Researches on Multidisciplinary Approaches Multidisipliner Akademik Yaklaşım Araştırmaları

Research Article RJ-45

Researches on Multidisciplinary Approaches 2026 (2) ISSN:2791-9099

Global Economic Policy Uncertainty and Bitcoin: A Transient Nexus

Ümit Yıldız / Assoc. Prof. Dr.
Bayburt University, Faculty of Economics and Administrative Sciences, Department of Economics
umityildiz@bayburt.edu.tr

Abstract

Uncertainty plays a significant role in shaping investment decisions, both directly and indirectly. In an uncertain economic environment, investors' motivations for decision-making may vary. While some investors tend to seek safe-haven assets, others may engage in speculative behavior. Therefore, uncertainty can influence financial instruments through various mechanisms. One of these instruments is Bitcoin, which is often regarded as the "gold" of cryptocurrencies. Compared to traditional financial investment instruments, Bitcoin exhibits higher volatility and is among the primary assets that may be affected by uncertainty. However, an important question is whether this effect is temporary or permanent. By adopting a frequency-domain causality approach, this study seeks to investigate the causal linkages between Global Economic Policy Uncertainty (GEPU) and Bitcoin price movements. In this context, the causal nexus between GEPU and BTC prices is examined for the entire period and for different frequencies. Although the study's findings show no causal nexus between the variables over the entire period, the analyses for the short, medium, and long run indicate a causal relationship from GEPU to BTC in the medium run. Accordingly, GEPU can be considered one of the factors affecting BTC price; however, its impact does not appear to be persistent.

Keywords: GEPU, Bitcoin, Frequency Domain Causality.

JEL Codes: C32, D80, G23

Citation: Yıldız, Ü. (2026). Global economic policy uncertainty and Bitcoin: A transient nexus. *Researches on Multidisciplinary Approaches (ROMAYA Journal)*, 2026(2).

Submission Date : 15.03.2026
Acceptance Date : 15.07.2026

1. Introduction

The world's monetary system has undergone various changes throughout history and the definition of money has changed accordingly. Today, money has moved to the virtual environment, and cryptocurrencies have taken their place in the mainstream financial system. Cryptocurrencies that emerged with Bitcoin, introduced by Nakamoto (2008), are popular investment tools today. In particular, cryptocurrencies are popular for their low transaction costs and the ability to trade in unregulated systems (Blau, 2017:493).

Investors often seek out safe havens in intense economic uncertainty and resort to hedging instruments. In such cases, some investors may turn to safer investments, such as gold, while others may turn to more volatile assets with higher risk, such as Bitcoin. Bitcoin shares certain hedging characteristics with gold and can be added to the range of tools market analysts use to mitigate market-specific risks (Dyhrberg, 2016). In his Modern Portfolio Theory (1952), Markowitz emphasises the importance of asset diversification in enabling investors to maximise expected returns within a given risk framework. Investors' search for safe havens or for hedging purposes, particularly in uncertain environments, combined with investor indecision and risk-diversification motivations stemming from economic policy uncertainty, is likely to create a transfer mechanism towards Bitcoin.

