Analysis of Safe Haven Quality of Cryptocurrencies under the Cryptocurrency Policy Uncertainty

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Abstract

This study aims to analyze the safe haven properties of the top three cryptocurrencies (BTC, ETH, and BNB), in comparison to returns of conventional financial assets (Gold, Oil, US Dollar Index, S&P500) under the Cryptocurrency Policy Uncertainty Index (UCRY) From 5 January 2014 to 3 January 2021 by using DCC-GARCH Model. In addition, this study also examines the lead-lag relationships between pairs of assets using Wavelet Coherence Model. The results show that BTC, ETH, and BNB are weak safe havens for Gold, while BTC is a weak safe haven for every traditional financial asset. Moreover, BTC and ETH display a lagging relationship with Gold, while BNB exhibits a positive correlation with Gold. Similarly, BTC ETH and BNB positively correlate with S&P500 during the COVID-19 pandemic.

Keywords: 1) Safe Haven 2) Cryptocurrency Policy Uncertainty Index (UCRY) 3) lead-lag relationship

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Introduction

Since 2008, the cryptocurrency market has been growing steadily resulting in the market price of cryptocurrency has reached $2.9 trillion as of November 10, 2021, cryptocurrency is classified as a high-risk asset and the value of the cryptocurrency coin exhibits significant volatility. In addition, the cryptocurrency market is also a market that is sensitive to situations such as war, the emergence of new epidemics, etc. where the value of cryptocurrency depends on the actual demand in the market in which its supply quantity is limited. Resulting in the rarity of digital currency; Bitcoin is the first digital currency to emerge which was created by Nakamoto Satoshi (2009). Bitcoin stores its data in a decentralized manner, and transactions are verified through cryptographic methods (Cryptography). Additionally, there is a consensus between users in the network, which is stored in the public account system called Blockchain. The characteristics of digital currency (Cryptocurrency) is an intangible or virtual currency. However, because currency (Cryptocurrency) has no assets as reserves. The value of cryptocurrencies depends on the buyer's demand and limited supply in the market and the buyer's confidence in the market. This poses a risk and credibility to the value of that currency. As a result, the price exhibits a highly volatile nature, characterized by wild fluctuations. This raises concerns about its suitability as a stable store of value or as a medium of exchange (Cheah and Fry, 2015, p. 4).

In terms of the relationship between digital currency and other assets, there are many related factors such as the global economy, the popularity of digital currency, technology, and financial factors. Therefore, it is crucial to identify correlations in cryptocurrencies with other assets, given that investors often lack knowledge or understanding of the relationships involving high-risk assets, which exhibit rapid price fluctuations. Gaining an understanding of the relationship between various assets is essential in comprehending their impact on trading, and can help improve analyzing price or market trends. Additionally, by comprehending these relationships, investors can adjust their investment strategies more effectively, allowing them to better accept and manage risks associated with investing in other assets. Baur, Hong and Lee (2018, p. 1) discovered that Bitcoin has no correlation with other traditional assets either during normal times or during financial crises. The conclusion drawn is that Bitcoin is primarily used for speculative purposes, based on the transaction account information of Bitcoin. Gkillas and Siriopoulos (2018, p. 1) found that strong correlations are not related to the volatility in the cryptocurrency market, but it is related to cryptocurrency market trends. Therefore, the study indicates that a strong correlation is observed to grow among the 10 cryptocurrency pairs during the Bear market rather than the Bull market. Baek and Elbeck (2015, p. 4) examined the relative volatility of Bitcoin and found that all external economic factors do not have a significant effect on the returns of Bitcoin market. However, market participants primarily affect Bitcoin returns.

During times of economic or financial crises, Investors, began to reduce (sell off) their investment in high-risk assets and look for (buy up) assets with low volatility to reduce the risk in the investment. While the returns from such assets may be relatively low, those possessing this safe property, commonly referred to as Safe Havens. Baur and Lucey (2010, p. 5) have given the definition that "A safe haven is defined as an asset that is uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil."

In addition, the safe haven assets will also help to protect investors' investments. It is also important for portfolio restructuring or investment risk diversification to reduce investment risks in the event of unexpected events such as economic crisis, war, or natural disasters which is an event that could cause a financial crisis. According to Conlon, Corbet and McGee (2020, p. 1), global market turbulence and recession resulting from the onset of the COVID-19 pandemic led to a significant surge in trading volumes for digital currencies, reaching their highest record during the early period of the pandemic, this uncertainty has manifested in the cryptocurrency market. Therefore, it is important to monitor the volatility or correlation and dynamics of the market especially, investors who are afraid of the risk in investment mostly seek assets that can be used to hedge their investments. Therefore, during financial crises, hedging or safe haven investments are frequently made in gold (Triki and Maatoug, 2021, p. 1), foreign currencies (Ranaldo and Söderlind, 2010, p. 1), and commodities (Bouri, et al., 2020, p. 1).

Cryptocurrency is often regarded with caution due to its absence of stringent financial regulations and its unique characteristics as a store of value, Bitcoin is progressively becoming a potent safe haven asset (Bouri, et al., 2017, p. 7). Particularly after the 2008 Global Financial Crisis, Islamic equities and bonds (Sukuk) have been touted as prospective safe haven investments. Yarovaya, Elsayed and Hammoudeh (2021, p. 1), on the other hand, asserted that Bitcoin and Islamic stocks and bonds do not have secure features. Conflicting opinions of an asset's safety attributes demonstrate that safe haven assets can change over time (Ji, Zhang and Zhao, 2020, p. 8). Therefore, safe haven assets need to be periodically assessed by academics or investors. Rubbaniy, Khalid and Samitas (2021, p. 14) Using wavelet coherence techniques examine the safe haven prospects in specific cryptocurrency returns (i.e., Bitcoin, Ethereum, and Ripple) in comparison to the VCRIX and the Global COVID-19 Fear Index. They come to the conclusion that cryptocurrencies do not exhibit safe haven features for financial risk proxies and are exclusively safe havens for nonfinancial risk proxies. This corroborates Kim, Trimborn and Härdel (2021, p. 1) that the safe haven characteristics of the cryptocurrency market depend on the risk proxy (EPU, VIX, Global COVID-19 Fear Index, VCRIX) used to measure market volatility or uncertainty.

