The role of Bitcoin as hedge, safe haven or diversifier for USA stock markets: Evidence from the DCC-GARCH approach

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Abstract

The aim of this paper is to examine the hedging, safe haven and diversification abilities of Bitcoin in the stock, energy and currency markets. To do so, we collected daily data from 03 January 2011 to 18 October 2019. The results suggest that Bitcoin is considered an effective diversification tool for the stock and energy markets. However, it is a strong hedge for the currency market. In addition, they reported that Bitcoin represents a safe haven for the stock and energy markets. American investors are advised not to include

Bitcoin in their portfolios massively as a safe haven, because this leads to increased volatility.

Key words: Bitcoin, hedge, safe haven, diversification, DCC-GARCH model

1. Introduction

Since the appearance of crypto-currency in 2009, the issue of Bitcoin has attracted the attention of several researchers and academics. Indeed, many researchers have shown that the existence of Bitcoin reduces the level of risk in the financial market and therefore increases its performance (Bouoiyour & Selmi, 2017, Stensås et al. 2019 and Hsu et al., 2021). More specifically, empirical studies on Bitcoin have brought mixed results. Some studies have proven that Bitcion could be considered as a diversifier and hedge, thus qualifying Bitcoin as digital gold (see among others Popper 2015, Bouri et al.,(2017 a, b) , Klein et al., 2018, Stensås et al., 2019, Hussain Shahzad et al., 2020 and Yang et al., 2022). However, other studies have shown that in case of economic or financial turmoil, Bitcoin can be a safe haven for investors (see among others Titcomb, 2017, Urban, 2017).

In this context, some authors have found that the benefits of Bitcoin differ depending on country-specific characteristics, i.e. whether it is a developed or developing country and the time horizon

of the investment decision (short, medium or long term). In this case, the advantage of Bitcoin for investors as a hedge, safe haven or diversifier depends on the level of uncertainty, transactions in financial assets, regulation, and development of the financial system and political stability which differs from country to country (see among others Krause 2016, Stensås et al., 2019).

Therefore, the main objective of this paper is to extend the literature on Bitcoin by analyzing the significance of its value as a new asset class. Specifically, we investigate its behaviour as a safe haven asset, a hedging asset or a diversification asset against the stock market, the energy market and the currency market.

The rest of this paper is divided into the following sections. The second section will present the data and the primary analysis. The methodology will be discussed in the third section. The fourth section will focus on the discussion of the empirical results. The conclusion will be the subject of a fourth section.

2. Data and summary statistics

This section will introduce the data used in the analysis of the second section and the preliminary tests required for the estimation.

For our empirical analysis, we use daily data from January 3rd 2011 to October 18th 2019. Bitcoin prices are obtained from Coindesk, which is a closing price of global Bitcoin-USD

exchange rates. Coindesk's price index averages Bitcoin (BTC) prices from four major trading platforms, namely Coinbase, Bitstamp, Bitfinex and itBit. The use of a price index combining the trading prices of the main Bitcoin exchanges is a common practice in the literature.

We collect prices for two asset classes, currency, oil and stock from Thomson Reuters Refinitiv Eikon. While BTC trades 24 hours a day, 7 days a week, the other data is only available for weekdays. We therefore only used weekday data to maintain similarity. To represent the energy market, we use West Texas Intermediate (WTI) spot prices. In addition, for the stock markets, the Dow Jones Industrial Average (DJIA) was chosen to represent the US stock market as it is a broad-based stock index. Finally, as an indicator for the currency market, the trade-weighted US Dollar Index (US Dollar), which measures the evolution of the dollar against the currencies of a large group of major US trading partners. The US Dollar Index is used as a benchmark. The US dollar's performance compared to a portfolio of major foreign currencies is measured by this index.