Cryptocurrencies can affect markets in various ways or be influenced by market changes. With this feature, they have become the focus of numerous studies, particularly in recent years. Among these studies, some examine cryptocurrencies in relation to economic policy uncertainty indices and whether they serve as hedges against economic and political uncertainty. Bouri et al. (2017) explore the potential of Bitcoin as a hedge against global economic policy uncertainty (GEPU). Their findings indicate that Bitcoin can effectively serve as a hedge against uncertainty. In another study, Conrad et al. (2018) analyze the causal connection between Bitcoin price (BCP) volatility and GEPU, discovering a strong association between Bitcoin volatility and global economic activity. Demir et al. (2018) argue that Bitcoin's daily return negatively correlates with the US economic policy uncertainty (EPU). Wu et al. (2019) say that Bitcoin cannot be a strong hedge against the US EPU. However, Matkovskyy et al. (2020) suggested that Bitcoin could serve as a hedge against uncertainty shocks. In another study examining the relationship between EPU and cryptocurrency prices on a country basis, Khan et al. (2021) investigate the connection between Bitcoin prices (BCP) and GEPU. The results from the full-sample analysis indicate no evidence of causality between BCP and GEPU. However, causality is observed within specific subsample periods. Haq et al. (2021) argue that cryptocurrencies exhibit varying degrees of connectedness to national EPUs, leading to differences in the effectiveness of risk mitigation across countries. Cheng and Yen (2020) concluded that while the Chinese EPU predicts the monthly return of Bitcoin, the US EPU is unable to do so. Lucey et al. (2022), who examined the relationship at the country level, show a dynamic connection between EPU and cryptocurrencies. In another study, Oldani et al. (2024) investigated the link between EPU and the volume of the cryptocurrency market, concluding that investors increase their demand for cryptocurrencies when uncertainty rises. He et al. (2024) state that EPU has a minimal impact on the cryptocurrency market in the short term. They state that Bitcoin and Ethereum can be hedged in the short term, but this effect decreases in the long term. However, the study emphasizes that Tether is positively correlated with EPU in the long term. Studies do not provide a clear conclusion on whether cryptocurrencies serve as a hedge against economic policy uncertainty.

The literature suggests that economic policy uncertainty is a factor influencing the price of Bitcoin, which forms the basis of this study. However, the study does not seek to determine whether economic policy uncertainty is a definitive determinant of Bitcoin or the direction and intensity of its impact. Numerous studies in the literature have sought to answer these questions. This study aims to investigate whether economic policy uncertainty is a cause of Bitcoin price fluctuations and, if so, whether these effects are temporary or permanent. Therefore, the causal linkages between the variables are first examined for the entire period, then examined at different frequencies to determine whether a causal relationship exists and, if so, whether it is temporary or permanent. In this respect, the study distinguishes itself from others in the literature, carries originality, and provides a significant contribution to the field. Identifying temporary or permanent causality provides clues regarding the decisions that will be made in uncertain environments.

2. Data and Methodology

Utilizing monthly data spanning from 2016M06 to 2024M09, this study investigates the causal linkages between Global Economic Policy Uncertainty[1] (GEPU) and Bitcoin[2]. The analytical framework first employs the Toda-Yamamoto (1995) causality test to assess the relationship over the entire sample pe-

[1] Data was obtained from https://www.policyuncertainty.com/global_monthly.html Access Date: 07.07.2026

[2] Data was obtained from https://www.investing.com/crypto/bitcoin/historical-data Access Date: 07.07.2026

riod; subsequently, it adopts the frequency domain approach introduced by Breitung & Candelon (2006) to decompose these causal effects across the short, medium, and long run.

Toda and Yamamoto (1995) developed a robust framework for examining Granger causality (1961) by estimating an augmented Vector Autoregression (VAR) model. This methodology uses a ($k + d_{max}$) lag structure, where k is the optimal lag length determined by information criteria and d_{max} denotes the max order of integration among the variables. A key advantage of the Toda-Yamamoto procedure over the conventional Granger causality test (1969) is its capacity to bypass the prerequisites of stationarity and cointegration testing, thereby mitigating the risks associated with pre-test biases.

The implementation of the Toda-Yamamoto procedure involves a three-stage estimation process. Initially, the maximum order of integration (d_{max}) is established by evaluating the stationarity properties of the variables. Subsequently, an optimal lag length (k) is determined through the construction of a Vector Autoregressive (VAR) model. Finally, a VAR model with a lag length of $k + d_{max}$ is estimated by incorporating the max order of integration into the optimal lag length.