Lucey, et al., (2021, p. 7) have developed the Cryptocurrency Policy Uncertainty Index (UCRY) by using a news-based article technique in accordance with Baker, Bloom and Davis (2016, pp. 6-19). This proxy captures economic shocks and high uncertainty events from the cryptocurrency market such as the Chinese ICO prohibition in September 2017, the hack of cryptocurrency exchanges (Zaif hack) in September 2018, the Covid-19 pandemic crisis in December 2019, and the announcement of SEC About Ripple (XRP) in November 2020. This has severely affected the volatility of cryptocurrency prices.Therefore, it can be said that UCRY policies could have an impact on cryptocurrency prices, returns, and volatility. According to this intriguing proxy, no research has been done to compare safe havens among other asset classes under UCRY.

Therefore, this study aims to investigate the safe haven properties of 4 traditional financial assets are represent assets in each group as Gold is a representative of metals, Oil represents energy, US dollar index (DXY) represents a group of exchange rates, and S&P 500 represents a group of stock indices with Cryptocurrencies against the Cryptocurrency Policy Uncertainty (UCRY) using an econometric model, DCC GRACH Model. For the Wavelet Coherence model, it is the study of being a leading asset (Leading) or following asset (Lagging) of each pair of assets as well where conducted this research.

The results of the study will be useful to investors seeking safe haven assets during times of crisis or uncertainty especially when the cryptocurrency market is unpredictable or highly volatile. This will enhance the accuracy of future investment decisions and reduce the risk of losses.

Literature Review

The literature on the safe haven qualities of cryptocurrencies in comparison to other assets will be reviewed briefly in this section. While the DCC GARCH model is typically used in research. To correlate cryptocurrency returns and measure their volatility during times of uncertainty.

Selmi, et al., (2018, p. 1) compared Bitcoin to gold as a safe haven, hedge, and/or diversifier against excessive oil price swings. They demonstrate how both Bitcoin and gold serve as safe havens and diversifiers for changes in oil prices, coming to the conclusion that both are investments that investors can place their money in during times of political and economic unrest. According to Naeem, et al., (2021, p. 1) COVID-19 had an impact on major cryptocurrencies' efficiency, with Bitcoin and Etherum taking the worst harm. Results also demonstrate that Ethereum offers a better safe haven than Bitcoin. Similary, Mariana, Ekaputra and Husodo (2021, p. 1), The DCC and cDCC results reveal that during the pandemic, Bitcoin and Etherum are safe haven assets for a short period, which is proven by its inverse correlation with S&P 500. Dutta, et al., (2020, p. 1) using The DCC-GARCH model's results on time-varying correlations indicate that gold may be a safe haven asset for global crude oil markets. Contrarily, Bitcoin simply serves to diversify the market for crude oil. Bouri, et al., (2017, p. 1) using DCCs, the empirical findings show that Bitcoin is a poor hedge and is merely useful for diversification. But Bitcoin can only act as a strong safe haven against weekly extreme down movements in Asian stocks.

Wu, et al., (2019, p. 1) using the GARCH model and Quantile regression. The results indicated that, during the extreme bearish and bullish markets, both gold and bitcoin can serve as a poor hedge and weak safe haven against EPU.

Hasan, et al., (2021, p. 1) analyzed the impact of UCRY policy on Bitcoin, Islamic Bonds (Sukuk), the DJ Islamic Index, the US Dollar, gold, and WTI crude oil using the Quantile-on-Quantile model to examine the hedging and safe haven of UCRY. The results show that the UCRY index has hedging behavior on gold and the DJ Islamic index. However, the UCRY index does not hedge the return on Bitcoin. It shows that Bitcoin, US dollars, and WTI crude oil are not categorized as safe haven assets. On the other hand, UCRY policy has a positive effect on gold, DJ Islamic, and Islamic Bonds (Sukuk), indicating them as safe haven assets. More closely related to our research, Karim, et al., (2022, p. 1) using the ADCC-GARCH model to analyze the hedge and safe haven prospects of the bond market against the UCRY policy. Except for SKUK (S&P green bonds), which they claim is a safe haven investment for UCRY policy.

Methods

The data used in this research were based on weekly time series secondary data. The variables used in the study were Cryptocurrency Policy Uncertainty (UCRY) by collecting data from websites www.brianmlucey.wordpress.com to use the top 3 of cryptocurrency market are Bitcoin (BTC) from January 5, 2014 to January 3, 2021, Ethereum (ETH) from March 13, 2016 to January 3, 2021, Binance Coin (BNB) from November 12, 2017 to January 3, 2021 with 4 traditional financial assets are Gold, WTI crude oil, DXY, S&P 500. All weekly data are collected from www.Investing.com covering the period from January 5, 2014 to January 3, 2021. All data is Converted into the form of log return by using the formula :

$$r_i = \ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right) \quad (1)$$

DCC-GARCH

Dynamic Conditional Correlation GARCH was developed from the GARCH model, a concept introduced by Engle Robert (2002). Under the DCC-GARCH model, correlation can be estimated that can vary over time (Bollerslev, 1990), aims to eliminate fluctuations in dummy random variables that cannot vary with time.