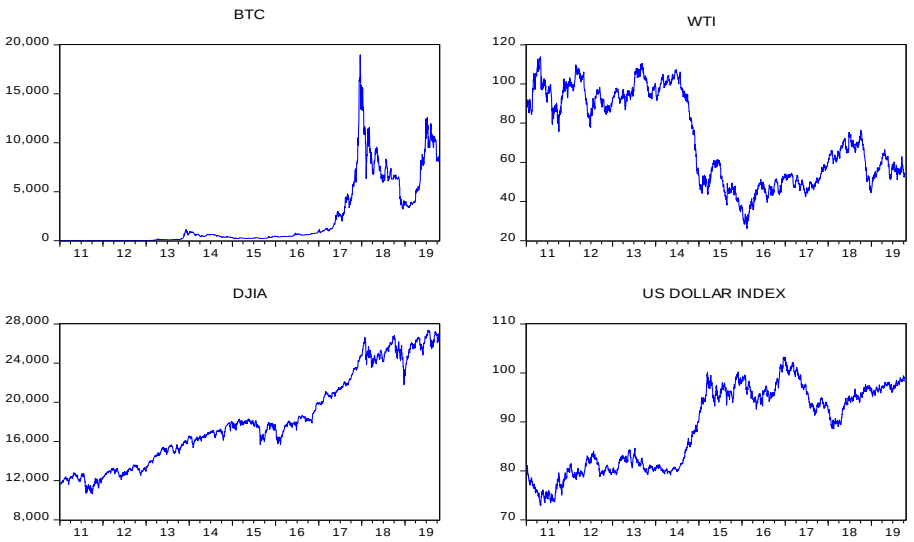
For the analysis, the price index and the natural logarithmic price difference are transformed to return as follows:

$$r_{i,t} = \ln\left(\frac{p_{i,t}}{p_{i,t-1}}\right)\times 100 \qquad (1)$$

Where, $r_{i,t}$ presents the percentage of daily compound returns for index i at time t, while $P_{i,t}$ represents the price value i at time t.

The time series in Figure 1 are clearly different. The Bitcoin price shows an explosive exponential behaviour, the DJIA and US Dollar Index levels show a general positive trend, while it is more difficult to discern a particular pattern for the oil price (WTI).

Figure 1. Daily prices



2.1 Descriptive statistics

The results of the descriptive statistics for all series are presented in table 1, as well as the Jarque-Bera test for normality. From Table 1, it is worth noting the speculative development that Bitcoin has experienced, with a minimum value of 44.37840 and a maximum value of 42.45795. We can see that at the average level, the crypto-currency Bitcoin is by far the highest with 0.446870. While oil has a negative average with 0.023099. In terms of standard deviation, we see that Bitcoin's price fluctuations are much larger than those of other asset prices. The skewness statistics for the four-return series reveal a positive Skewness coefficient for crude oil and the US dollar index, which tells us that the distributions are characterized by right-spreading. In contrast, the Skewness coefficients for BTC and DJIA are negative, corresponding to a leftward spread of the distribution. The Kurtosis kurtosis coefficient is well above 3 for all variables. These statistics show the existence of a leptokurtic form of the distributions and therefore imply the non-normality of the distributions. This result is also validated by the Jaque-Bera test which indicates that the distribution of the variables deviates from the normality hypothesis.

Table 1. Descriptive statistics

	BTC	DJIA	WTI	DXY
Average	0.446870	0.036524	-0.023099	0.009020
Median	0.220652	0.037621	0.000000	0.003195
Maximum	42.45795	4.153333	13.69440	2.448721
Minimum	-44.37840	-5.706112	-10.72635	-2.088239
Standard deviation	5.912580	0.857920	2.116301	0.429882
Skewness	-0.149082	-0.596895	0.069263	0.047303
Kurtosis	11.95154	7.295292	6.720636	4.941413
Jarque-Bera	7670.941	1900.515	1325.585	361.2744
Probability	0.000000	0.000000	0.000000	0.000000
Sum	1025.566	83.82249	-53.01250	20.69994
Sum Sq. Dev.	80195.03	1688.445	10274.21	423.9282
Observations	2295	2295	2295	2295

2.2Correlation matrix

To determine the strength of the relationship between the relative movements of two or more variables, the correlation coefficient must be used. The variables with a positive correlation move in the same direction, while those with a negative correlation have an inverse relationship. Variables with a negative correlation move in the opposite direction, while those with a positive correlation move in the same direction. When the components of a portfolio are unrelated, this means that the portfolio is well diversified, i.e. when one asset changes price, the other asset should minimise the effect. Within this framework, the results obtained regarding the relationship between BTC and other assets are presented in Table 2. These results show the absence of multi-colinearity since the correlation coefficients between two variables do not exceed 0.8. More

specifically, we observe that BTC and other assets DJIA and WTI are positively correlated, and a negative correlation between BTC and US dollar index. Indeed, the US dollar index is negatively correlated with the other two variables. As Table 2 shows, we can see that there is no problem of multi-coherence between the variables.

