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Cryptocurrencies as a Speculative Asset: How Much Uncertainty is Included in Cryptocurrency Price?

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Abstract

The aim of this paper is to examine the relationship between uncertainty indices (Geopolitical Uncertainty Index and Global Economic Policy Uncertainty Index) and cryptocurrencies. This study evaluated the behavior of cryptocurrencies with the evolution of uncertainties (GPU, EPU) on returns and volatility in terms of safe heaven as in traditional specualtive assets it increases their volaitility and reduces risk. For this purpose, this study examines the relationship between uncertanities indices, gold returns and crptocurrency by using the OLS regression for the monthly data from April 2017 to April 2022. The findings of this study indicate that the return and volatility of cryptocurrency increases. In particular, we note that the cryptocurrency market could serve as a weak hedge and safe against GEPU during a bull market; It could be considered a strong hedge, but in most cases could not serve as a safety against GPR. However, in case of Gold it is found that it serves as weak hedge against uncertainity indices and is not considered as safe heaven against GEPU and GPR. This study expands the current research on uncertainity indices and provides unique insight about the speculative nature of cryptocurrencies and safe heaven.

Keywords

uncertainty, speculative asset, geopolitical risk, global economic policy, cryptocurrency

Introduction

The global financial crisis triggered widespread distrust in the established financial system, along with severe uncertainty about the economic policy actions governments and central banks would take. Emergence of digital currencies should be treated as one of the most remarkable financial innovations in 21 centuries. Since its launch in 2009, the cryptocurrencies have significantly grown in popularity due to its innovative features and independence from governments and other central authorities (Fang et al., 2019). Interestingly, the huge price rise of the first digital currency—Bitcoin, made its total market value reach more than $891 billion at the beginning of April 2022 (https://coinmarketcap.com/). Recently, a change in the approach to the issue of cryptocurrencies can be observed. To a lesser extent, the technical aspect of these assets or the stylized facts of cryptocurrency markets are taken up in the conducted research (Corbet et al., 2018; Dwyer, 2015). Instead, the researchers' attention is focused on the volatility (Balciar et al., 2017), market efficiency (Urquhart, 2016), the relationship between cryptocurrencies and other financial and non-financial assets (Bouri et al., 2017) or the speculative nature of digital currencies (Blau, 2017). This rapid expansion has prompted a surge of academic interest to identify the economic and financial influencers that could shape cryptocurrency prices (digital). Notably, researchers like Demir et al. (2018) have shown an interest in this area, especially since this cryptocurrency path seems to stand apart from traditional economic and financial trends (Kristoufek, 2015; Polasik et al., 2015).

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Many studies assert that digital currencies become more appealing during times of economic instability and eroding confidence in conventional economic and financial systems (Bouri, Gupta, et al., 2017a; Demir et al., 2018; Fang et al., 2019; Luther & Salter, 2017). Along these lines, suggestions have been made that digital cryptocurrencies could serve as an effective hedge against the inefficiencies of these systems by acting as a protective measure against stock market volatility (Bouri, Gupta, et al., 2017a; Demir et al., 2018; Dyhrberg, 2016; Fang et al., 2019; Guesmi et al., 2019; Selmi et al., 2018). These cryptocurrencies act as hedge or safe heaven against the evolution of uncertainties is still a question. This question arises due to the speculative nature, price volatility, bubble formation, and scandals that are linked to them (Bouri et al., 2019; Corbet et al., 2018; Selmi et al., 2018).

Due to the diversity of the results obtained, there is still a discussion whether cryptocurrencies should be treated either as a means of exchange or rather a speculative commodity (Baek & Elbeck, 2015). Their risky nature and explosive price behavior do not exclude the latter (Yermack, 2015). Baur et al. (2018) suggested that Bitcoin is "mainly used as a speculative investment and not as an alternative currency and medium of exchange." In support of these words Enoksen et al. (2020) confirm that cryptocurrency transactions are linked with permanent volatility and the possibility of bubbles. The uncertainty level is exacerbated by the lack of regulations related to the functioning of cryptocurrency market and trading of digital currencies (Enoksen et al., 2020). According to Al-Yahyaee et al. (2019), risks consisting in conflicts, political instability, terrorism, and macroeconomic uncertainty should be considered in works related to the creation of these regulations.

