Revisiting Bitcoin Price Behavior Under Global Economic Uncertainty

Khalid Khan¹, Jiluo Sun², Sinem Derindere Koseoglu³, and Ashfaq U. Rehman⁴

Abstract
This study examines the relationship between global economic policy uncertainty (GEPU) and bitcoin prices (BCP) employing the rolling window method. The full sample test shows that there is no causality between GEPU and BCP. However, the full sample causal relationship between the variables can be different when considering structural changes. The finding of the rolling window test indicates that there is causality in different subsamples. It has found both positive and negative bidirectional causalities between GEPU and BCP across various subsamples. The decision makers need to accelerate the development of blockchain technology that can be used for hedging and portfolio diversification. Moreover, enacting laws and regulations on state interventions and prohibitions ensures investor confidence. Information about policy changes should be incorporated into portfolio selection to avoid random market fluctuations. Its unregulated nature makes it more turbulent in the short term and has undergone sudden changes, so investors should be able to obtain comprehensive information about global economic and policy changes. Policy makers should ensure investor confidence by making legal regulations on state interventions and prohibitions.

Keywords
bitcoin, global economic uncertainty, Granger causality, bootstrap rolling window, digital currency

Introduction

The purpose of the study is to assess the causal nexus between global economic policy uncertainty (GEPU) and bitcoin prices (BCP) considering the time variation aspect. It has become increasingly important as an electronic payment tool and a speculative financial asset, which makes bitcoin (BTC) a digital gold (Urquhart, 2016). The low transaction costs and trading in unregulated systems make it popular (Blau, 2017; Kristoufek, 2015). It is considered a substitute for mainstream currencies and the last choice for investors in economic uncertainty (Bouri, Molnár, et al., 2017). During the higher GEPU period, investors seek safe havens such as gold and the BTC market for investment (Bouri, Gupta, et al., 2017). BTC remains highly unpredictable than traditional assets, especially due to events related to economic policy and changes in market regulations (Balcilar et al., 2017; Dyhrberg, 2016). Economic uncertainty is directly related to the market disorder, which may lead to “flight to safety” which often changes with economic and financial policies (Khan, Su, Umar, et al., 2020; Sarwar, 2017). The payment system is not guaranteed by a central bank or any institution, which makes BTC more unstable. These recent developments have increased the importance of examining GEPU to predict the BTC market behavior.

Compared with other financial assets, BTC has special characteristics, creating new possibilities for risk management and portfolio analysis (Dyhrberg, 2016). BTC experiences several ups and downs (Balcilar et al., 2017); BCP observe to increase significantly between 2010 and 2013. The market value rises from US$277,000 in 2010 to US$14 billion in 2013, an increase of 50,000 times (Garcia et al., 2014). BTC starts as a payment method by e-commerce companies such as eBay, Baidu, and Taobao, and trades on China’s top exchanges. BCP increased in November 2013 by 20% because China entered the market and it beat the yen and the dollar. However, in December 2013, China bans the use of BTC as legal tender to stop money laundering and ensure that Renminbi (RMB) is legal tender. BCP drop by 50% due to the e-commerce company’s decision not to...
accept BTC as payment (Gloudeman, 2014). However, the referendum on Britain’s exit from the European Union (EU) leads to a 10% fall in the pound’s value and a rise in BCP, and during this time, BTC rises 65% from US$517 to US$860. Overall, BCP are less volatile in 2015 than a year earlier due to uncertainty over global and local economic policies (Bouoiyour & Selmi, 2016).

However, 2016 has been an eventful year, with high levels of uncertainty across the globe. BCP almost double in 2016, driven by events such as the Brexit vote and the U.S. presidential election. To deal with the uncertainty, institutional investors, such as banks, pension funds, insurance companies, hedge funds, and asset managers, move their investments into BTC. Similarly, investors in other countries, such as China, Japan, and South Korea, start to use BTC as an alternative investment. Furthermore, Japan introduces legislation allowing BTC to be legal tender, and Russia’s position on BTC has changed. Likewise, BCP continue to rise during the U.S. election campaign and witness an increasing trend till March 2017. BTC gains 184.3% between 2013 and 2017 with 276 billion market value. BTC’s market value and trading volume reached its highest level in December 2017, with a market share of 44.8%. Speculation is widespread in the markets where the BTC bubbles burst, suggesting further capital losses for investors. The main reason is the introduction of many regulations and restrictions in various countries and stock exchanges. Likewise, banks are prohibited from using debits and credits in BTC. However, BCP decline by 65% in January 2018, mainly because of trade competition between China and the United States. The imminent threat of a trade war has caused BCP to fall since February 2018. Moreover, China’s response to higher tariffs on U.S. products weighs on the stock markets, which fall almost 10% as regulations are tightened. In March 2020, BCP have slumped because of the uncertainty caused by a coronavirus which recovers quickly (Conlon & McGee, 2020). However, demand for BTC increased in November 2020 due to institutional investors’ interest in BTC, which pushes BCP highest level.