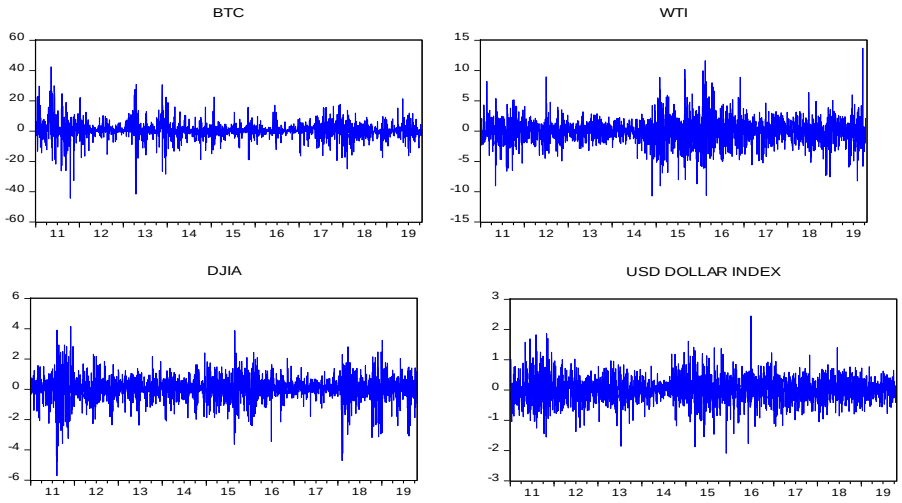
Table 2. Correlation matrix

	BTC	DJIA	WTI	DXY
BTC	1			
DJIA	0,036603	1		
WTI	0,012547	0,308122	1	
DXY	-0,020413	-0,159717	-0,178646	1

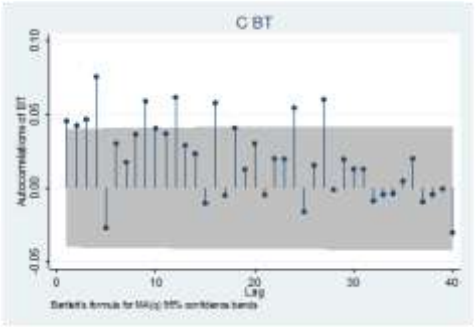
2.3 Stationarity test

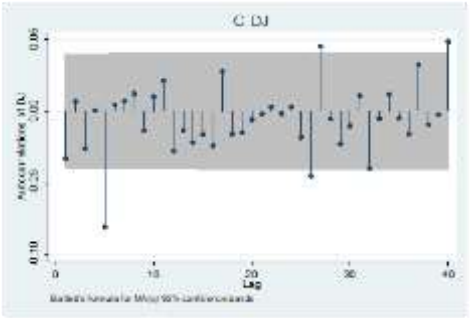
In order to study the stationarity of the series, it is first necessary to analyse the descriptive graphs and correlograms to better understand the statistical nature of the evolution of the series. The graphs below illustrate the evolution of the daily returns of each of the variables retained in the present study during the period from 11/01/2011 to 18/10/2019. It should be noted that, graphically, a variable is stationary if there is a level of convergence towards which the series periodically converges or a fluctuation around a mean.

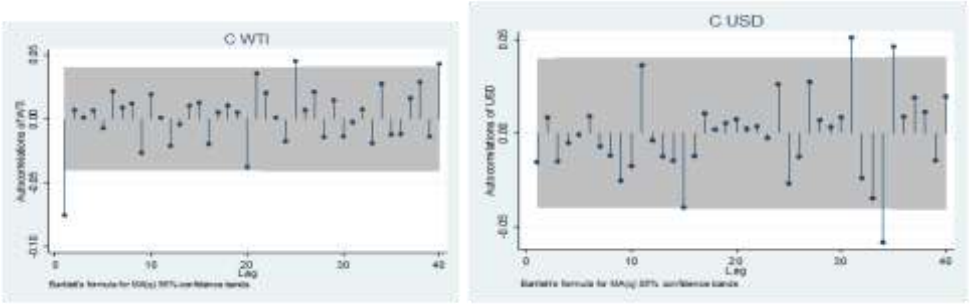
Figure 2. Evolution of daily returns



The four graphs illustrated above show that the variables selected are, a priori, stationary in that there is a fluctuation around a given level.