In view of the great attractiveness to investors over periods of unparalleled economic and political uncertainty, there is an emerging interest in studying the role of uncertainty measures on cryptocurrencies prices in the financial economics literature (Bouri et al., 2017; C. Chen et al., 2020; Panagiotidis et al., 2019). These measures may be utilized in order to evaluate different types of uncertainty. Most frequently economic policy uncertainty index (EPU) and volatility uncertainty index (VIX) are applied (Al-Yahyaee et al., 2019; Bouri et al., 2017; Enoksen et al., 2020). While the former is used to measure the economic policy uncertainty, the latter is for determining the financial markets uncertainty (C. Chen et al., 2020; Enoksen et al., 2020) . Considering the fact of high level of volatility of cryptocurrencies usually seen over a short period of time, the uncertainty indices may be perceived as a factor that supports investors to predict price returns of these assets. Demir et al. (2018) argues that an increase in uncertainties makes the trust of investors on conventional financial markets to drop and simultaneously the rise of attractiveness of cryptocurrencies.

The relationship between cryptocurrencies and uncertainty Indices may have useful implications for different groups of interest, not least practitioners responsible for investment decisions and hedging strategies as well as authorities' representatives who perceive cryptocurrencies as part of foreign reserves or create regulations aimed at introducing national digital currencies. Although some academics have undertaken research to find a link between uncertainty and the price of cryptocurrencies, this has been done merely for one digital currency (usually bitcoin) or one uncertainty index (Al-Yahyaee et al., 2019; Aysan et al., 2019; Demir et al. 2018; Fang et al., 2019; G.-J. Wang et al., 2019). In this paper, greater number of cryptocurrencies and greater number of uncertainty indices will be analyzed. This will allow to verify more accurately how the valuation of individual cryptocurrencies may be affected by a certain type of uncertainty.

This paper aims to examine the relationship between uncertainty indices, Global Economic Policy Uncertainty Index (GEPU) and Geopolitical Uncertainty Index (GPR) the representative of political and economic uncertainty respectively and a set of cryptocurrencies namely cryptocurrencies, namely Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Dogecoin (DOGE), and USD Coin (USDC). Provided analysis gives useful information as to whether uncertainty indices have any predictability power for cryptocurrency market. We, therefore, make an endeavor to address following research questions: (i) is there any relationship between uncertainty indices such as GEPU (Global Economic Policy Uncertainty Index), GPR (Geopolitical Uncertainty Index) and price returns of proposed cryptocurrencies such as Bitcoin, Tether, Ethereum, Dogecoin, and USD Coin? (ii) Are uncertainty indices useful for potential investors to predict price returns of cryptocurrencies? (iii) How political uncertainty versus economic uncertainty affects price returns?

The methods that have been utilized will be used in this study is mainly empirical analysis on the basis of regression techniques.

The structure of this article is as follows: The first section presents general information about speculative nature of cryptocurrencies and the tools used for measuring the uncertainty in this type of assets. The second section deals with the conception and basic features of the study and statistical methodology. In the last section, the results of the empirical analysis are presented, and the main conclusions are discussed.

Literature Review

Recently, very few innovations in financial markets have drawn more attention by investors and regulators than

digital currencies. Among the reasons why cryptocurrencies have become so popular, its unregulated structure and lower transaction fees should be mentioned (Blau, 2017). Nevertheless, despite the indicated desired interactions, concerns have been raising about the negative externalities related to cryptocurrencies. Apart from the frequently mentioned problem that digital currencies have been used to finance criminal activity, experts from the world of finance pointed to the volatility of digital currencies and thus the performance of a speculative function by this group of financial assets (Al-Yahyaee et al., 2019; Aysan et al., 2019). In principle, if digital currencies are subject to speculative operations, their role as a means of payment is diminishing. Following that avenue cryptocurrencies acts less like currencies themselves and more like a speculative investment. This raises a number of questions, including those related to the possible speculative bubbles or inefficiency that can be expected in this market (Enoksen et al., 2020; Urquhart, 2016).