The VAR model of the Toda - Yamamoto test is set up as follows (Dritsaki, 2017:123):

$$y_t = \mu_0 + \left\{\sum_{i=1}^{k} a_{1t} y_{t-i} + \sum_{i=k+1}^{d_{max}} a_{2t} y_{t-i}\right\} + \left\{\sum_{i=1}^{k} \beta_{1t} x_{t-i} + \sum_{i=k+1}^{d_{max}} \beta_{2t} x_{t-i}\right\} + \varepsilon_{1t}$$

$$x_t = \Phi_0 + \left\{\sum_{i=1}^{k} \gamma_{1t} x_{t-i} + \sum_{i=k+1}^{d_{max}} \gamma_{2t} x_{t-i}\right\} + \left\{\sum_{i=1}^{k} \delta_{1t} y_{t-i} + \sum_{i=k+1}^{d_{max}} \delta_{2t} y_{t-i}\right\} + \varepsilon_{2t}$$

Causal inferences within this framework are drawn by imposing parameter restrictions on the estimated model. Specifically, the null hypotheses, stating that Y does not Granger-cause X, and vice versa, are evaluated using a Wald test statistic that follows a chi-square distribution with k degrees of freedom. If the calculated Wald test statistic exceeds the critical threshold of the χ^2 distribution, the null hypothesis of no Granger causality is rejected. Consequently, this provides statistical evidence for the presence of a significant causal nexus between the variables under consideration.

Breitung & Candelon (2006) highlight in their research that the Granger causality test does not account for differences across various frequencies. This limitation was also observed in Geweke's (1982) and Hosoya's (1991) studies. However, the Frequency Domain Causality test introduced by Breitung & Candelon (2006) enables the identification of causality relationships among variables over the long, medium, and short terms. This approach allows for distinguishing whether the identified causality is enduring or transient.

The method Breitung & Candelon (2006) proposed, which determines causality at specific frequencies by applying linear restrictions to the VAR model, is fundamentally rooted in the work of Geweke (1982). The causality measurement introduced by Geweke (1982) and Hosoya (1991) can be expressed as:

$$M_{X\ Y}(\omega) = log\left[1 + \frac{|\psi_{12}(e^{-i\omega})|^2}{|\psi_{11}(e^{-i\omega})|^2}\right]$$

At $\psi_{12}(e^{-i\omega})=0$, $M_{X\ Y}(\omega) = 0$, it is stated that Y does not Granger-cause X at the specified frequency ω. In the framework proposed by Breitung & Candelon (2006), the null hypothesis of no Granger causality at frequency ω is evaluated by imposing a set of linear restrictions on the model parameters. This hypothesis is formally tested using an F-distributed statistic under these linear constraints, allowing for the identification of causal relationships across specific frequency ranges.

$$\sum_{j=1}^{p} \theta_{12,j}\ cos(j\omega) = 0$$

$$\sum_{j=1}^{p} \theta_{12,j}\ sin(j\omega) = 0$$

The calculated F-statistic follows an F-distribution with (2, T−2p) degrees of freedom for the frequency range ω∈(0, π). In this specification, 2 means the two linear restrictions, while T and p denote the total number of observations and the optimal VAR lag order, respectively.

3. Findings

In time series analysis, a graphical representation of the series is important to understand the series. Figure 1 shows the changes in the values of these two variables over time.