As shown in the four Correlograms above, the returns of the four study variables show a stationary trend as there is a rapid return and discontinuous convergence towards the value 0. This tends to affirm (not definitively) that the study data are stationary. Thus, to be able to statistically confirm the stationary nature of the selected variables, it is necessary to proceed with the Augmented Dickey-Fuller (ADF) test.

The objective is to study the stationarity of the variables with robustness and precision and to determine the order of integration which must be the same for all the variables. To do this, the ADF test should be used. The results of the test are shown in table 4 below:

Table 4. ADF test results

	Statistical test	1% critical value	5% critical value	10 % critical value
BTC	**-46.934**	**-3.430**	**-2.860**	**-2.570**
WTI	**-52.959**	**-3.430**	**-2.860**	**-2.570**
DJIA	**-50.752**	**-3.430**	**-2.860**	**-2.570**
USD	**-49.866**	**-3.430**	**-2.860**	**-2.570**

The results of the Dickey-Fuller stationarity test allow us to conclude that the four observed series are statistically stationary (the value of the test is below the critical value) at the 1% threshold:

- For the Bitcoin return, the test value is -46.934 versus -3.43.

- For the WTI return, the test value is -52.959 against -3.43.

- For the DJ return, the test value is -50.752 against -3.43.

- For the USD return, the test value is -49.866 against -3.43.

3. Methodology

We present the econometric modelling employed for our empirical study. First, we construct the DCC-GARCH model. This model will allow us to examine the dynamic conditional correlations between Bitcoin and other assets (stock, energy and currency indices). Next, we investigate in more detail the capacity of Bitcoin to be a safe haven, a hedge asset or a diversification asset, while relying on a dummy variable regression. Finally, empirical results are presented.

3.1 The DCC-GARCH model

The methodology adopted to determine whether an asset should be classified as a hedge asset, diversification asset or safe haven varies from one to another. In our study, the DCC-GARCH approach adopted follows Bouri et al. (2017a, b), Klein et al (2018), Stensås et al (2019) on hedge and refuge values for gold.

Several types of multivariate GARCH models have already been used in the literature for the evaluation of the financial capacities of several assets, such as the constant conditional correlation (CCC) and BEKK (Baba-Engle-Kraft-Kroner) models. However, these models according to Bouri et al. (2017 a,b) may encounter unreasonable parameter estimates. The CCC approach is constrained by the constant conditional correlation hypothesis. It is unable to capture interactions between assets (Hafner and Reznikova, 2012). In addition, other studies suggested that the conditional correlation between Bitcoin and other assets is dynamic (Klein et al., 2018). The DCC-GARCH model of Engle (2002) is a generalization of the DCC model of Bollerslev (1990). It captures the dynamic and time-varying relationship between the series of returns. Finally, it takes into account heteroscedasticity problem (Engle, 2002).

3.2Estimation of the MGARCH DCC model

According to Stensås et al. 2019, the DCC-GARCH model is evaluated for couples of distinct return series and not for all returns simultaneously. The estimation of the DCC model, which directly parameters the conditional correlations, is performed in two steps. The first step is to estimate of the univariate GARCH (1, 1) model. The step tow is to calculate a time-varying correlation matrix from the residuals standardised. The equation of the DCC model is specified as follows:

$$r_t = \mu_t + \omega r_{t-1} + \varepsilon_t \quad (2)$$

where r_t is the vector of Bitcoin returns and that of the other asset, μ_t is the conditional mean vector of r_t and ε_t is a vector of residuals.

The variance equation is specified as follows:

$$h_t = c + a\varepsilon_{t-1}^2 + bh_{t-1} \quad (3)$$

where h_t represents the conditional variance; c indicate the constant; a is ARCH effect (or the parameter that captures the short-term persistence) ; and b designate GARCH effect (or the long-term persistence of the volatility).