The current study contributes by evaluating the mutual relationship between GEPU and BCP because most of the previous studies focus on the causal link running from GEPU to BTC and lack the association in other directions. The finding confirms the bidirectional causality between the related variables. Second, BCP observe several changes as a result of GEPU. Thus, the present study evaluates the relationship in the subsample and considers the time-varying characteristics between GEPU and BCP. Finally, the study highlights the reason for instability in the BCP over the study period. It shows that different political events and economic policy changes result in BCP changes. The widespread uncertainty around the world creates instability, leads to a lack of trust in traditional currencies, and helps to create BTC. The results show both positive and negative two-way causality in different subsamples. The results show that BTC, as a safe haven, can effectively restrain the unexpected effects of global economic and policy changes. Therefore, decision makers need to highlight the development of blockchain technology that can be used for hedging and portfolio diversification. It should ensure investor confidence by enacting laws and regulations on state interventions and prohibitions. Knowledge-related policy changes should be incorporated into portfolio selection to avoid random market fluctuations. Its explosive and unregulated nature makes it more turbulent in the short term and has undergone sudden changes, so investors should be able to obtain comprehensive information about global economic and policy changes.

The remaining article is organized as follows. The “Literature Review” section elaborates the previous literature. The “Method” section explains the methodology. The “Data” section describes the data followed by the “Empirical Analysis” section. The “Conclusion” section concludes.

Literature Review

Garcia et al. (2014) find that information on the media has a significant impact on BCP. Dyhrberg (2016) shows that uncertainty in the United States harms BCP. Bouri, Molnár, et al. (2017) analyze the association between BTC and uncertainty in the United States, and the outcomes show that volatility would damage the return of BCP. Bouoiyour et al. (2016) note that BCP are determined by long-term fundamentals. Bariviera (2017) investigates the long memory of the BTC daily returns and daily volatility. The outcome shows persistent behavior during all the periods, while daily returns indicate persistence only between 2011 and 2014. Bouoiyour and Selmi (2016) analyze the impact of different global events and reveal that both GEP and BTC move in the same direction. X. Li and Wang (2017) study the determinants of BTC and conclude that BCP are related to changes in economic and market conditions. Bouri, Gupta, et al. (2017) study whether BTC can be used as a hedge against GEP. The finding suggests that BTC can indeed hedge against uncertainty. Conrad et al. (2018) examine the causal relationship between BCP and GEP, and find that BCP volatility is closely related to global economic activities. Bouri, Azzi, and Dyhrberg (2017) investigate the characteristics of the BTC market before and after the 2013 price crash, and the results support the safe haven phenomenon. It can be seen that during the economic turmoil, BCP increase, and investors buy more BTC and pass higher uncertainty to the BTC market. However, BCP decline during an upward trend in the stock market, and investors sell their BTC and pass low volatility to the BTC market.

X. Li and Wang (2017) point out that economic uncertainty fundamentals lead to a rise in BCP. Bouri et al. (2018) show that the global financial stress index Granger causes BCP. Demir et al. (2018) analyze the impact of economic policy uncertainty on BTC earnings and find that the GEP leads BCP. Al-Khazali et al. (2018) find that BCP trend to
decrease in response to economic policy news related to the United States. Corbet et al. (2018) find that cryptocurrencies are highly disconnected from other traditional assets. Therefore, they conclude that the cryptocurrency market is a new investment asset class and can be used as a hedging instrument. G. J. Wang et al. (2019) analyze uncertainty spillover on BCP which is negligible in most conditions and BTC can be used as a safe haven under uncertainty shocks. P. Wang et al. (2020) study the effects of GEPUs on the BTC market in the United Kingdom and the United States. The outcomes display that the returns around the highest GEPUs are significantly greater than those around the lowest GEPUs.