Starting from the GARCH model:

$$r_t = \mu_t + E_t \quad (2)$$

$$E_t = H^{\frac{1}{2}}{}_t z_t \, ; z_t \sim i.i.d\left(0,1\right) \quad (3)$$

With the conditional covariance matrix, H_t, it is assumed that the residual vector E_t has a normal distribution. The standardized residual vector, z_t, that can be separated from the residual vector, E_t, is shown in Equation 3.

$$H_t = D_t R_t D_t \quad (4)$$

$$D_t = \begin{bmatrix} \sqrt{h_{ii,t}} & 0 \\ 0 & \sqrt{h_{jj,t}} \end{bmatrix} \quad (5)$$

$$h_{ii,t} = \omega_i + \alpha_{ii}\varepsilon^2{}_{i,t-1} + \beta_{ii}h_{ii,t-1} \quad (6)$$

$$h_{jj,t} = \omega_j + \alpha_{jj}\varepsilon^2{}_{j,t-1} + \beta_{jj}h_{jj,t-1} \quad (7)$$

Equation 4 illustrates the decomposition of the covariance matrix, H_t, into 3 components. The diagonal matrix of conditional standard deviations is called the D_t matrix. The DCC model presupposes that the univariate GARCH method, as illustrated in Equation 6 and 7, can estimate the values of $h_{ii,t}$ and $h_{jj,t}$ in matrix D_t. The conditional correlation matrix, or Matrix R_t, allows each element's value to change over time as indicated in the following equation:

$$R_t = \begin{bmatrix} 1 & \rho_{ij,t} \\ \rho_{ji,t} & 1 \end{bmatrix} \quad (8)$$

where $\rho_{ij,t} = \rho_{ji,t}$ is time-varying conditional correlation between the return on cryptocurrencies and the return on financial assets. The DCC model presupposes that matrix R_t can be divided into 3 pieces as given in the following equation in order to estimate the conditional correlation matrix.

$$R_t = Q_t^{*^{-1}} Q_t Q_t^{*^{-1}} \quad (9)$$

$$Q^{*^{-1}} = \begin{bmatrix} \sqrt{q_{ii,t}} & 0 \\ 0 & \sqrt{q_{jj,t}} \end{bmatrix} \quad (10)$$

$$Q_t = \begin{bmatrix} q_{ii,t} & q_{ij,t} \\ q_{ji,t} & q_{jj,t} \end{bmatrix} \quad (11)$$

Equation 9 can $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} \times q_{jj,t}}}$ ensure that the value of conditional correlation, which guarantees that matrix R_t will be positively definite, will be between -1 and 1. The correlation matrix Q_t must be supplied as it is in the following equation for the DCC model.

$$Q_t = \left(1 - a^{DCC} - b^{DCC}\right)\overline{Q} + a^{DCC} z_{t-1} z'_{t-1} + b^{DCC} Q_{t-1} \quad (12)$$

Where $0 \le a^{DCC} + b^{DCC} < 1$,while $\overline{Q}$ can be estimated by $\overline{Q} = \frac{1}{T}\sum_{t=1}^{T} z_t z'_t$

Linear Regression

Using the correlation, from Equation 8 in DCC GARCH for test the Safe Haven properties of assets in the Linear regression model.

$$\rho_{ij,t} = \gamma_0 + \gamma_1 \rho_{ij,t-1} + \gamma_2 UCRY_t + u_{i,t} \quad (13)$$

Where $\rho_{ij,t}$ is the correlation in DCC GARCH, $\rho_{ij,t-1}$ is the correlation in DCC GARCH at week t-1, $UCRY_t$ is Cryptocurrency Policy Uncertainty.

Baur and Mc Dermott (2010, pp. 8-11) If γ_2 is negative and statistically significant (insignificant), then it is interpreted cryptocurrencies (BTC, ETH, BNB) as a strong (weak) safe haven for traditional financial assets (Gold, Oil, DXY, S&P 500), respectively under Cryptocurrency Policy Uncertainty (UCRY). while if γ_2 is positive means not a safe haven.

Wavelet Coherence Model

Grinsted, Moore and Jevrejeva (2004, p. 1), a wavelet is just a wave that may be stretched over time (t) to obtain frequency (f). Between paired cryptocurrencies and financial assets returns is the subject of this study. Following Torrence and Compo (1998, pp. 15-16), we describe the cross wavelet transform of two time series of assets, i(t) and j(t), to derive the wavelet coherence.

$$W_{ij}(t,f)|r_t = W_i(t,f) W_j^*(t,f) \quad (14)$$

where $W_i(t,f)$ and $W_j^*(t,f)$ are the continuous wavelet transforms and "*" is a complex conjugate. According to Torrence and Webster (1999, pp. 7-11), the square of Wij(t,f) can be used to display the local covariance between the series at each scale but not the comovement between the assets. They therefore proposed the constructible squared wavelet coherence, which can be constructed

$$R^2(t,f) = \frac{\left|S\left(s^{-1}W_{ij}(t,f)\right)\right|^2}{S\left(s^{-1}\left|W_i(t,f)\right|^2\right) S\left(s^{-1}\left|W_j(t,f)\right|^2\right)} \quad (15)$$

where S is the smoothing operator and $R^2(t,f)$ is the localized coherency coefficient over time–frequency with ranges between 0 and 1. If $R^2(t,f)$ is close to 0, this indicates the low correlation between assets i(t) and j(t) at time t. If $R^2(t,f)$ is close to 1, this indicates the high correlation between assets i(t) and j(t) at time t. However, $R^2(t,f)$ does not provide the direction of the correlation. In order to distinguish between a positive and negative correlation, we therefore take into account the wavelet coherence phase difference (Torrence and Compo, 1998, p. 16).

$$\phi_{i,j}(t,f) = \tan^{-1}\left(\frac{Im\left\{S\left(s^{-1}W^{ij}(t,f)\right)\right\}}{\mathrm{Re}\left\{S\left(s^{-1}W^{ij}(t,f)\right)\right\}}\right) \tag{16}$$

where Im and Re are the imaginary operator and real parts operator, respectively. The black arrows in this study's bi-dimensional show the phase differences and causality between two assets. For example, → and ← indicate that markets i(t) and j(t) have a positive and negative relationship, respectively. Moreover, ↗ means that asset i(t) leads asset j(t), while ↙ means that asset j(t) leads asset i(t).