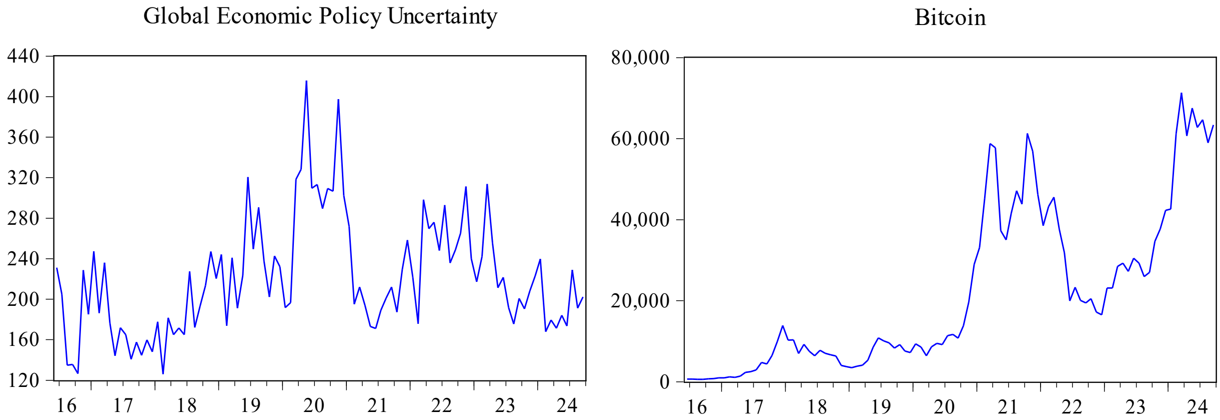

Figure 1. GEPU Index and Bitcoin Price

In the graphs, the horizontal axis represents the period, while the vertical axis shows the level values of the series. Both graphs provide clues that the series contains a trend. However, prior to the causality analysis, it is imperative to determine the stationary properties of the variables through unit root testing. To this end, the results of the Augmented Dickey-Fuller tests are summarized in Table 1.

Table 1. ADF Unit Root Tests Results

		GEPU	BTC
I(0)	ADF unit root test	-3.1007 (0.1120)	-2.0887 (0.5454)
	Unit root test with a breakpoint	-3.8467 (0.2156) 2018M06	-2.756007 (0.8077) 2020M09
I(1)	ADF unit root test	-14.7460 (0.0000)	-8.6496 (0.0000)
	Unit root test with a breakpoint	-8.523301 (<0.01) 2021M02	-9.480322 (<0.01) 2021M05

According to the ADF tests, the series are stationary at I(1) in all models. This information is used in the Toda-Yamamoto (1995) & Breitung & Candelon (2006) tests.

Although the Toda-Yamamoto procedure is robust to non-stationarity and varying integration properties, identifying the maximum order of integration (d_{max}) remains a methodological prerequisite. Based on the preliminary unit root analysis, d_{max} is determined to be 1 for the variables under consideration. After establishing the integration order, selecting the optimal lag length (k) for the Vector Autoregressive (VAR) framework is critical for the valid execution of the causality test.

While the FPE and AIC criteria suggest an optimal lag length of 2, the SC and HQ criteria indicate a lag length of 1. The VAR(1) model suffers from both heteroskedasticity and autocorrelation issues. Therefore, a lag length of 2, as suggested by the FPE and AIC criteria, has been preferred as the optimal lag for the VAR model. Diagnostic tests indicate that the VAR(2) model is free from these econometric issues.

Table 2. Optimal Lag Order

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1541.306	NA	1.28e+12	33.55012	33.60494	33.57225
1	-1394.809	283.4390	5.76e+10	30.45237	30.61683*	30.51875*
2	-1388.963	11.05645	5.53e+10*	30.41224*	30.68635	30.52287
3	-1388.214	1.383930	5.94e+10	30.48291	30.86666	30.63780
4	-1384.747	6.255253	6.01e+10	30.49451	30.98790	30.69364
5	-1383.037	3.011806	6.33e+10	30.54428	31.14732	30.78767
6	-1380.977	3.536942	6.61e+10	30.58646	31.29914	30.87411
7	-1375.058	9.907893*	6.35e+10	30.54475	31.36707	30.87664
8	-1371.782	5.341454	6.47e+10	30.56048	31.49245	30.93663

Table 3. Autocorrelation and Heteroscedasticity Tests

VAR (1)			VAR (2)		
Autocorrelation LM Test					
Lags	**LM stat.**	**Prob.**	**Lags**	**LM stat.**	**Prob.**
1	10.93839	0.0273	1	1.762012	0.7794
2	7.087728	0.1313	2	1.504731	0.8258
3	5.215414	0.2659	3	5.073189	0.2799
White Heteroscedasticity Test					
Chi-sq	**df**	**Prob.**	**Chi-sq**	**df**	**Prob.**
36.26707	15	0.0016	49.55434	42	0.1973

On the other hand, the structural stability of the estimated VAR(2) model is evaluated by examining the inverse roots of the characteristic AR polynomial. As illustrated the AR roots graph, all inverse roots lie strictly within the unit circle. These results confirm that the AR(2) specification satisfies the stability condition, ensuring the reliability of the subsequent causality analysis.