Bouri and Gupta (2019) consider the role of uncertainty measures for forecasting BTC returns. They use two different uncertainty measures as news-based information and internet-search-based information. The results find that investors often make their decisions depending on the internet-search-based information, which shows that individual searches on the internet for words aiming to measure uncertainty, and allow investors to construct a portfolio with BTC providing better hedging strategies. Both Yu (2019) and Fang et al. (2019) examine the effects of the economic policy uncertainty on BCP volatility, and conclude its powerful role in future volatility. Fang et al. (2019) state that GEPUs information can be used to predict BCP volatility. Cheng and Yen (2019) find that China’s uncertainty can only predict BCP returns among the group of cryptocurrencies. Gozgor et al. (2019) confirm a positive correlation between BCP returns and GEPUs during periods of regime change. Walther et al. (2019) find that BCP volatility is driven by the global business cycle rather than country-based data. Also, global economic activity is considered to be the best predictor of BCP. Ailamidis et al. (2019) find that there is a similar mean correlation among different cryptocurrencies. The study also examines the correlation against others such as stocks, bonds, and gold returns, and concludes that the behavior of cryptocurrencies is different from the other traditional assets. Qin et al. (2021) confirm that GEPUs have both positive and negative impacts on BCP and can consider hedging policy uncertainty.

An evaluation of the existing literature on the causal relationship between GEPUs and BCP shows that these studies utilize conventional methods. None of these conventional techniques of causality can resolve the time-varying relationship between GEPUs and BCP. The bootstrap rolling window Granger causality test helps to identify the full sample and subsample associations between GEPUs and BCP, and to reveal how this association varies over time, which is not recognized by most conventional methods used in the literature. This article contributes to the existing methods by considering the time variation characteristics of the time series. The results of the entire sample may undergo structural changes, leading to unstable results (Balciar et al., 2010). This problem can be resolved by using the bootstrap rolling window test to check the connection between GEPUs and BCP. The traditional techniques cannot detect the causal relationships between complete samples and subsamples, as well as the ability to capture time changes. The bootstrap rolling window offers a substitute method for detecting the association in the whole sample and the subsample (including time changes).

**Method**

The Granger causality test assumes that time series is stationary, and there may be no standard asymptotic distribution without satisfying the stationary hypothesis. In the absence of the standard asymptotic distribution (Sims et al., 1990; Toda & Phillips, 1993, 1994), the estimation of the vector autoregression (VAR) model is difficult. Toda and Yamamoto (1995) propose an improved Wald test to explore the asymptotic distribution through the enhanced VAR variables. Shukur and Mantalos (2004) study the size characteristics of the revised Wald test using Monte Carlo simulation and explore the correct size of the small–medium size. Shukur and Mantalos (1998) point out that the bootstrap method based on residuals solves the problem of the size and power consumption. A large number of studies show that the residual-based bootstrap RB method is better demonstrated than the standard asymptotic distribution with or without cointegration (Balciar et al., 2010; Mantalos, 2000). The greatest effect of Shukur and Mantalos (2000) is to realize that likelihood ratio LR testing with a small sample size has superior efficacy. This study employs improved LR statistics subject to RB to evaluate a causal relationship between GEPUs and BCP.

The VAR(p) can be estimated as follows:

\[ \tau_t = \theta_0 + \theta_1 \tau_{t-1} + \cdots + \theta_p \tau_{t-p} + \varepsilon_t, \quad t = 1, 2, \ldots, T, \]  

(1)

where \( \varepsilon_t = (\varepsilon_{t1}, \varepsilon_{t2})' \) is a white noise process with zero mean and covariance matrix \( \Sigma \). Equation 1 are divided into two subsectors:

\[
\begin{bmatrix}
\text{GEPU}_t \\
\text{BCP}_t
\end{bmatrix} = \begin{bmatrix}
\theta_{10} \\
\theta_{20}
\end{bmatrix} + \begin{bmatrix}
\theta_{11} (L) \theta_{12} (L) \\
\theta_{21} (L) \theta_{22} (L)
\end{bmatrix} \begin{bmatrix}
\text{GEPU}_{t-1} \\
\text{BCP}_{t-1}
\end{bmatrix} + \begin{bmatrix}
\varepsilon_{t1} \\
\varepsilon_{t2}
\end{bmatrix}.
\]  

(2)

In the empirical section, the latter variable is BCP \( \theta_{i,j} (L) \theta_{i,k} (L), i, j = 1, 2 \), and L is the lag length operator. As the size characteristic of the revised Wald test using Monte Carlo simulation, the Granger causality test assumes the constancy of the V AR model. However, these features do not hold as a result of the structural changes (Granger, 1969). In the case of the structural changes, the causality test for the full sample data is