Results

Table 1 reports the descriptive statistics for cryptocurrencies and financial asset returns. The results indicate that the highest average return of BNB ETH BTC was at 0.0198 0.0191 0.0101 respectively. On the other hand, the average return of Oil had a negative value of -0.0016 while the highest standard division belongs to BNB at 0.1715, followed by ETH, BTC. Thus, the lowest risk compared to other cryptocurrencies is BTC but all variables have a higher standard division than mean returns, including S&P 500 Has the maximum Jarque-Bera and kurtosis values, indicating an abnormality. These characteristics indicate high volatility. Furthermore, the stability of the data was examined by the ADF-test method, it was found that the value of the return test for all assets was at a significance level of 0.01, indicating that all series are stationary.

Table 1 Summary statistics of cryptocurrencies and financial asset returns.

	BTC	ETH	BNB	Gold	Oil	DXY	S&P 500	UCRY
Mean	0.0101	0.0191	0.0198	0.0011	-0.0016	0.0003	0.0020	0.0001
Median	0.0079	0.0173	0.0058	0.0008	0.0011	0.0007	0.0032	-0.0003
Maximum	0.7797	0.4989	1.0911	0.0991	0.2758	0.0404	0.1142	0.0296
Minimum	-0.5587	-0.6597	-0.6922	-0.0979	-0.3469	-0.0443	-0.1623	-0.0161
Std. Dev.	0.1199	0.1532	0.1715	0.0206	0.0586	0.0099	0.0233	0.0056
Skewness	0.0616	-0.0349	1.2988	0.0083	-0.6364	0.0859	-1.3271	0.7682
Kurtosis	10.0106	4.9005	13.5625	5.8777	9.2482	4.7242	13.9341	6.4768
Jarque-Bera	749.7388	37.9752	813.4125	126.2951	620.0753	45.7867	1930.6210	220.3418
ADF-test	-18.447***	-13.624***	-11.561***	-20.075***	-15.047***	-21.428***	-20.812***	-20.562***
Q-statistics(1)	1.9060	7.4044***	14.346***	0.0006	7.8943***	2.5515	11.665***	54.476***
ARCH-LM(1)	45.0169***	57.3933***	45.2571***	20.5885***	344.1945***	9.8094***	32.3808***	8.8426***

Note: Asterisks indicate statistical significance at the 10% (*), 5% (**), 1% (***) level

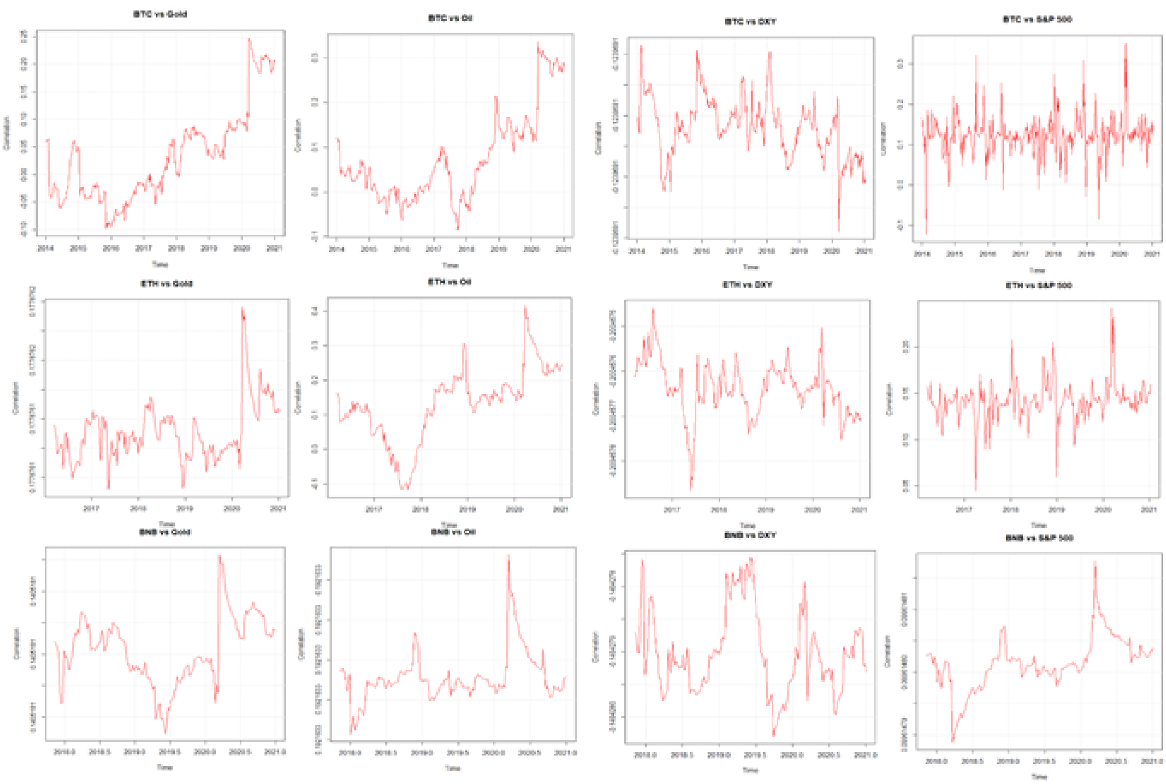

Figure 1 The estimated dynamic conditional correlation of returns for the pair of Bitcoin (BTC) in the periods from JAnuary 5, 2014 to January 3, 2021. The pair of Ethereum (ETH) in the periods from March 13, 2016 to January 3, 2021. The pair of Binance Coin (BNB) the periods from November 12, 2017 to January 3, 2021.