The equation of DCC (1, 1) is then written as follows:

$$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1} \quad (4)$$

where, Q_t is the time-varying unconditional ε_t correlation matrix; ε_t is a vector of standardised residuals obtained from the estimation of the first step of the GARCH (1,1) process; and α and are parameters representing the effects of previous shocks and DCCs on the current DCC'respectively. The dynamic correlation between Bitcoin and other asset can be calculated as follows:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\left(\sqrt{q_{ii,t}}\sqrt{q_{ij,t}}\right)} \quad (5)$$

where, $q_{ij,t}$ represents the conditional covariance between BTC and other asset i. $q_{ii,t}$ and $q_{jj,t}$ represent the conditional variances of BTC and other asset i, respectively.

In this case, we have employed diagnostic tests, namely autocorrelation and heteroscedasticity tests, to check the acceptance of the DCC model. Subsequently, we derive dynamic conditional correlations to estimate the hedging and safe haven properties of Bitcoin.

To examine the capabilities of the studied crypto currency as a hedging, diversification and safe haven asset against energy market, currency market and stock market movements. Using the DCC model, it would be useful to calculate dynamic conditional correlations. These correlations are then regressed on dummy variables (D).[1]

(6)

$$DCC_t / \rho_{it} = c_0 + c_1 D\left(r_{other\ asset} q_{10}\right) + c_2 D\left(r_{other\ asset} q_5\right) + c_3 D\left(r_{other\ asset} q_1\right) + \nu_t$$

[1] These dummy variables represent extreme movements in the lower 10th, 5th or 1st percentile of the return distribution.

where ρ_{it} are the dynamic correlations, D is the dummy variable to capture extreme price movements in the market, r, q_{10}, q_5 and q_1 are the 10%, 5% and 1% quantiles of the returns on asset i, respectively, and vi, t is the residual term. From equation (6), the coefficients c_1, c_2 and c_3 and their statistical significance are estimated. Furthermore, the conditional correlation between Bitcoin and each of the other assets studied is denoted by DCC. In addition, $r_{other\ asset}$ reflects the return of each of the other assets and v_t is the error term. According to Stensås et al (2019), diversification against the movements of the other asset thus represents Bitcoin in the case where the coefficient (c_0) is positive and statistically significant.

To determine whether Bitcoin is a hedge asset, a safe haven or a diversifier, three conditions must be considered:

the first condition is when the coefficient (c_0) is positive, Bitcoin is a diversifier against the movements of the other asset. The second condition is when the coefficient (c_0) is zero, Bitcoin is a weak hedge asset with respect to the movements of the other asset. The third condition is that when the coefficient (c_0) is negative, Bitcoin is a strong hedge, the last and fourth condition is that when the coefficients c_1, c_2 and c_3 are not significantly different from zero (or if these coefficients are negative), Bitcoin is perceived as a safe haven against movements in the other asset.

4. Empirical results and discussion

According to Engle (2002), the result of the Lagrange Multiplier (LM) test indicated the presence of high ARCH effects in the residuals of the BTC return. These effects prove that GARCH modelling is the most appropriate for our data. The regression results are presented in Table 5.

Table 5. Maximum likelihood estimates of the t-DCC model on the daily returns of BTC, DJIA, USD and WTI

Parameters	Estimator	St.Err.	Ratio-t	Probability
Lambda1_BTC	0.625	0.069	9.10	0.000
Lambda1_DJIA	0.229	0.036	6.44	0.000
Lambda1_USD	0.055	0.022	2.52	0.012
Lambda1_WTI	0.232	0.046	5.07	0.000
Lambda2_ BTC	0.391	0.045	8.70	0.000
Lambda2_ DJIA	0.982	0.110	8.95	0.000
Lambda2_USD	1.198	0.238	5.04	0.000
Lambda2_WTI	0.763	0.183	4.16	0.000
delta1	0.015	0.002	8.39	0.000
delta2	0.974	0.003	344.3	0.000
df	4.340	0.222	19.54	0.000
Log-vraisemblance	-16065.27			