**Parameter Stability Test**

The full sample causality assumes the constancy of the VAR model. However, these features do not hold as a result of the structural changes (Granger, 1969). In the case of the structural changes, the causality test for the full sample data is

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\varepsilon_{t1} \\
\varepsilon_{t2}
\end{bmatrix}.
\]  

(2)
proved to be invalid and unbalanced. The rolling window is used for the estimation to solve this problem. Andrews and Ploberger (1994) studies the short-run parameter stability by Sup-F, Mean-F, and Exp-F. In the case of cointegration, the VAR model needs to be modified by error correction. Therefore, the parameter stability of the long-term relationship needs to be tested. The above tests are calculated based on a sequence of LR statistic that measured the stability of the parameters in the complete sample. The bootstrap procedures are applied to calculate \( p \) values. Also, as per Andrews (1993), for the Sup-F, Mean-F, and Exp-F, 15% trimming is needed from both ends of the sample.

**Subsample Rolling Window Causality Test**

Structural changes will lead to instability, which is a difficult task in the current research. We incorporate modified bootstrap estimation in the rolling window subsample framework. The inconstancy and instability of the subsample data justify the use of the rolling window method. It scrolls from the beginning to the end of the full sample, founded on a fixed size subsample (Balcilar et al., 2010). A permanent rolling widow with \( l \) information of full size is transformed into the classification of \( T – l \) subsamples of \( \tau = l+1, \tau l, ..., T \) for \( \tau = l+1, ..., T \). Next, each subsample causality is subject to the RB-based adjusted LR-causality method. It supplies the deviation and degree of the connection between GEPUs and BCP. The effect of the GEPUs and BCP is equivalent to the average of the whole bootstrap estimation, which can be obtained by the formula \( N_b \sum_{l=1}^{p} g_{2l+1} \), where \( N_b \) represents the number of bootstrap repeats. Again, the formula \( N_b \sum_{l=1}^{p} g_{2l+1} \) shows the effect of BCP on GEPUs. Given the above parameters, the window size should be selected in a way that is both accurate and representative. The specific literature does not provide a rule of thumb for obtaining the rolling window size and suggests that it is calculated according to the root mean of the square process (Pesaran & Timmerman, 2005).

**Data**

This study evaluates the relationship between GEPUs and BCP between 2011:04 and 2020:03. BTC gains importance when it is issued in China in 2011, and the prices remain below 100 dollars. However, GEPUs is at a high level in 2011 due to the Eurozone sovereign debt crises, intense battles over fiscal and health care policies in the United States, and leadership transition in China (Davis, 2019). BCP start massive fluctuation, and reach the highest level in 2013 and decline rapidly. GEPUs are Index developed by Caldara and Iacoviello (2018) is a weighted average of national news articles which deliberate GEPUs each month for 20 countries and retrieved from https://www.policyuncertainty.com/global_monthly.html. The study observes several economic events and policy changes that have generated uncertainty over time, such as the Eurozone debt crisis, the U.S. fiscal issue, changes in the Chinese leadership, European immigration crisis, Brexit, the U.S. elections, U.S.–China trade war, the slowdown of major economies, and coronavirus pandemic. These factors play an important role in global economic affairs. This has made the market volatile, especially during the recession, the U.S. fiscal cliff, and the Chinese leadership transition, which exacerbated the economic uncertainty. During the period, BCP have grown stronger because many believe BTC can cover up the uncertainty that prevails in the economic and banking system, price increases, which attracts BTC especially in the Eurozone which has affected by debt (Bouri, Molnár, et al., 2017). It is retrieved from https://www.coindesk.com/price/bitcoin. Figure 1 indicates that GEPUs remains low from the end of 2013 to the middle of 2014. On the contrary, BTC transactions continue to grow until the first quarter of 2014, mainly due to the strong interest of Chinese investors in BTC purchases and the acceptance of digital currency by the largest e-commerce companies. Europe faces a migration crisis in 2015–2016 which pushes GEPUs. Similarly, Brazil is experiencing a crisis, as well as India and Venezuela introduce demonetization policies, which produce GEPUs. In 2016, there are two major political events: Brexit and the U.S. presidential election have a major impact on future direction of policy, driving global uncertainty, which will make financial markets more uncertain. It raises the level of concern about the success of economies and financial systems that control traditional currencies and financial systems (Bouoiyour & Selmi, 2017). At the same time, we have witnessed the rising trend of BCP, mainly triggered by the widespread GEPUs, which undermines investors’ confidence in the stability of the banking system and future economic security. BTC has filled this gap, which gains momentum and providing an alternative to fiat currencies with a decentralized system outside of the politics of a single during periods of economic and geopolitical turmoil. The heteroscedasticity test results are illustrated in Table A2 in the appendix, which can support data trends.