The discussion about the function performed by cryptocurrencies pursues, because the results of the conducted research, concerning mainly a Bitcoin case, have been considered ambiguous. Nevertheless, much more frequently in the recent period, a "substantial speculative component" in the price of cryptocurrencies is indicated. For example, Yermack (2015) considers Bitcoin more like a speculative investment than a currency. The author also emphasizes that Bitcoin's volatility is much higher than that of traditional currencies. Moreover, bitcoin's daily exchange rates do not correlate with common currencies and gold, making this digital currency unsuitable for use in the risk management process. In similar vein Cheah and Fry (2015) recognize that Bitcoins prices contain a considerable speculative component, and the fundamental value of bitcoin is zero. Due to speculative nature of cryptocurrencies, they are attractive to amateur investors who have the potential to translate publicly available information differently from institutional investors. While institutional investors would be sensitive to changes in policy uncertainty, amateur investors may be more strongly affected by general media attention toward cryptocurrencies and their price volatility (Lucey et al., 2022). Hence, the impact of uncertainty on cryptocurrency markets will depend on types of uncertainty and the type of digital assets.

The use of uncertainty indices is broad and goes beyond financial markets (Bilgin et al., 2018; Gozgor et al., 2016; Jones & Sackley, 2016). Despite the attempts to apply different uncertainty measures (i.e., skewness, volatility, partisan conflict, geopolitical risk index, cryptocurrency uncertainty index) in the research to date, the most frequently used uncertainty indices include VIX and EPU (Bouri, Gupta, et al., 2017a; Demir et al., 2018; Selmi et al., 2018). The VIX index is a gauge of market expectations for short-term volatility transmitted by U.S. stock index option prices (Al-Yahyaee et al., 2019). The VIX is calculated based on real-time S&P 500 Index call and put options and is broadly followed by global investors as an indicator of financial market uncertainty (Mele et al., 2015). Accordingly, the VIX is regarded as benchmark for international investors, which means that its evolution impacts portfolio risk assessments (Chung & Chuwonganant, 2018). This is the reason why the VIX is commonly called a fear index (Whaley, 2000). On the other hand, EPU measures economic policy uncertainty about both regulation and legislation and includes three elements: newspaper coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expire in future years, and disagreement among economic forecasters as a proxy for uncertainty (http://www.policyuncertainty.com/methodology.html). The EPU index is constructed by measuring the news articles in 10 large US newspapers which contain a combination of words like "economy + regulation + uncertainty" (Enoksen et al., 2020).

Although it is believed that financial markets are influenced by uncertainty through a variety of channels, cryptocurrencies are linked to uncertainty more specifically through their hedging and safe haven properties, particularly when taking into account the fact that the price of cryptocurrencies depends on other factors than in case of traditional assets (Bouri, Gupta, et al., 2017a). While uncertainty measures provide an increase in case of conventional assets' volatility, it may not hold true for the cryptocurrencies. In other words, the increase in EPU or VIX dynamics may encourage investors to increase their involvement in cryptocurrencies considered as a hedge or safe haven. For this reason, recently a lot of research has been devoted to testing the properties of cryptocurrencies in times of crises and an increased level of uncertainty, considering theirs positive or negative correlation with traditional financial assets and commodities (Demir et al., 2018; Mokni, 2021; Mokni et al., 2022; Selmi et al., 2018; Wu et al., 2019). It is recognized that the results of above-mentioned studies support investors in making decisions regarding risk management and hedging opportunities of cryptocurrencies.