Table 6. Correlations and unconditional volatilities

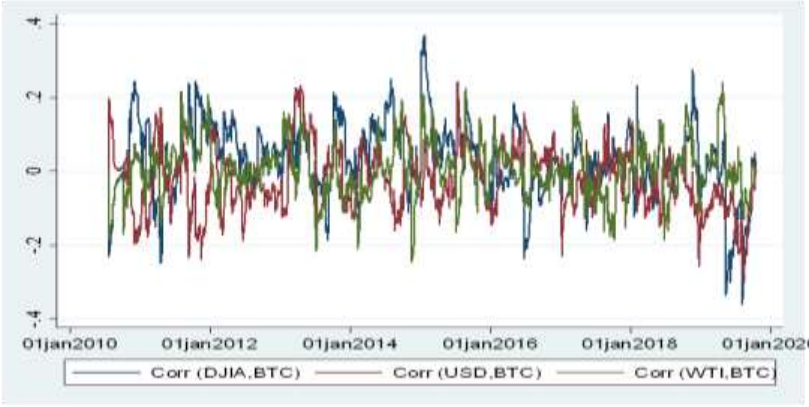
	BTC	DJIA	USD	WTI
BTC	0.045	-0.015	-0.036	0.006
DJIA	-0.015	0.110	-0.051	0.263
USD	-0.036	-0.051	0.238	-0.134
WTI	0.006	0.263	-0.134	0.183

Table 7. Unconditional volatility rankings of the four indices

No.	Indices	Unconditionally Volatilities
1.	BTC	0.083
2.	DJIA	0.102
3.	WTI	0.117
4.	USD	0.133

The evolution of the conditional correlations of BTC, DJIA, USD and WTI are illustrated in Figure 2.

Figure 2: Conditional correlations: BTC, DJIA, USD and WTI, 2011-2019



After estimating the DCC model, dynamic conditional correlations are used to assess the hedging and refuge properties of BTC. Table 6 presents the coefficient estimates of the regression model specified in Eq. 6.

Table 8. Hedge and safe properties: Main results

VARIABLES	10% quantile (c_1)	5% quantile (c_2)	1% quantile (c_3)	Hedge (c_0)
DJIA	**-0.265*** **	**-0.471*** **	**-11.925*** **	**0.031*** **
USD	**0.340*** **	**0.675*** **	**185.853*** **	**-0.022*** **
WTI	**-0.071*** **	**-0.143*** **	**0.267*** **	**0.005*** **

Note: This table presents the results of the estimation of equation 5. *** indicates statistical significance at the 1% level.

Table 6 reports the coefficient estimates of the regression model specified in equation 5. The coefficients (c_0) are positive and statistically significant at the 1% level. This result is explained by the fact that Bitcoin cannot be used as a hedge.

Following this result, it is important to note that BTC is an effective diversifier for DJIA and WTI investors. Specifically, BTC represent a strong hedge for (US) investors as the parameter (c_0) is negative and statistically significant at 1%. These results indicate that Bitcoin's hedging capabilities vary across three market indices: energy, stock market and currency. As a result, Bitcoin fluctuates across markets and is an attractive hedging tool for US investors in the currency sector (US). Specifically, investors are needed to integrate Bitcoin into their stock portfolio to hedge against uncertainty and risk. This result is similar to that found by Stensås et al. (2019) where the authors found that Bitcoin is considered a strong hedge for investors. In the same

vein, Bouri et al. (2017a) showed that Bitcoin is perceived as a hedge against uncertainty only for the case of investments made in the short term. As for safe haven, Bitcoin seems to be used as a safe haven for the DJIA and WTI indices. We discovery evidence that BTC is a strong safe haven in the 1%, 5% and 10% stock quantiles for DJIA in the stock market, and in the 5% and 10% quantiles for WTI in the energy market. Stensås et al (2019) show that Bitcoin appears as a safe haven for investors in developing markets only for the case of India and Zimbabwe.

5. Conclusions

In this paper, we investigate the hedging, safe haven or diversification abilities of BTC in three main markets, namely the stock, energy and currency markets. To do so, we use daily data from 03 January 2011 to 18 October 2019. The results exhibited the existence of a qualitative difference between the indices that differ from a market and the capacity of Bitcoin. In the case of the stock and energy markets, the results showed that BTC can be used by investors as an important diversifier. However, it is a strong hedge for the currency market. From these results, it appears that the presence of Bitcoin in such a portfolio and its capabilities differ from one sector to another. In addition, the results suggested that Bitcoin can be used as a safe haven for the stock and energy markets. In sum, investors, regulators and governments are advised to be vigilant about

including Bitcoin in any portfolio as the use of Bitcoin as a safe haven generates excessive volatility. In addition, Bitcoin is characterized by insufficient liquidity. This is likely to hamper the transfer of funds between Bitcoin and financial (equity) and energy products.

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