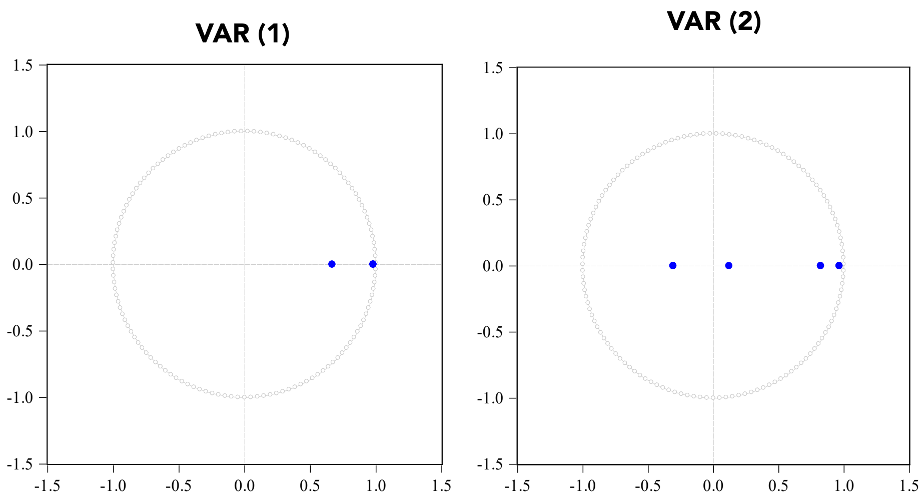

Figure 2. Inverse Roots of AR Characteristic Polynominal

The ADF unit root tests results already confirm that the max order of integration is I(1). This implies that the d_{max} is 1. On the other hand, the optimal lag length is determined as 2. Therefore, the $(k+d_{max})$th order is 3. So, the 3rd-order VAR needs to run in the Toda-Yamamoto procedure. The Toda-Yamamoto test results run with this information are shown in Table 4.

Table 4. Toda-Yamamoto Test Results

Toda-Yamamoto (1995)			
	Chi-sq	**Lag**	**Prob.**
GEPU ⟶ BTC	2.728559	3	0.4352
BTC ⟶ GEPU	0.600769	3	0.8963

According to the Toda-Yamamoto test results, there is no causal nexus between the variables at the 5% significance level for the entire period. Cryptocurrency markets can be quite volatile periodically. Therefore, even if there is no causal nexus between GEPU and Bitcoin prices in the relevant period, causal relationships can be seen between these variables in different time periods. For this reason, within the frequency domain causality approach framework developed by Breitung & Candelon (2006), the causal relationships between variables were examined at different frequencies.

In the frequency domain approach, causal relationships are classified according to different time horizons. Frequencies range from 0 to 3.14. Lower frequencies represent long-run causality, whereas higher frequencies represent medium- and short-run causality (e.g., ω=0.01 and ω=0.05 denote the long-run; ω=1.00 and ω=1.50 the medium-run; and ω=2.00 and ω=2.50 the short-run). The causal relationship across all frequencies is illustrated in Figure 3.