Although several papers have analyzed the impact of uncertainty on cryptocurrency market, they concern one digital currency (most often BTC) or one uncertainty index. Demir et al. (2018) confirmed the prediction power of EPU on BTC returns in years 2010-2017 indicating that BTC returns are negatively associated with the changes in the EPU. Bouri et al. (2017) claim based on standard OLS regression that VIX index negatively affects BTC returns. Additionally, BTC is considered to serve as a hedge against uncertainty at shorter investment

horizons. C. Chen et al. (2020) agrees that increasing fear (a Google search-based fear sentiment measure) of the coronavirus leads to negative Bitcoin returns, which confirms that Bitcoin behaves like other financial assets rather than traditional safe-haven assets. such as gold. As a consequence, it may not be desirable for investors to allocate resources to Bitcoin to reduce their risk exposure, since it may not serve as a safe haven during the time of crisis. The analysis of a larger number of cryptocurrencies in relation to one measure of uncertainty—EPU—was carried out by Mokni et al. (2022). Based on the obtained research, the authors concluded that cryptocurrencies cannot act as a strong hedge or safe haven against EPU before and during the health crises. At the same time, they can be considered weak haven for the whole sample period, before and during the COVID-19 pandemic.

This study uses a more comprehensive research concept based on a greater number of uncertainty indices and financial instruments in the form of cryptocurrencies. Such an approach results, inter alia, from the decline in the importance of bitcoin in relation to the percentage of total cryptocurrency market capitalization. While in 2016 the share of BTC was over 90%, it has now decreased to ~40% (https://coinmarketcap.com/) (Feder et al., 2018).

The association between stock market returns and uncertainty has gained the interest of numerous scholars. Sarwar delved into the correlation between the Volatility Index (VIX) and returns in the European stock market, identifying a notable negative correlation between the two. Similarly, Brogaard and Detzel (2015) discovered that a 1% surge in Economic Policy Uncertainty (EPU) results in a decrease in concurrent market returns by 2.9%. A significant body of research has also focused on understanding the influence of consumer sentiment or measures of uncertainty on the cryptocurrency market. Multiple indicators such as the VIX (Bouri et al., 2017), the EPU Index (W. Cheng & Yen, 2019; Demir et al., 2018; Fang et al., 2019; H. Wang et al., 2020; Wu et al., 2019), the Crude Oil Volatility Index (Al-Yahyaee et al., 2019), the Geopolitical Risk Index (Al Mamun et al., 2020; Aysan et al., 2019), and the Trade Policy Uncertainty (Gozgor et al., 2019) have been utilized in these studies.

There are studies like Boutchkova et al. (2012) which have also correlated political uncertainty with stock market volatility. Meanwhile, Pastor and Veronesi (2012) have established a general equilibrium model that foresees a drop in stock prices on average, following the declaration of a policy shift. Durnev (2011) detected reduced sensitivity of corporate investment to stock prices during election years. Goodell and Vähämaa (2013) have found evidence suggesting that as investor predictions about future macroeconomic policies evolve, U.S. stock market volatility rises with the election chances of the ultimate winner. Sum (2012) offers empirical proof of the detrimental influence of economic policy uncertainty on European stock market returns. Furthermore, Fang et al. (2019) have factored in the global EPU, asserting that it enhances the predictability of Bitcoin price fluctuations. It's noted that the global EPU negatively impacts the Bitcoin-debt correlation, while positively influencing the correlations of Bitcoin with equities and commodities. Based on these arguments, this study proposes the following hypothesis; As levels of uncertainty escalate, cryptocurrencies return function as a safe haven or strong hedge.

Sample Construction, Variable Description, and Methodology

Sample Construction

The sample of this study is based on Bitcoin (BTC), Ethereum (ETH), Tether (USDT), Dogecoin (DOGE), and USD Coin (USDC) as these are the major cryptocurrencies in the world and constitutes 78% of total market capitalization. The data is collected on daily basis is for these currencies. Following Katsiampa, pricing and volatility data for each currency is obtained from the website (coinmarketcap.com). whereas the data on two major uncertainty indices GEPU and GPR is obtained from data source (policyuncertainty.com) following Baker et al. The starting date of the empirical analysis depends on the availability of the data and the daily frequency data are used. data on uncertainty indices is available from 1970 onwards, however, historical data on cryptocurrencies is unavailable from that period. Therefore, the sample spans from April 2017 to April 2022 yielding 420 cryptocurrency-month observations.