Based on the Q-statistics values, it was determined that significant autocorrelation issues existed in all cases except for BTC, Gold, and DXY at the 0.01 significance level. Similarly, the ARCH-LM test indicated significant problems with heteroskedasticity across all cases at the same level of significance. Consequently, the widely adopted GARCH model was employed to mitigate these autocorrelation and heteroskedasticity.

Fig. 1 displays the estimated dynamic conditional correlation of returns for the pair of cryptocurrencies and financial asset returns. The correlation between DXY return and BTC, ETH, and BNB was moving in a negative area with the average DCC GARCH value at -0.1240, -0.2005, and -0.1494.The DCC moving in the positive area were BTC-S&P500, ETH-Gold, ETH-S&P500, BNB-Gold BNB-Oil, and BNB-S&P 500 with the average DCC value at 0.1224, 0.1779, 0.1421, 0.1405, 0.1922, 0.0996 respectively. The DCC fluctuated and swung between positive and negative areas were BTC-Gold, BTC-Oil, and ETH-Oil with the average DCC value at 0.0310, 0.0749, 0.1779.

Table 2 indicates the estimated parameters for DCC GARCH (1,1) model, The constraint of the DCC GARCH model, that the ARCH (α) and GARCH (β) coefficients show that the relationship between cryptocurrencies and financial asset returns varies over time (Fig. 1) which effects are positive and the sum of their coefficients is less than one.($\alpha + \beta < 1$).

Thus, α_{ii} and β_{ii} are estimated in Eq.(6). As α_{jj} and β_{jj} are estimated in Eq.(7). α_{ii} are significant in the pair of BTC-Gold, BTC-Oil, BTC-DXY, BTC-S&P500, BNB-Gold, BNB-DXY except the pair of ETH-Gold, ETH-Oil, ETH-DXY, ETH-S&P500, BNB-Oil are insignificant. Though, all of β_{ii} are strongly significant which shows the conditional heteroskedasticity. α_{jj} are significant except the pair of ETH-Gold, BNB-Gold while, β_{jj} are significant except the pair of BNB-Gold, BNB-DXY are show no sign of conditional heteroskedasticity.

The estimated results of DCC GARCH (1,1) in Equation 12 are shown in the row of a^{DCC} and bDCC. For the pairs of cryptocurrencies and financial asset returns, the estimated results of a^{DCC} are insignificant in all case while the estimated results of bDCC are significant in all case except pairs of BTC-S&P500, ETH-S&P500, and BNB-Gold.

Table 2 Estimated parameters for DCC GARCH (1,1) models.

Coefficient	BTC-Gold	BTC-Oil	BTC-DXY	BTC-S&P500	ETH-Gold	ETH-Oil	ETH-DXY	ETH-S&P500	BNB-Gold	BNB-Oil	BNB-DXY	BNB-S&P500
ω_i	0.0028**	0.0030**	0.0038**	0.0031**	0.0000	0.0000	0.0000	0.0000	0.0070***	0.0000	0.0076***	0.0000
	[0.0012]	[0.0013]	[0.0014]	[0.0013]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0026]	[0.0000]	[0.0025]	[0.0001]
α_{ii}	0.2523***	0.2890***	0.2571***	0.2846***	0.0000	0.0000	0.0000	0.0000	0.3960**	0.0000	0.4640**	0.0000
	[0.0817]	[0.0981]	[0.0865]	[0.0933]	[0.0018]	[0.0021]	[0.0019]	[0.0017]	[0.1845]	[0.0006]	[0.2352]	[0.0002]
β_{ii}	0.5351***	0.5005***	0.4914***	0.4981***	0.9990***	0.9990***	0.9990***	0.9990***	0.3651***	0.9954***	0.3215**	0.9954***
	[0.1141]	[0.1221]	[0.1172]	[0.1189]	[0.0000]	[0.0001]	[0.0001]	[0.0001]	[0.1275]	[0.0005]	[0.1302]	[0.0002]
ω_j	0.0001**	0.0004***	0.0000	0.0000**	0.0000	0.0005***	0.0000***	0.0000**	0.0000	0.0006***	0.0000***	0.0001*
	[0.0000]	[0.0001]	[0.0000]	[0.0000]	[0.0001]	[0.0001]	[0.0000]	[0.0000]	[0.0031]	[0.0002]	[0.0000]	[0.0001]
α_{jj}	0.0911***	0.2056***	0.1336***	0.3047***	0.1141	0.2061***	0.1432***	0.4533**	0.1355	0.2519***	0.3349**	0.4179**
	[0.0210]	[0.0546]	[0.0452]	[0.0987]	[0.1017]	[0.0675]	[0.0161]	[0.1818]	[5.2044]	[0.0815]	[0.1322]	[0.1853]
β_{jj}	0.8798***	0.6479***	0.8362***	0.6605***	0.8453**	0.6264***	0.7278***	0.5457***	0.8284	0.5866***	0.0426	0.4915***
	[0.0284]	[0.0599]	[0.0589]	[0.0439]	[0.3478]	[0.0647]	[0.0334]	[0.0810]	[9.6884]	[0.0665]	[0.1663]	[0.1205]
a^{DCC}	0.0107	0.0141	0.0000	0.0508	0.0000	0.0198	0.0000	0.0179	0.0000	0.0000	0.0000	0.0000
	[0.0088]	[0.0098]	[0.0001]	[0.0772]	[0.0000]	[0.0219]	[0.0000]	[0.0585]	[0.0041]	[0.0000]	[0.0000]	[0.0000]
b^{DCC}	0.9815***	0.9791***	0.9253*	0.2609	0.9119***	0.9567***	0.9010***	0.4619	0.9311	0.9250***	0.9061***	0.9309*
	[0.0078]	[0.0102]	[0.5318]	[0.2287]	[0.1385]	[0.0400]	[0.2211]	[0.4775]	[6.4906]	[0.1401]	[0.1781]	[0.5362]

Note: Asterisks indicate statistical significance at the 10% (*), 5% (**), 1% (***) level.

