	1.32	1.40	1.45	1.47	1.48
EPU	0.07	1.94	4.34	6.59	8.56	10.22	11.59	12.72	13.64	14.37
GPR	99.31	96.91	94.27	91.82	89.69	87.91	86.45	85.28	84.35	83.61
USEMV	0.00	0.55	0.61	0.59	0.57	0.56	0.55	0.55	0.54	0.54
Variance decomposition of USEMV										
BTC	5.55	5.67	5.67	5.68	5.73	5.80	5.88	5.98	6.08	6.17
EPU	12.16	14.15	16.19	17.77	18.85	19.53	19.94	20.15	20.26	20.29
GPR	13.70	20.08	21.67	21.99	21.99	21.92	21.85	21.79	21.74	21.70
USEMV	68.59	60.10	56.47	54.56	53.44	52.75	52.34	52.08	51.93	51.84

Table 4 *(continued)*

	Period									
	1	2	3	4	5	6	7	8	9	10
Model 2 (ETH)										
Variance decomposition of ETH										
ETH	100.00	97.20	92.92	88.13	83.35	78.89	74.85	71.28	68.14	65.40
EPU	0.00	1.01	3.18	5.92	8.79	11.57	14.14	16.45	18.51	20.31
GPR	0.00	1.79	3.89	5.93	7.79	9.44	10.88	12.11	13.16	14.07
USEMV	0.00	4.13e-06	0.01	0.03	0.06	0.10	0.13	0.16	0.19	0.22
Variance decomposition of EPU										
ETH	2.54	6.83	11.33	15.97	20.61	25.03	29.03	32.44	35.20	37.32
EPU	97.46	89.20	82.89	77.82	73.36	69.27	65.54	62.20	59.30	56.86
GPR	0.00	3.93	5.66	6.03	5.83	5.49	5.24	5.17	5.32	5.64
USEMV	0.00	0.04	0.12	0.18	0.20	0.20	0.20	0.19	0.18	0.17
Variance decomposition of GPR										
ETH	0.33	0.51	0.79	1.00	1.14	1.22	1.27	1.29	1.30	1.31
EPU	0.03	4.29	8.02	10.74	12.68	14.06	15.06	15.78	16.29	16.66
GPR	99.64	94.71	90.53	87.55	85.46	83.98	82.93	82.18	81.65	81.27
USEMV	0.00	0.48	0.65	0.70	0.73	0.74	0.75	0.75	0.76	0.76
Variance decomposition of USEMV										
ETH	5.12	5.84	6.33	6.82	7.37	7.97	8.61	9.25	9.87	10.46
EPU	10.67	11.69	13.12	14.13	14.66	14.86	14.86	14.78	14.68	14.59
GPR	14.81	22.41	24.11	24.38	24.30	24.13	23.95	23.77	23.62	23.48
USEMV	69.40	60.07	56.45	54.67	53.67	53.04	52.58	52.20	51.83	51.46
Model 3 (BNB)										
Variance decomposition of BNB										
BNB	100.00	95.22	91.05	87.89	85.44	83.45	81.79	80.37	79.13	78.04
EPU	0.00	0.02	0.02	0.06	0.17	0.33	0.52	0.74	0.96	1.18
GPR	0.00	4.73	8.83	11.86	14.13	15.90	17.31	18.48	19.45	20.29
USEMV	0.00	0.03	0.10	0.18	0.26	0.32	0.37	0.42	0.46	0.50
Variance decomposition of EPU										
BNB	12.39	13.68	14.80	15.86	16.87	17.86	18.80	19.70	20.55	21.36
EPU	87.61	85.07	82.94	81.33	80.08	79.05	78.14	77.30	76.50	75.72
GPR	0.00	1.13	2.02	2.49	2.68	2.71	2.67	2.61	2.56	2.54
USEMV	0.00	0.12	0.24	0.32	0.37	0.39	0.40	0.40	0.39	0.39
Variance decomposition of GPR										
BNB	0.34	0.33	0.36	0.42	0.51	0.63	0.77	0.94	1.13	1.34
EPU	0.16	1.35	2.91	4.21	5.17	5.87	6.36	6.72	6.97	7.16
GPR	99.50	97.94	96.15	94.70	93.60	92.76	92.11	91.57	91.12	90.72
USEMV	0.00	0.38	0.58	0.67	0.71	0.74	0.76	0.77	0.78	0.79
Variance decomposition of USEMV										
BNB	6.80	7.05	7.40	7.75	8.06	8.35	8.61	8.84	9.06	9.27
EPU	8.87	10.72	12.69	14.27	15.40	16.15	16.62	16.92	17.09	17.19
GPR	15.78	22.37	23.90	24.02	23.83	23.60	23.41	23.26	23.14	23.04
USEMV	68.55	59.86	56.01	53.96	52.71	51.90	51.36	50.98	50.71	50.50