Variable Description

Like previous cryptocurrency studies (G.-J. Wang et al., 2019), this study adopts the monthly logarithmic returns for each cryptocurrency i in month t, as dependent variable. We employ economic policy uncertainty and geopolitical risk measures as the main independent variables of interest. The GEPU Index measures the frequency of terms related to economic and policy uncertainty mentioned in newspapers in 20 developed countries (Davis, 2016). Following Caldara and Iacoviello, we use Geopolitical Uncertainity Index as a measure of tensions between countries.

Table 1. Descriptive Statistics for Monthly Cryptocurrency Returns, Uncertainty Measures.

Panel-A: Return on Top 5 cryptocurrencies					
Cryptocurrency	*N*	Mean	*SD*	MIN	MAX
BTC	61	9.403	0.923	7.742	11.024
ETH	61	6.251	1.151	4.670	8.440
DOGE	61	−4.734	1.886	−6.771	−1.089
USDT	61	0.000	0.009	−0.016	0.058
USDC	61	0.000	0.006	−0.015	0.034
Panel-B: Independent variables					
Uncertainty indices	*N*	Mean	*SD*	MIN	MAX
Ln (GPR)	61	4.540	0.303	4.106	5.801
LN (GPRU)	61	5.414	0.285	4.819	6.064

Note. Table 1 indicates the descriptive statistics of BTC, ETH, DOGE, USDT, and USDC. This also provides descriptive statistics of GPU and GPRU. This key descriptive statistics includes mean (Mean), standard deviation (*SD*), minimum value (MIN), and maximum value (MAX).

Methodology

We employ panel OLS regression to examine the effect of uncertainty indices on cryptocurrency returns. Using panel datasets in this type of economic research allows us to control for individual heterogeneity and quantify the effects of unobservable variables in the data (Hsiao, 2003). The following OLS model is estimated:

$$R_{i,t} = \beta_0 + \beta_1 \Delta \ln (Uncertainity\ Indices)_t + \beta_2 D90 \Delta \ln (Uncertainity\ Indices)_t + TIMEFE + \varepsilon_t \quad (1)$$

where the dependent variable $R_{i,t}$ is the return on each cryptocurrency i in month t. This model is used for gold and cryptocurrency. We use the change in the first differences of the logarithm of each uncertainty measure $\Delta \ln(GEPU)_t$ *and* $\Delta \ln(GPR)_t$. D90 is a dummy variable if the change in each uncertainty measure is higher than the 90% quantile, and 0 otherwise. This dummy variable helps us to determine whether these five currencies could be considered as a safe heaven against the uncertainty understood as GEPU and GPR. According to Wu et al. (2019) this could be interpreted as if a change in cryptocurrency returns (Bitcoin [BTC], Ethereum [ETH], Tether [USDT], Dogecoin [DOGE], and USD Coin [USDC]) are positively correlated (uncorrelated) with change in uncertainty indices (GEPU and GPR) such as $\beta 1 > 0$, then we define cryptocurrencies as a strong (weak) hedge against uncertainty. If cryptocurrency returns are positively correlated (uncorrelated) with the change in uncertainty on average at the 90% quantile ($\beta 1 + \beta 2 > 0$), then we define cryptocurrencies as a strong (weak) safe haven against uncertainty

Results

Summary Statistics

Tables 1 and 2 summarizes the descriptive statistics of the monthly returns as well as the explanatory variables used in this study. Panel A of Table 1 shows that, overall, the returns on cryptocurrencies are highly skewed. For example, the augmented Dickey-Fuller (ADF) test confirms that all our variables are stationary. Additionally, we confirm the normality of the variables in our model using the Shapiro-Wilk test and the skewness-kurtosis (Jarque-Bera) test.