Similarly, China’s economic slowdown in 2016 severely hinders the future of global economic status and increases GEPUs. We notice that there is a remarkable upward trend in GEPUs in the last quarter of 2017 and it reaches the highest price in November 2017, mainly due to the uncertainty in Japan and North Korea that lead to investors entering the BTC market. Similarly, BCP begin another sudden drop in January 2018, resulting in a 54% drop in BCP, which is seen as the result of the trade war between China and the United States.

The dispute between the world’s two largest economies has raised the level of uncertainty, with investors more cautious about investing in traditional assets. The forthcoming crisis has a major impact on the BTC market and prices drop sharply. BTC’s emergence during the 2008 global financial crisis leads to a lack of confidence in the global financial system. During this period, BCP experience greater fluctuations, which show an upward trend and exceed the
international gold price (Yermack, 2015). On the contrary, GEPU experiences numerous ups and downs, which leads to the formation of BCP. Due to technology and fundamental factors, prices have fallen in 2019. BCP decline rapidly due to the 2020 pandemic and reverse within a week. However, the greater demand for BTC from institutional investors led to the highest level of BCP in November 2020 (Conlon & McGee, 2020). All these events prompt this article to evaluate the relationship between BCP and GEPU. Table 1 illustrates the summary statistics. It shows that BCP have a higher standard deviation, which is evident by the numerous successive ups and downs. Similarly, BCP are skewed to the left because the skewness value is negative, while GEPU is skewed to the right. The kurtosis values for both variables are less than 3 which means platykurtic distribution. Finally, the Jarque–Bera test shows non-normality for GEPU and BCP.

Empirical Analysis

We use various unit root tests, for example, augmented Dickey–Fuller (Dickey & Fuller, 1981), Phillips–Perron (Phillips & Perron, 1988), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS, Kwiatkowski et al., 1992) tests, to evaluate the stationarity of GEPU and BCP. The results are shown in Table 2. We observe stationarity of GEPU and BCP at the level (Su et al., 2020). This supports the application of the bivariate VAR model to explore the full sample causality between GEPU and BCP. We selected lag 2 based on Schwarz information criterion (SIC). Similarly, the unit root test with structural breaks is performed through Zivot and Andrews (1992). The finding confirms that GEPU and BCP show structural breaks.

Table 3 shows the complete sample results, indicating that GEPU does not Granger cause BCP, and vice versa. The results of the full sample show that there is no causal relationship between GEPU and BCP. We illustrate the cointegration test results in Table A1 in the appendix to support the VAR model.

It is accepted that only one causal correlation occurs in the full sample with no structural changes (Balcilar et al., 2010). This may lead to a shift in the causal association between GEPU and BCP, and make this relationship unstable and thus impossible to assess (Zeileis et al., 2005). The parametric stability test explains this problem, which determines whether there are structural changes in the sample (Khan, Su, Xiao, et al., 2020). We can achieve this by using the Sup-F, Mean-F, and Exp-F tests recognized by Andrews (1993) and Andrews and Ploberger (1994) to explore the temporal stability of parameters in the VAR models. The Lc test evaluates the overall stability of the VAR model, and Table 4 contains the finding of the parameter stability test. In these two equations, the Sup-F is employed to investigate the parameter constancy for a sharp change of parameters. The results show a sharp change of parameters and reject the null hypothesis, and thus forecast the short-term parameter unpredictability. Mean-F and Exp-F test the possibility that the parameter may evolve gradually under the null hypothesis and follow the Martingale course. The finding of the GEPU equation shows that the Sup-F test rejects the null hypothesis of parameter consistency for a sharp change. The Mean-F and Exp-F reject the null hypothesis of the Martingale process and evolve.

![Figure 1. Trends of GEPU and BCP.](image)

**Table 1. Summary Statistic.**

| Variables | M   | SD  | Skewness | Kurtosis | J-B  |
|-----------|-----|-----|----------|----------|------|
| GEPU      | 5.104 | 0.382 | 0.304 | 2.199 | 4.847*** |
| BCP       | 6.233 | 2.527 | -0.535 | 2.189 | 8.642*** |

**Note:** J-B = Jarque–Bera; GEPU = global economic policy uncertainty; BCP = bitcoin prices. ***denote significance at the 1% level.
the Sup-F test for the BCP equation rejects the null hypothesis of parametric consistency for a one-time sharp shift. The Mean-F and Exp-F reject the null hypothesis of a Martingale method, so BCP develop gradually over time. It displays a significant indication that the parameters change gradually over time. The Lc test explores that the entire estimation model is invariable and offers a suggestion of short-term instability, and outcomes are unacceptable.