The variance decomposition results for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) are summarized in Table 4 over 10-months period. For Model 1 (BTC), the results indicate EPU and GPR are the most exogenous variables compared to USEMV and BTC as they have high proportion of shocks to explained their own innovations. The forecast error variance for EPU and GPR explained its own innovation at the end of 10 months are 80.56% and 83.61%, while USEMV and BTC are 48.77% and 51.84% respectively. At the end of period, EPU have greater impact on BTC compared to GPR and USEMV where forecast error variance of EPU (34.47%) higher than GPR (12.74%) and USEMV (4.02%). Furthermore, the GPR is strongly endogenous compared to ETH, EPU and USEMV in the Model 2 (ETH). After 10 months, the forecast error variance for GPR, ETH, EPU and USEMV to predict its own are 81.27%, 65.40%, 56.86% and 51.46% respectively. The EPU and GPR forecast error variance in explaining the ETH are 20.31% and 14.07%. However, the ETH is insignificant explained by USEMV. The Model 3 (BNB) shown GPR, BNB, and EPU strongly influences itself with forecast error variance of 90.72%, 78.04% and 75.72% respectively in comparison with USEMV which 50.50%. The GPR have 20.29% forecast error variance in explaining BNB, while EPU and USEMV are weak influence in predicting BNB.

Besides, impulse response function can provide information on the relations between variables in addition to variance decomposition. Figure 1-3 presents the impulse response functions for Model 1 (BTC), Model 2 (ETH) and Model 3 (BNB) respectively. BTC, ETH and BNB response to EPU are lying on the positive region and shown increase gradually over the period when shocks occur which EPU have gradual positive effect on BTC, ETH and BNB. In contrast, GPR has gradual negative effect as the response of BTC, ETH and BNB to GPR are gradually decrease in the negative region. For USEMV, the response of ETH and BNB are slightly increase in the positive region, but BTC lying in the negative region and increase gradually over the period.

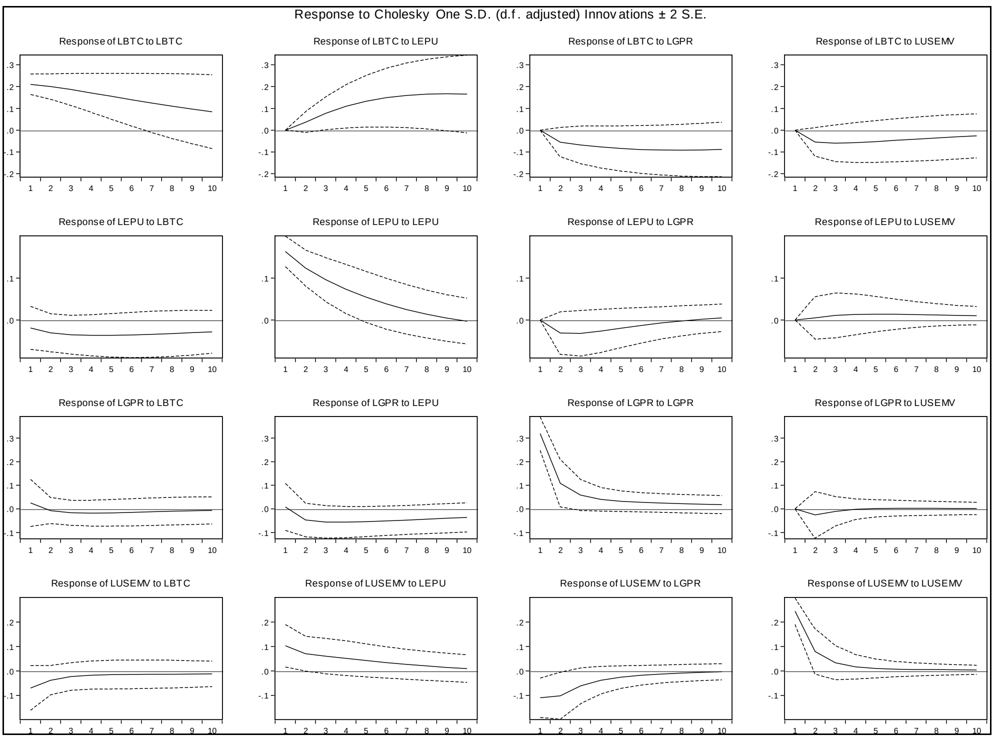

Figure 1: Impulse function for Model 1 (BTC)