Uncertainty and Cryptocurrency Return

Table 3 reports the estimation results between cryptocurrency returns (BTC, ETH, DOGE, USDT, USDC) and changes in each uncertainty measure (GPRU and GPR). GPRU result is reported in Table 3. We can see that GPRU is significant in the column of BTC and ETH at 10% and 5% level of significance which indicates that β value is less than .05. However, in the case of DOGE, USDT, and USDC the relationship between GPRU is not significant. This could be interpreted that BTC and ETH cryptocurrencies are not a hedge against GPRU. However, in case of DOGE, USDT, and USDC these cryptocurrencies are considered as safe heaven against uncertainty of GPRU. $B1 + \beta 2 > 0$ indicates that, on average, the cryptocurrency market is a weak safe against GPRU.

Panel B presents the estimation results using GPR as a proxy for uncertainty. In OLS regression, $\beta 1 > 0$ and is significant at the 1% level in all the specifications of cryptocurrency (BTC, ETH, DOGE, USDT, USDC), indicating that these cryptocurrencies are a strong hedge against

Table 2. Descriptive Statistics for Monthly Gold Returns, Uncertainty Measures.

Panel-A: Return on Top 5 cryptocurrencies					
Cryptocurrency	*N*	Mean	*SD*	MIN	MAX
GOLD	61	0.025	0.912	5.67	9.58
Ln (GPR)	61	4.540	0.303	4.106	5.801
LN (GPRU)	61	5.414	0.285	4.819	6.064

Note 2. Table 2 indicates the descriptive statistics of GOLD. This also provides descriptive statistics of GPU and GPRU. This key descriptive statistics includes mean (Mean), standard deviation (*SD*), minimum value (MIN), and maximum value (MAX).

Table 3. Estimation Results Between Cryptocurrency Returns and GPRU and GPR Via OLS.

Variables	BTC	ETH	DOGE	USDT	USDC
Panel-A					
ãln(GPRU)	−0.172* (−1.791)	−0.22** (−2.321)	−0.064 (−0.596)	0.018 (−0.134)	−0.313 (−1.042)
ãln(GPRU) × D90	0.211 (−1.258)	−0.245 (−1.375)	0.28 (−1.474)	0.188 (−1.056)	0.655* (−1.863)
Test β1 + β2 = 0	0.024	−0.375	0.216	0.206	0.342
Panel-B					
ãln(GRP)	0.357*** (−5.704)	0.222*** (−2.761)	0.316*** (−3.62)	0.432*** (−5.873)	0.460*** (−2.597)
ãln(GRP) × D90	−0.424*** (−4.546)	0.439*** (−2.909)	−0.201* (−1.946)	0.476*** (−5.471)	−0.565** (−2.462)
Test β1 + β2 = 0	−0.067	−0.217*	0.115	−0.044	−0.105

Note. Table 3 provides the estimation results of OLS regression of uncertainity indices on crptocurrency returns.
*, **, and *** shows the level of significance at 10%, 5%, and 1% level of sinificance.

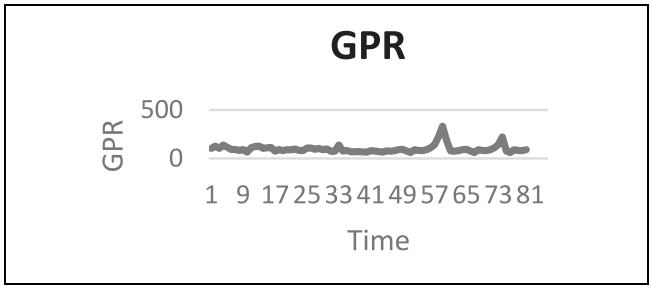

Figure 1. GPR uncertainty index.

GPR; however, β1 + β2 < 0, which suggests that these cryptocurrencies are not a safe against GPR.

Overall, our panel regression analyses with GPR are in line with the studies of Demir et al. (2018) and Aysan et al. (2019), which insist that cryptocurrency returns could be considered a hedge against GPR during a bull market; consistent with Wu et al. (2019), we find that the cryptocurrency return could serve as a weak hedge against GPRU in bull market conditions.