The parameter stability test shows the instability caused by the existence of structural changes that disrupt the reliability of the causal link between GEPU and BCP. The problem is solved by using the bootstrap rolling window method, which detects how the system develops, as well as instability at the subsample level (Balcilar et al., 2010). The RB bootstrap modified LR is used to explore the nexus between the GEPU and BCP. Figure 2 displays the outcomes of the bootstrap rolling window causality test between GEPU and BCP. Given the bootstrap p values, GEPU does Granger cause BCP at a 10% significance level in some subsamples. In the subsample 2013:10–2014:06, GEPU has a negative impact on BCP, which means that as GEPU increases, BCP will decrease. Our results are similar to that of Demir et al. (2018), who state that economic uncertainty has a negative impact on BCP. During the period, BCP witnesses several explosive bubbles followed by corrections, and the key driver is the entry of China into the market. This development in the global market results in an incredible peak in BTC trading, evidence of the high correlation of the RMB with the dollars (Kristoufek, 2015). BTC is accepted as a mode of payment by several e-commerce Chinese companies (e.g., eBay, Baidu, and Taobao), and BTC is started to trade on China’s top exchange market. In October 2013, BTC beat the Japanese and the U.S.-dollar-denominated trades, which result in the BTC surge. However, this boom came to a sudden stop on December 5, 2013, when the Bank of China bans BTC as the legal currency to discourage the risk of money laundering and protecting the RMB as statutory currency. On December 16, an ultimatum is given to the e-commerce companies to close the transaction of BTC by January 31, 2013. Similarly, BTC China is prohibited from the new purchase of BTC, which shocks the market, and prices collapse over 50% (Glauderman, 2014).

### Table 2. Unit Root Tests.

| Series | Levels | First difference |
|--------|--------|------------------|
|        | ADF    | PP               | KPSS  | ADF    | PP               | KPSS  | ZA      |
| GEPU   | -2.755* | -2.473           | 0.874*** | -9.030*** | 19.880**** | 0.500 | 5.232*** |
| BCP    | -1.513  | -1.503           | 1.122*** | -9.168*** | 9.126***   | 0.126 | 3.667*** |

Note. KPSS = Kwiatkowski–Phillips–Schmidt–Shin; GEPU = global economic policy uncertainty; BCP = bitcoin prices. ADF = augmented Dicky Fuller; PP = Phillips-Perron; KPSS = Kwiatkowski–Phillips–Schmidt–Shin; ZA = Zivot and Andrews. * and *** denote significance at 10% and 1% levels, respectively.

### Table 3. Full-Sample Granger Causality Test.

| Statistics | p value | Statistics | p value |
|------------|---------|------------|---------|
| Bootstrap LR test | 0.276 | 0.920 | 1.851 | 0.480 |

Note. GEPU = global economic policy uncertainty; BCP = bitcoin prices.

### Table 4. Parameter Stability Test.

| Statistics | p values | Statistics | p values | Statistics | p values |
|------------|----------|------------|----------|------------|----------|
| Sup-F      | 17.525** | .011       | 93.199***| .000       | 25.284***| .007     |
| Mean-F     | 6.036*   | .051       | 8.884*   | .060       | 12.042** | .015     |
| Exp-F      | 5.152**  | .023       | 42.472   | 1.000      | 9.698*** | .005     |
| Lc         |          |            | 2.163*** | .008       |          |          |

Note. GEPU = global economic policy uncertainty; BCP = bitcoin prices. *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively.
The subsamples from 2016:08 to 2017:05, GEPU is leading BCP, imply that as GEPU increases, BCP rise. We witness that, from the last quarter of 2016 to January 2017, the global uncertainty increases quickly and the major reason is the U.S. presidential election and the political crisis in Brazil, France, and South Korea. The United Kingdom leaving the EU may disrupt the common market for trade and can have serious consequences that may cause the emergence of another crisis. Similarly, the higher probability of Donald Trump being elected as U.S. president has risen the level of uncertainty as for his pledge to bar immigrants and the erection of a wall along the Mexico border resonate in the financial market. During the study period, BCP start rising which are mainly caused by various economic and financial development. BTC has the characteristics of hedging, which can replace gold to resist a variety of risks and provide investors with a safe haven, thereby increasing the demand for BTC (Dyhrberg, 2016). BTC speculation has increased investors’ attention to digital currencies, which leads to the demand for BTC. This sensitivity tends to revolve around global news about economic policies that control BTC price dynamics. The process of demonetization in India and Venezuela has increased investors’ attention to hedging risks. However, in the first quarter of 2017, BCP start rising in China because of irregular performance of the stock markets along with the continuous fall of the RMB against the U.S. dollar which