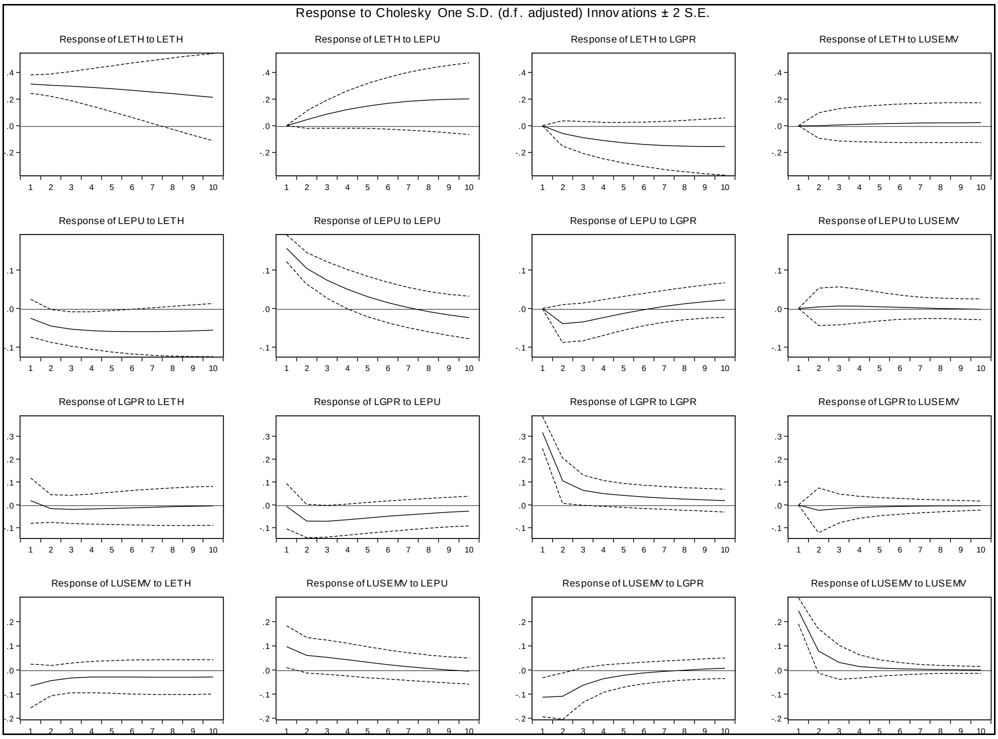

Figure 2: Impulse function for Model 2 (ETH)

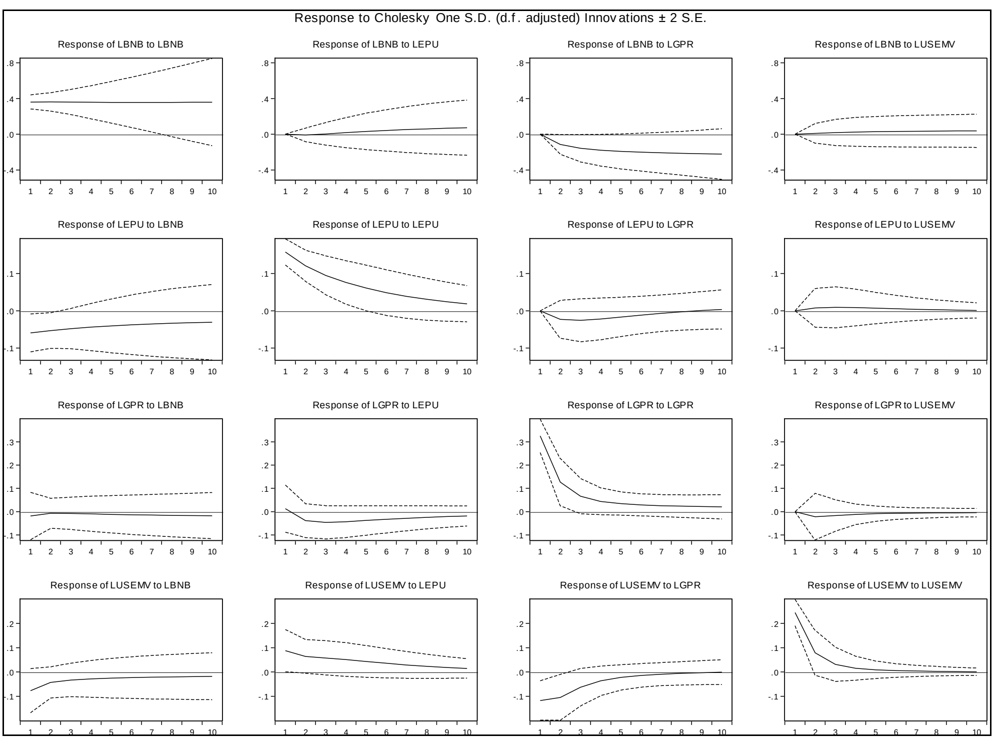

Figure 3: Impulse function for Model 3 (BNB)

5. Conclusion

This paper examines the impact of geopolitical risk (GPR), economic policy uncertainty (EPU) and US equity market uncertainty (USEMV) on the Bitcoin (BTC), Ethereum (ETH) and Binance Coin (BNB) by monthly data from December 2017 until May 2021 using cointegration and causality testing. This study extended the analysis by adopted the variance decomposition and impulse response function to examine the variable's exogeneity. The results shown EPU, GPR and USEMV are cointegrated when BTC is the dependent variable, but not cointegrated when ETH act as the dependent variable. However, BNB only cointegrated with GPR. Model 1 (BTC) exhibits EPU, GPR and USEMV Granger cause BTC, while in Model 3 (BNB) only GPR Granger cause the BNB. Our results suggested the investor and policymaker can keep an eye on the EPU, GPR and USEMV to forecast the BTC and pay close attention to GPR while forecast the BNB price. For further implication, we suggested employ other cryptocurrency and adopt other uncertainty measure to further explore the relation between cryptocurrency and uncertainty risk as well as consider utilize other methodology.

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