Table 3 The coefficient of cryptocurrencies and financial asset returns

Coefficient	γ_0	γ_1	γ_2
BTC-Gold	0.0008017	0.9924985***	-0.0601593
	[0.0007620]	[0.0086883]	[0.1280327]
BTC-Oil	0.001468	0.990575***	-0.029067
	[0.001107]	[0.008956]	[0.158620]
BTC-DXY	-1.240e-01***	1.546e-08	-1.268e-08
	[4.836e-09]	[3.906e-08]	[4.524e-08]
BTC-S&P500	0.082844***	0.324712***	-0.241423
	[0.006455]	[0.049179]	[0.424836]
ETH-Gold	1.779e-01***	-2.687e-08	-1.027e-07
	[1.946e-08]	[1.096e-07]	[2.009e-07]
ETH-Oil	0.004389.	0.973555***	0.202288
	[0.002412]	[0.014313]	[0.250475]
ETH-DXY	-2.005e-01***	1.483e-07	-5.82e-07
	[6.076e-08]	[3.037e-07]	[6.274e-07]
ETH-S&P500	0.083525***	0.413881***	0.144316
	[0.007413]	[0.051779]	[0.188443]
BNB-Gold	1.405e-01***	-4.975e-09	-8.963e-09
	[2.205e-09]	[1.574e-08]	[2.672e-08]
BNB-Oil	1.922e-01***	3.221e-11	-4.028e-10
	[7.828e-11]	[4.086e-10]	[9.484e-10]
BNB-DXY	-1.494e-01***	2.131e-07	1.901e-08
	[6.321e-08]	[4.243e-07]	[7.657e-07]
BNB-S&P500	9.961e-02***	-1.580e-08	2.950e-08
	[4.162e-09]	[4.191e-08]	[5.042e-08]

Note: Asterisks indicate statistical significance at the 10% (.), 5% (*), 1%(**), 0.1%(***) level

Table 3 shows that Regression results analyzing the pairs of cryptocurrencies and financial asset returns as safe havens, the results suggest that the γ_2 value is negative and insignificant, indicating a weak safe haven under Cryptocurrency Policy Uncertainty (UCRY). There will be pairs of BTC-Gold, BTC-Oil, BTC-DXY, BTC-S&P500, ETH-Gold, ETH-DXY, BNB-Gold, BNB-Oil, mean that BTC is a weak safe haven for every traditional financial asset. ETH is a weak safe haven for Gold and DXY. BNB is a weak safe haven for Gold and Oil under Cryptocurrency Policy Uncertainty (UCRY). While, γ_2 is positive and insignificant indicating not safe haven under Cryptocurrency Policy Uncertainty (UCRY), there will be the pair of ETH-Oil, ETH-S&P500, BNB-DXY, BNB-S&P500.

Evidence suggests that Bitcoin is a strong safe haven for crude oil, but it is a weak safe haven for the S&P500 index. (Corbet, Katsiampa and Lau, 2020, p. 1), the FTSE 250 index, and the DAX index. Ethereum also appears to be a weak safe haven when compared to the S&P500, STOXX600 index, the DAX index, and the FTSE 250 index (Bédowska-Sójka and Kliber, 2021, p. 1).

Bitcoin can be utilized as short-term safe havens against the stock market in periods of extreme volatility and uncertainty, as was the case during the COVID-19 era (Corbet, et al., 2020, p. 1; López-Cabarcos, et al., 2021, p. 5).

However, data suggests that cryptocurrencies in general cannot be viewed as safe havens from stock markets (Conlon, Corbet and McGee, 2020, p. 1; Goodell and Goutte, 2021, p. 9; Jiang, et al., 2021, p. 1; Thampanya, Nasir and Huynh, 2020, pp. 10-11 and Gold (Corbet, Katsiampa and Lau, 2020, p. 1).