Figures 1 to 7 shows the relationship of each variable (e.g., Geopolitical Uncertainty Index, Global Economic Political Uncertainty, BTC, ETH, DOGE, USDT, USDC). As we can see, the *X*-axis shows that period and the *Y*-axis shows the uncertainty value and returns, respectively, for each cryptocurrency. The relationship between geopolitical uncertainty and global economic policy uncertainty is not the same. As these figures show, geopolitical uncertainty is steadily increasing over time. However, global political uncertainty is increasing significantly. This would be due to the COVID-19 crisis. For cryptocurrencies, the behavior of BTH and ETH is almost the same. On the contrary, the behavior of USDT and USDC is the same. But in the case of DOGE, this behavior is completely different from all other cryptocurrencies.

Uncertainity and Gold Returns

Table 4 reports the estimation results between speculative asset (GOLD) and uncertainity indices. The OLS regression is used, and the results are presented in Table 4. This table indicates that the value of GOLD return is significant at 5% level of significance. This significance level indicates that the β value is less than .05. It could be interpreted as that gold is not a hedge against GPRU. As the value of B1 + β2 > 0 indicates that, on average, the speculative assets market is a weak safe against GPRU. Panel B presents the same situation where this is significant at the 5% level of significance which indicates that GOLD is not a safe heaven against GPR.

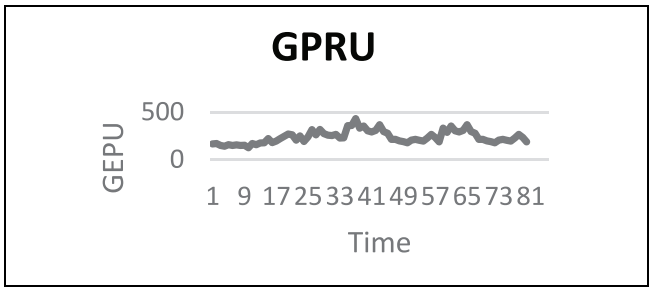

Figure 2. GEPU uncertainty index.

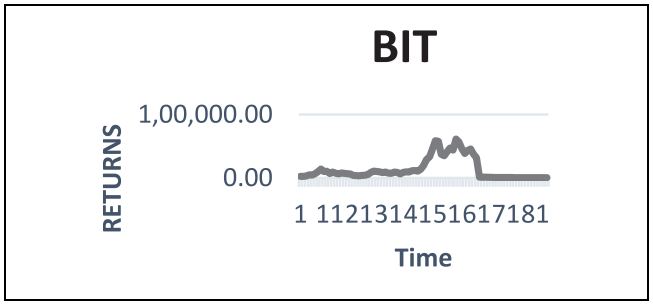

Figure 3. BIT returns.

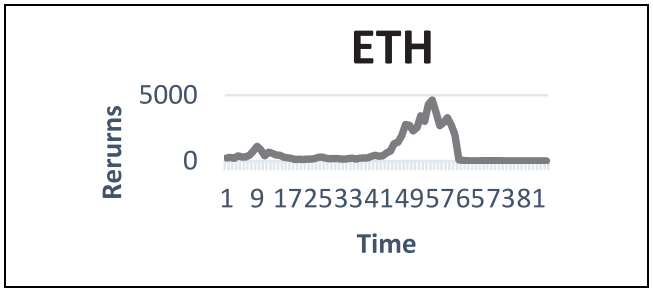

Figure 4. ETH returns.

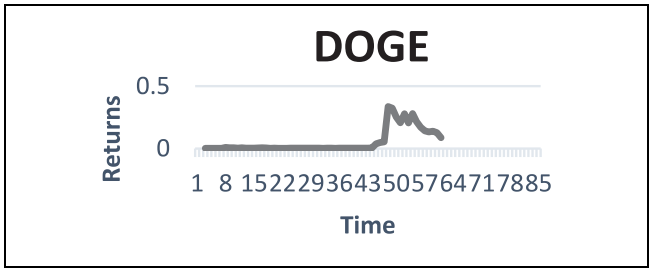

Figure 5. DOGE returns.