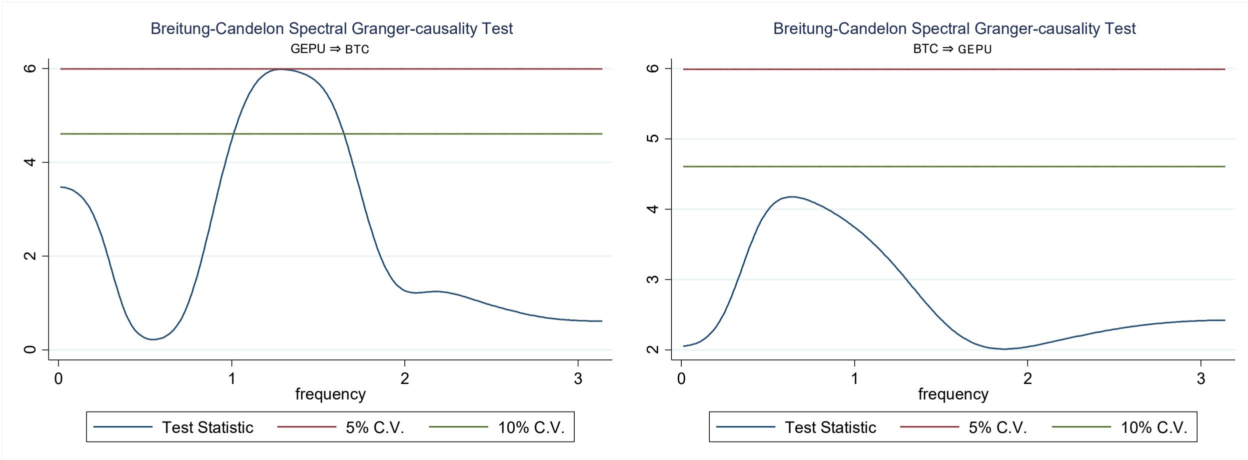

Figure 3. Breitung & Candelon Spectral Granger Causality Test

The left column of Figure 2 shows causality from GEPU to BTC, while the right column shows causality from BTC to GEPU. To be able to speak of causality, the calculated test statistics must be above the critical value at the 5% significance level. Upon examining the graphs, the empirical results reveal a statistically significant causal linkage running from GEPU to Bitcoin specifically within the medium-run frequency band (at ω=1.00 to 1.50). Conversely, no causal relationship from BTC to GEPU was observed across the short, medium, or long run.

As demonstrated in Taştan's (2015: 1161) study, the duration of causal relationships can be calculated using the formula 2π/ω. Since this study utilizes monthly data, the duration of the causal relationship between GEPU and BTC is approximately 5 months when calculated using the aforementioned formula. This finding provides evidence that the identified causal link is not permanent, suggesting that the connection between these variables is transitory in nature. Causality at a low frequency level of 0.1 indicates permanent shocks (Ciner, 2011). Conversely, as you observed in analysis of the GEPU-Bitcoin relationship, causality at higher frequencies suggests that the transmission of shocks is transitory and tends to wash out over time.

4. Conclusion

In this study, the causality relationship between GEPU and Bitcoin prices was examined for the period 2016M06-2024M09. While the Toda-Yamamoto (1995) causality test for the entire period revealed no significant link, the Breitung & Candelon (2006) frequency-domain test demonstrated a unidirectional causality from GEPU to BTC specifically in the medium run. This finding is significant, as it suggests that the influence of GEPU on Bitcoin is not a permanent, long-term determinant, but rather a transient effect.

The existence of this medium-term causality confirms that the market undergoes a transition process shaped by a specific transmission mechanism. Within this mechanism, the 4-month period provides the necessary time for investors to interpret macroeconomic signals, revise their expectations, and rebalance their portfolios. In the long run, however, the global economy reaches a new equilibrium; the initial shock caused by GEPU eventually becomes the 'new normal,' and thus ceases to be a primary pricing criterion for investors.

While cryptocurrency markets are very volatile and can be affected by many macroeconomic and political factors, including global economic policy uncertainty, this causal relationship should not be seen as a final or main determinant. Instead, the evidence suggests that GEPU may be one of the factors that contributes to Bitcoin's price, but its effect is not permanent. This conclusion provides useful information for investors, especially in helping them avoid making quick decisions during times of high uncertainty.

These findings gain further context when considering Bitcoin's market position. Bitcoin holds significant dominance in the overall market thanks to its high market value and is often referred to as the 'gold' of the cryptocurrency world. Its characteristics make it less volatile and more resilient to political and economic shocks compared to other cryptocurrencies, where analysis might reveal more diverse causal links between policy uncertainty and asset prices. Ultimately, given that cryptocurrencies are known for substantial intraday fluctuations, the connections between political or economic factors and digital assets can produce varying outcomes across different frequencies, reinforcing the importance of a frequency-dependent analytical perspective.