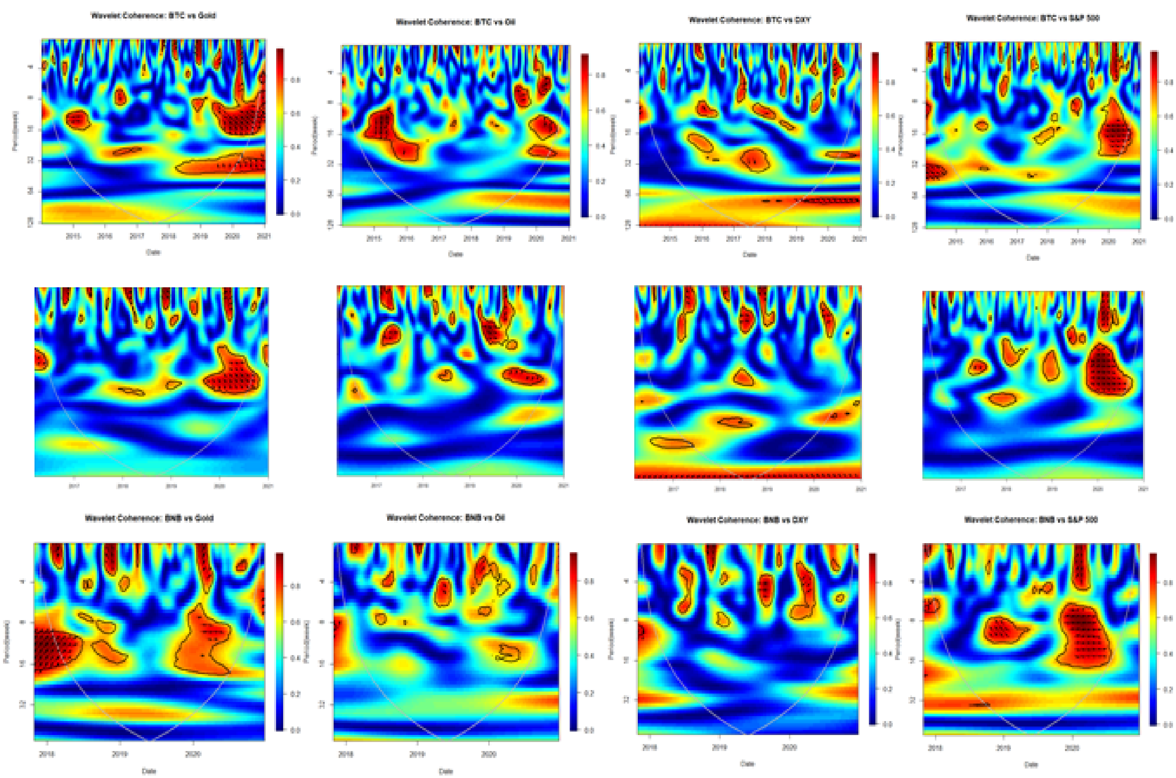

Figure 2 Wavelet power spectra of the considered returns for the pair of Bitcoin (BTC) in the periods from January 5, 2014 to January 3, 2021 and the 4–128 weeks bands. The pair of Ethereum (ETH) the periods from March 13, 2016 to January 3, 2021 and the 4–64 weeks bands. The pair of Binance Coin (BNB) the periods from November 12, 2017 to January 3, 2021 and the 4–32 weeks bands.

Fig. 2 illustrates the correlation of cryptocurrencies (BTC, ETH and BNB) and financial asset returns (Gold, Oil, US Dollar Index, S&P500). In the context of asset relationships, interpretation can be done through both arrow indications and color gradient. Specifically, a red color denotes a significant and strong relationship between the two assets, signifying high relevance. Conversely, a blue color indicates a weak correlation. In this research, the focus will be on periods marked by a strong relationship, denoted by the red color, where the relationship arrow is prominently displayed.

In the case of BTC, in the period 10-16 weeks band in September 2014 -June 2015, BTC exhibits negative relations with Gold (←) then the connectedness between BTC and Gold is highly strong and significant during the period 8-20 weeks band in May 2019-December 2020 the arrows in the plot suggest BTC is lagging Gold (↘) during the unprecedented COVID-19 period, but it turned to lead Gold (↖) at the period 28-46 weeks band in March 2018-January 2021. Our findings are consistent with those of Siddique, Kayani and Ashfaq (2021, pp. 13-14), who discovered that while BTC has weak relationships with other hedge assets, it does have some connections to Gold, particularly during the COVID-19 pandemic. This is because, according to Ozturk (2020, p. 1), investors can lower the risk of an adverse event in their investment portfolios by purchasing BTC and Gold as hedge assets. BTC has some connection with Oil at a certain time and frequency scales, at the period 9-30 weeks band in September 2014-March 2016 BTC has a lag relationship with Oil. (↙) (after the oil price shock of June 2014) In 2015, the drawdowns in oil prices ensued volatilities in the foreign exchange markets. It is implied that the Bitcoin price is affected by changes in the price of oil (WTI) changes both in bullish and bearish market conditions since market participants tend to flee to safer assets like gold or Bitcoin during times of market turbulence (Das and Kannadhasan, 2018). Although period 4-20 weeks band in March 2019-July 2020, It was found that there were 3 red contours that were significant 5% from the arrows, it was found that BTC leads Oil. (↗) BTC and DXY have a weak relationship. However, The red contours in the lower right corner show that BTC is leading DXY (↖) at period 65-80 weeks band in March 2019 - December 2020 during COVID-19 which is consistent with the study results of Maneejuk, et al., (2022, p. 14), the arrows in the plot suggest BTC was influenced by USD at the beginning of 2020 but it turned to lead USD (↖) at the end of 2020. The correlation between BTC and S&P500, at period 32-48 weeks band in January 2014 - September 2014, BTC lag S&P 500. (↘) After that BTC has a positive correlation (→) with S&P 500 in dark red at period 7-28 weeks band in September 2019-September 2020. This result is consistent with Goodell and Goutte (2021, p. 6).

In the case of ETH, the period 7-20 weeks band in June 2019-September 2020, indicates that ETH is lagging Gold (↘) during COVID-19. Hsu, Sheu and Yoon (2021, p. 19) found a negative co-volatility spillover effect in both Bitcoin and Ethereum can be considered a safe haven for exchange rates or gold in times of extreme market turmoil and uncertainty, such as the COVID-19 pandemic. In the period 5-7 weeks band in February 2017- September 2017, The relations between ETH and Oil are negative. (←) even though became a positive relation (→) in March 2019-August 2019. After the period of 16 weeks band, which is consistent with Naeem, et al., (2023, p. 15) who find the results highlight that Oil returns correlate positively with ETH returns when markets are regular and bullish, acting as a diversifier for ETH. However, ETH has a weak linkage with Oil as indicated by the large proportion of blue spectra. Moreover, at period 0-6 weeks band ETH has some connectedness with DXY. In the period 0-5 weeks band in January 2020-March 2020 ETH lead S&P 500. (↗) At 6-16 weeks band in September 2019-September 2020, ETH also has a strong positive comovement with S&P 500 (→) during COVID-19.This finding is supported by Frikha, et al. (2023) the strong dependence between Ethereum and the S&P500 index at the early of health crisis, them observe area of positive correlation, which persists even during the pandemic. The findings also point out the benefits of using cryptocurrency as part of a diversification and risk management plan. During the time leading up to the COVID-19 epidemic, Bitcoin, Ethereum, BNB, Ripple, and gold behaved like hedging assets toward the stock market.