Conclusion

The aim of this paper is to examine the relationship between uncertainty indices (Geopolitical Uncertainty Index and Global Economic Policy Uncertainty Index) and cryptocurrencies. Furthermore, it also examines the

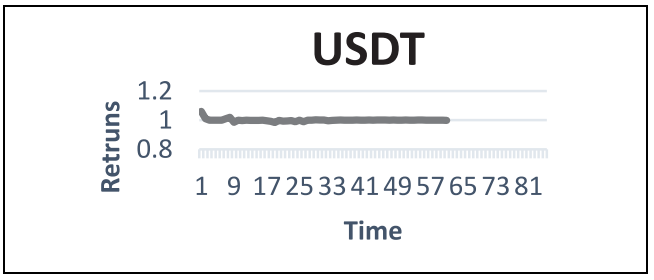

Figure 6. USDT returns.

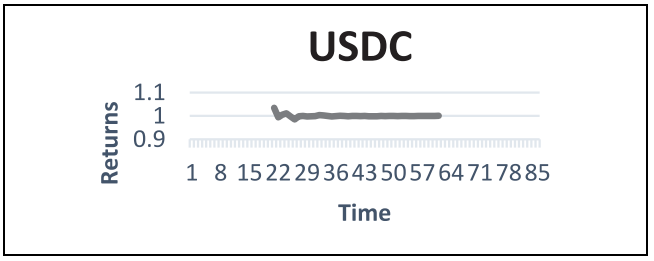

Figure 7. USDC return.

Table 4. Estimation Results Between Cryptocurrency Returns and GPRU and GPR Via OLS.

Variables	GOLD
Panel-A	
Δln(GPRU)	−0.201** (−1.892)
Δln(GPRU) × D90	0.311 (−1.267)
Test β1 + β2 = 0	0.030
Panel-B	
Δln(GRP)	−0.287*** (−4.765)
Δln(GRP) × D90	−0.388*** (−3.968)
Test β1 + β2 = 0	0.0689

Note. Table 4 provides the estimation results of OLS regression of uncertainity indices on Gold returns.
Note "*", "**", and "***" shows the level of significance at 10%, 5%, and 1% level of sinificance.

impact of uncertainty indices on gold returns. For this purpose, this study examined the relationship between uncertanities indices, gold returns and crptocurrency by using the OLS regression for the monthly data from April 2017 to April 2022. The findings of this study indicate that the return and volatility of cryptocurrency increases. In particular, we note that the cryptocurrency market could serve as a weak hedge and safe against GEPU during a bull market; It could be considered a strong hedge, but in most cases could not serve as a safety against GPR. However, in the case of Gold it is found that it serves as weak hedge against uncertainity indices and is not considered as safe heaven against

GEPU and GPR. The analysis provided useful information on whether uncertainty indexes have predictability power for the cryptocurrency market.

This study contributes to previous research efforts by expanding the discussion on the hedging and safe-haven properties of cryptocurrencies versus uncertainty indices (GPR, GEPU). We show that cryptocurrency returns respond to GEPU and GPR, but responses to cryptocurrency uncertainty are heterogeneous. In particular, we note that the cryptocurrency market could serve as a weak hedge and safe against GEPU during a bull market; It could be considered a strong hedge, but in most cases could not serve as a safety against GPR.

The relationship between cryptocurrencies and indices of uncertainty can have useful implications for various stakeholders, not least for practitioners responsible for investment decisions and hedging strategies, as well as for officials who perceive cryptocurrencies as part of foreign exchange reserves or create regulations for the launch of national digital currencies. This study could be extended by including the transaction volume and volatility.

Author Note

This research was conducted while Mubashir Ali Khan was at University of Chenab. He is now at University of Warsaw and may be contacted at mubashirgc@gmail.com.

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Data Availability Statement

The data that support the findings of this study are available upon request.

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