Despite these findings, this study has some limitations that should be considered. First, the analysis focuses only on the causal relationship between Global Economic Policy Uncertainty and Bitcoin. Therefore, it does not examine the effects of other macroeconomic factors or include other cryptocurrencies such as altcoins. Future studies could expand this analysis by adding more macroeconomics and financial indicators and comparing different digital assets. This would provide a broader understanding of how various cryptocurrencies respond to global economic uncertainty and economic shocks

References

Blau, B. M. (2017). Price dynamics and speculative trading in bitcoin. Research in International Business and Finance, 41, 493–499.

Bouri, E., Gupta, R., Tiwari, A. & Roubaud, D. (2017). Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23, 87–95.

Cheng, H. P. & Yen, K. C. (2020). The relationship between the economic policy uncertainty and the cryptocurrency market. Finance Research Letters, 35: 101308.

Ciner, C. (2011). Commodity prices and inflation: Testing in the frequency domain. Research in International Business and Finance, 25(3), 229-237.

Conrad, C., Custovic, A. & Ghysels, E. (2018). Long- and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis. Journal of Risk and Financial Management, 11, 1–12.

Demir, E., Gözgör, G. & Lau, C. K. M. & Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation, Finance Research Letters, 26, 145-149.

Dritsaki, C. (2017). Toda-Yamamoto causality test between inflation and nominal interest rates: evidence from three countries of Europe. International Journal of Economics and Financial Issues, 7(6), 120-129.

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? Finance Research Letters, 16, 139–144.

Geweke, J. (1982). Measurement of linear dependence and feedback between multiple time series. Journal of The American Statistical Association, 77(378), 304-313.

Granger, C. W. J. (1969). Investigating Causal Relations By Econometric and Cross-Sectional Methods. Econometrica, 37(3), 424–438.

Haq, I. U., Maneengam, A., Chupradit, S., Suksatan, W. & Huo, C. (2021). Economic policy uncertainty and cryptocurrency market as a risk management avenue: A systematic review. Risks, 9(163),1-24.

He, C., Li, Y., Wang, T. & Shah, S. A. (2024). Is cryptocurrency a hedging tool during economic policy uncertainty? An empirical investigation. Humanities and Social Sciences Communications, 11(1), 1-10.

Hosoya, Y. (1991). The decomposition and measurement of the interdependency between second-order stationary processes. Probability Theory and Related Fields, 88(4), 429-444.

Khan, K., Sun, J., Derindere Koseoglu, S, & Rehman, A. U. (2021). Revisiting bitcoin price behavior under global economic uncertainty. Sage Open, 11(3),1-13.

Lucey, B. M., Vigne, S. A., Yarovaya, L. & Wang, Y. (2022). The cryptocurrency uncertainty index. Finance Research Letters, 45, 102147.

Markowitz, H. (1952). Portfolio Selection. Journal of Finance, 7(11), 77-91.

Matkovskyy, R., Jalan, A. & Dowling, M. (2020). Efects of economic policy uncertainty shocks on the interdependence between Bitcoin and traditional fnancial markets. The Quarterly Review of Economics and Finance, 77, 150–155.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System.

Oldani, C., Bruno, G. S. & Signorelli, M. (2024). Economic policy uncertainty and cryptocurrencies. Eurasian Economic Review, 14, 709-728.

Taştan, H. (2015). Testing for spectral Granger causality. The Stata Journal. 15(4), 1157-1166.

Toda, H. Y. & Yamamoto, T. (1995). Statistical Inference in Vector Autoregressions with Possibly Integrated Processes. Journal of Econometrics, 66, 225-250.

Wu, S., Tong, M., Yang, Z. & Derbali, A. (2019). Does gold or Bitcoin hedge economic policy uncertainty? Finance Research Letters, 31, 171-178.