**Figure 2.** The $p$ values of rolling test statistics.
*Note. GEPU = global economic policy uncertainty; BTC = bitcoin.*

**Figure 3.** Coefficients of GEPU impact on BCP.
*Note. GEPU = global economic policy uncertainty; BCP = bitcoin prices.*
results in BTC trading. In the subsample 2017:12–2018:04, GEPU is causing BCP which means that as the level of the global uncertainty increases, BCP move upward. It touches the highest point in December 2017, which coincides with a decreasing level of GEPU. During the period, two main events occur at a global level, which leads the uncertainty to rise: first is the rising tension between North Korea and Japan in the last quarter of 2017, which generates uncertainty that pushes the investors into the BTC market. We observe a record upward trend and BCP touch the highest price in November 2017. However, this higher price is followed by a sudden decrease in December 2017, resulting in a 54% price drop till the first quarter of 2018. The U.S.–China trade war, between the two largest economies of the world, has raised the level of uncertainty and investors as well as traders are more cautious regarding investment in traditional assets (Bouri et al., 2020). The robustness test is demonstrated in the appendix to support the main results.

The result of BCP impact on GEPU is illustrated in Figure 4. It shows that there are several subsamples, including 2015:05–2015:08 and 2016:03–2016:08, where BCP cause GEPU. Figure 5 illustrates the results of the bootstrap estimates of the rolling window and shows that BCP have a positive influence on GEPU in several subsamples. Globally, BTC has become more attractive than many foreign currencies and cryptocurrencies. Also, although it is not a reliable investment tool in terms of the state guarantee, it has started to be preferred significantly. Especially those with problems in the national economy, and investors from countries with high inflation rates, can take risks to invest in BTC. This may increase the volatility and uncertainty in the market. For instance, BTC is seen as a speculative investment by Yermack (2015). In addition, Bouri, Molnár, et al. (2017) investigate the volatility persistence in the BTC market. Their empirical results show significant evidence against the efficient market hypothesis. The inefficiency of the BTC market may lead to the inefficiency in the general economy. The findings of Bouri, Azzi, and Dyhrberg (2017) show that the BTC market supports the safe haven phenomenon. Investors buy more BTCs during economic turmoil, which also transmits the increased uncertainty to the BTC market; this also leads to increase turmoil. However, in the subsample, 2015:05–2015:08 BCP remained less volatile as compared with 2014. At the same time, GEPU is one higher level due to the condition of the global economy, which is predicted to grow at a slow rate. World trade remains at a low level along with rising concern about China decelerating economic growth. Similarly, the emerging economies’ economic growth and trade volume decline due to contraction in Asian imports, which cause global economic uncertainty and attract investors toward BTC.

In the subsample 2016:05–2016:08, BCP have a positive impact on GEPU and suggest uncertainty may cause a boost in the BTC market. At the same time, it is observed that the rising trend in the global GEPU and the main reason behind the Brexit phenomenon have created uncertainty over Europe. Similarly, many European countries facing immigration issues mostly from the war-ravaged countries such as Syria, Afghanistan, and Iraq, put pressure on the EU economies and the emergence of unpredictability. Economic growth at the global level, particularly European and Chinese economies, witnesses a diminishing rate along with the slowing down of trade, which has the combined impact of the economic fear of the future outlook. This precarious situation has also influenced the stock markets around the world, which push the investors toward an alternative as the digital currency and BCP rise.