In the case of BNB, at period 9-17 weeks band in November 2017-June 2018, BNB very strong lead Gold (↗) and a positive correlation (→) at period 6-17 weeks band in August 2019-June 2020 during the COVID-19. In addition, González, Jareño and Skinner (2021, p. 9) they use The Pearson correlation test, The outcome showed that there was an expansion of COVID-19 sub-period (from January 1 to June 30, 2020) positive and statistically significant relationship between Gold price returns and 12 cryptocurrency returns. The key finding reveals that when the economy is in turmoil like it was during the COVID-19 crisis, there is a stronger correlation between Gold price returns and cryptocurrency returns. Furthermore, BNB has weak relations with Oil. In the period 3-7 weeks band in June 2019-September 2019, BNB has negative comovement with DXY,(←) and weak lag (↙) at period 2-8 weeks band in February 2020-May. In the period 8-12 weeks band in September 2018-May 2019, BNB lead S&P 500 (↖) and strong positive relations (→) in 6-18 weeks band in September 2019-July 2020 and supported the findings of Ahmed, et al. (2023) that the negative correlation in short-run and long-run effects of the historical returns of Bitcoin, Ethereum, Ripple, Binance, and Tether on S&P500 returns.

Conclusion and Discussion

The suitability of cryptocurrencies as safe haven assets is subject to variations in response to prevailing market conditions, as indicated by several studies (Bédowska-Sójka and Kliber, 2021, p. 1; Conlon and McGee, 2020, p. 4) Interestingly, cryptocurrencies have shown promise as reliable safe haven investments during times of extreme uncertainty (Hsu, Sheu and Yoon, 2021, p. 1; Jareño, et al., 2020, p. 1).

However, the overall verdict on whether cryptocurrencies exhibit safe haven characteristics remains inconclusive. There exists significant interest in understanding how different asset classes react to shocks and uncertainty, with a particular focus on the behavior of cryptocurrencies. My investigation involved an exploration of safe haven assets and the correlations between cryptocurrency movements and those of traditional financial assets. The findings reveal that none of these asset pairs can be considered strong safe-havens. However, some pairs exhibit weak safe haven characteristics, such as BTC is a weak safe haven for every traditional financial asset (Gold, Oil, DXY, S&P500). ETH is a weak safe haven for Gold and DXY while BNB is a weak safe haven for Gold and Oil under Cryptocurrency Policy Uncertainty (UCRY). Whereas other pairs do not display safe haven characteristics, as assessed under the Cryptocurrency Policy Uncertainty (UCRY).

The role of an asset as a leading or lagging in a given context is a crucial consideration when analyzing relationships between assets with varying characteristics over time. The results indicate that BTC and ETH is lagging with Gold when economic and financial market conditions are uncertain and volatile, Investors opt for gold investments due to its status as a safe haven asset, supported by research findings that BTC, ETH, BNB are weak safe haven for Gold or Gold is a weak safe haven for BTC, ETH, BNB ($\rho_{ij,t} = \rho_{ji,t}$) under Cryptocurrency Policy Uncertainty (UCRY) These findings align with those of Hassan, Hasan and Rashid (2021, p. 1), suggesting that gold is a preferred option for investors in times of cryptocurrency market uncertainty since it exhibits steady and reliable safe haven features. While BNB has a positive correlation with Gold during the COVID-19 pandemic. Furthermore, BTC correlates with Oil during an Oil shock, although BTC and ETH leading Oil during the COVID-19 crisis as the demand for oil decreased, a consequence of travel restrictions imposed during the pandemic and economic downturn. In the early stages of the pandemic, ETH and BNB demonstrate a negative correlation with the US Dollar index because the US dollar is the main reserve currency. Through research, it was discovered that BTC, ETH as weak safe haven for US dollar index (DXY) under Cryptocurrency Policy Uncertainty (UCRY), while BTC leads the US Dollar index. Moreover, BTC, ETH and BNB exhibit a positive correlation with S&P500 during the COVID-19. This implies that these two asset types often exhibit similar movement patterns. Consequently, simultaneous investment in both may lead to a loss of diversification and risk mitigation benefits. Additional evidence suggests that the correlations between stock indexes and cryptocurrencies are generally positive and have strengthened during the COVID-19 pandemic. As a result, as a collective asset class, cryptocurrencies do not offer significant diversification benefits (Goodell and Goutte, 2021, p. 1). It is widely acknowledged that during economic downturns, the interconnections among most assets and asset classes tend to increase (Bekaert, Hodrick and Zhang, 2009, p. 1). Additionally, as indicated by Charfeddine, Benlagha and Maouchi (2020, p. 1), the relationship between cryptocurrencies and conventional assets is susceptible to outside shock.

Furthermore, the results concerning the secure nature of cryptocurrencies offer essential insights for policymakers as they decide the role of the cryptocurrency market within their financial frameworks. Each cryptocurrency is impacted differently by the UCRY Policy, particularly during significant events. Therefore, investors need to assess each cryptocurrency separately and modify their investment approaches based on evolving market circumstances. In addition to existing risk and uncertainty factors, investors should take UCRY policy into account to minimize potential future risks.

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