**Conclusion**

We examine the causal link between GEPU and BCP by employing the rolling window causality. It finds no
relationship based on the full sample test. By including the structural fluctuations, the parameter constancy test shows short-run variability. There are many subperiods that show GEPU causes BCP. The direction of the relationship is both positive and negative for different subperiods. This is one finding of many studies that as the demand for BTC increases, BCP rise due to high GEPU, so there is a positive correlation between GEPU and BCP (Demir et al., 2018; X. Li & Wang, 2017; P. Wang et al., 2020). However, it can also be observed that GEPU has a negative impact on BCP in one subperiod. When examining the characteristics of this period, we can see that there are state interventions and prohibitions. Therefore, as the GEPU increases, BCP decrease in this specific subperiod. If these state interventions do not exist, it can be concluded that the uncertainty will affect BCP positively. Thus, it can be concluded that as long as there is no national prohibition and intervention, uncertainty will have a positive impact on BTC. According to our empirical results, BCP cause GEPU in two different subcycles. The main reason here is that news about manipulative buying and selling of BTC in certain periods may be interpreted as increasing economic uncertainty. These empirical discoveries show us the power of our methodology, and we should not just accept a period of research. The subperiod should be investigated. The study has many practical implications for policy makers. Policy makers need to develop blockchain technology on priority basis, as it can be used in hedging and portfolio diversification. However, regulations are required for BTC exchanges, as uncertainty in the BTC market appears to increase economic uncertainty according to the results. Policy makers should ensure investor confidence by making legal regulations on state interventions and prohibitions. Economic uncertainty is driving the major global currencies. In this study, we see that it also affects the first and the most important cryptocurrency too. Other leading cryptocurrencies such as Ethereum and Ripple also can be affected by GEPU. Cryptocurrencies’ explosive and unregulated nature has made them more volatile in the short term and has seen sudden changes, so investors need comprehensive information about changes in the global economy and policy. Policy changes related to knowledge should be incorporated into portfolio selection to avoid random market fluctuations.

Appendix

Cointegration Test

The cointegration test is conducted to check whether global economic policy uncertainty (GEPU) and bitcoin prices (BCP) have a long-term relationship. The outcome is exhibited in Table A1, which suggests that GEPU and BCP have no long-run association.

| Null hypothesis | Trace value | p values | Maximum eigenvalue | p values |
|-----------------|-------------|----------|--------------------|----------|
| r = 0           | 9.959       | 0.283    | 8.888              | 1.070    |
| r = 1           | 1.070       | 0.300    | 0.295              | 0.300    |
**Heteroscedasticity Test**

We have transformed the data into logarithmic form to control the heteroscedasticity, and the result confirms that GEPU and BCP have no such issues.

| Table A2. Heteroscedasticity Test: Breusch–Pagan–Godfrey. |
|-----------------|-----------------|-----------------|-----------------|
| $F$ statistic   | $\times R^2$    | $F(1,113)$      | $\chi^2(1)$    | Prob. $F(1,113)$ | Prob. $\chi^2(1)$ |
| 1.728           | 1.733           | 0.191           | 0.188          |

**Robustness Test**

We use the cryptocurrency index to check the validity of our main results and illustrate them in Figure A1. It shows that GEPU Granger causes the cryptocurrency index during 2018:03–2018:06 and 2018:08–2018:11. Figure A2 shows that during 2018:03–2018:06, the most important event is the trade war between the United States and China, which results in uncertainty, and the bitcoin (BTC) market witness a 50% sell-off. Similarly, the fear about the regulatory crackdown in Asia, especially in China and South Korea diving the sell-off.

Likewise, during 2018:08–2018:11, BCP decline because of higher U.S. interest rate and sluggish demand of investors. On the contrary, GEPU shows a rising trend because of Turkey’s debt issue and U.S. uncertain policies (Qin et al., 2021).

**Figure A1.** The $p$ values of rolling test statistics.

*Note.* GEPU = global economic policy uncertainty; GBI = global bitcoin index.

**Figure A2.** Coefficients of GEPU impact on cryptocurrency index.

*Note.* GEPU = global economic policy uncertainty.
Figure A3 shows the BCP causal impact on GEPU. The results indicate that as BCP rise so the GEPU rise decrease in the same direction. On the contrary, BCP cause GEPU in 2018:02–2018:06 and 2019:01–2019:04, as shown in Figure A4. However, during 2018:02–2018:06, BCP have a positive impact on GEPU. The trade war between the two largest economies triggers higher uncertainty, and BCP remain under pressure which ultimately shows a considerable price decline. Likewise, there is an apprehension that regulators in Asia may drive the sell-off.

Similarly, BCP are causing GEPU from 2019:01 to 2019:04 negatively. The main reasons can be the improvement in public confidence, which results in the decline of BTC demand and its price. Moreover, the U.S. dollar appreciated which makes investments profitable in dollars and decreases BCP.

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ORCID iD
Khalid Khan https://orcid.org/0000-0002-2574-9232

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