RESEARCH ARTICLE

Relationship between Bitcoin and the stock market – can bitcoin serve as a safe haven for investors?

Julija Božan[1, 2], Josip Višković[1]

[1] Faculty of Economics, Business and Tourism, University of Split, Split, Croatia

[2] OTP Leasing d.d., Split, Croatia

Correspondence to:
Josip Višković
University of Split, Faculty of Economics, Business and Tourism, Department of Finance, Cvite Fiskovića 5, 21000 Split, Croatia
josip.viskovic@efst.hr

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Aim: As a new asset class, Bitcoin and other cryptocurrencies can be interesting for investors in the context of return stabilization, especially in times of crisis. We aimed to analyse whether Bitcoin can serve as a safe haven for investors in times of crisis.

Methods: The data covers the period from September 17, 2014, to April 29, 2021, with 382 observations. Yahoo! Finance served as the source for the Bitcoin prices and Investing.com for the values of the Standard & Poor's 500 (S&P500) Index. We used the maximum likelihood method to estimate the dynamic conditional correlation model.

Results: Due to the high volatility during the analysed period, Bitcoin achieved a higher risk-adjusted return compared to the S&P500 Index. The DCC model showed a positive correlation between the returns of the S&P500 and Bitcoin during the analysed period.

Conclusions: Our results suggest that Bitcoin may not serve as a safe haven for investors in times of crisis. However, its role in this context should be further evaluated by examining its relationship with other traditional asset classes (gold, commodities) and other types of cryptocurrencies such as stablecoins.

Keywords: Bitcoin; S&P500; volatility; MGARCH; safe haven; crisis

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Introduction

As a type of digital money based on cryptography, Bitcoin was not created primarily as an investment asset. It was developed by Nakamoto (*1*) who designed it as a highly secure and transparent peer-to-peer payment network that does not require physical banknotes and intermediaries, and is not governed by a centralized authority. Financial transactions completed and validated in Bitcoin are permanently recorded in an immutable electronic ledger (Bitcoin blockchain) that is freely accessible via the Internet.

The price of an individual coin and the total capitalization of the Bitcoin network have been continuously growing since 2009, reaching a value of 69,000 dollars per coin in 2021. Moreover, compared to stocks, gold, oil, and other investments, Bitcoin is extremely volatile as its total mass is hard capped (21 million coins) and as it is deflationary, unlike fiat money. These two facts open up the possibility of large short-term earnings, making Bitcoin attractive to investors and speculators as an investment asset. Currently, Bitcoin accounts for more than 50% of the total cryptocurrency market capitalization (*2*).

An investment asset can be considered as a diversifier or a safe haven. A diversifier is a type of investment asset managed in a portfolio to reduce the total risk of investments, and it is not perfectly positively correlated with other assets (*3*). A safe haven, meanwhile, is an investment asset that is expected to retain or increase in value during times of market turmoil (*3*). Thus, by investing in a safe haven such as gold, investors can limit their exposure to losses in the event of market turbulence. Due to many similarities, Bitcoin is often compared to and defined as digital gold (*3*). Namely, gold and Bitcoin both have limited supply, making them scarce and costly to extract. They are both 'mined' by several independent operators and companies (*4*). They also have a decentralized nature and are not controlled by any government or central authority, meaning that their value is based on the market and not dependent on the local policies of some country or economy. They both have liquid markets and are interchangeable with fiat money. Finally, as Bitcoin is becoming globally accepted and as its supply is limited, it could be considered as a store of value like gold. Yet unlike gold, Bitcoin still needs to prove its stability over time, as it remains subject to significant price volatility (*5*).

The abovementioned similarities to gold indicate that Bitcoin might be useful as a safe haven. However, existing empirical research on its usefulness as a diversifier or a safe haven is ambiguous, with some authors supporting the notion of Bitcoin's safe haven properties (*4*, *6*-*12*) and others contesting it (*13*-*17*). In general, most of these studies agree that, although speculative and highly volatile, Bitcoin represent a new asset that could serve as a safe haven for investors in periods of crisis. Nevertheless, not every combination of Bitcoin and other financial assets has been shown to be beneficial. Furthermore, the effect of the coronavirus disease 2019 (COVID-19) pandemic on the valuation of Bitcoin and its role as a safe haven has not been sufficiently researched – a gap we seek to address with this research. Specifically, we want to contribute to the existing body of knowledge by applying the dynamic conditional correlation (DCC) generalized autoregressive conditional heteroskedasticity (GARCH) model defined by Engle (*18*) to time series data from the COVID-19 period, where we will compare data for the Standard & Poor 500 index (S&P500) and Bitcoin. This model is fit for investigating whether the correlation between capital market returns and Bitcoin is constant or time-varying. Since this analysis will include data from the pandemic, our results will show whether Bitcoin can serve as a safe haven during such periods of crisis, which is our main research question. In this way, we will also address the following questions: how volatile, i.e., risky is Bitcoin compared to the traditional stock market and can it serve as a safe haven during periods of crisis?

Methods

For this paper, we used S&P500 data as the representative capital market and Bitcoin as the cryptocurrency. We extracted data for the period between 17 September 2014 and 29 April 2021, with 382 observations from Yahoo! finance and Investing.com (*19*, *20*), noting that daily updates to these sites may cause discrepancies with current figures. Since the sampling interval is weekly, a small deviation from the averages is to be expected, as large portions of the extreme values are not included. Employing weekly returns and avoiding outliers, which can be observed at higher sampling frequency, enables enough data for estimations to be made. We thus used a maximum likelihood (ML) method estimate the dynamic conditional correlation (DCC) model. According to Arnerić and Mateljan (*7*), the most common model in previous works is the univariate symmetric GARCH (1,1) model defined by Bollerslev (*21*). When two or more time series are taken into account, it is necessary to consider multivariate testing methods that simultaneously test the difference in two or more variables. We then set up a multivariate GARCH model that implements conditional correlation models that then use nonlinear combinations of univariate GARCH models to represent conditional covariance is implemented in Stata, version 13 (StatCorp LLC., College Station, TX, USA).

According to Engle (*22*), the conditional variance and correlation models of the main multivariate GARCH model are based on the idea of modeling conditional variance and correlation instead of directly modeling the conditional covariance matrix. The conditional covariance matrix is divided into conditional standard deviations and the correlation matrix:

$$1)\ H_t = D_t R_t D_t$$

where H_t represents the conditional covariance matrix; R_t represents the conditional correlation matrix of returns between the cryptocurrency market and the capital market; and D_t represents a diagonal matrix of the conditional standard deviations $\sigma_{j,t}$ for $j=1,2$ and $t=1,2, \ldots, 2.417$. Moreover, each of the variances is described by the univariate GARCH (p, q) model. Since the lags p and q do not need to be the same for each market, the estimates of the parameters will not be the same.

$$2)\ \sigma_{12,t} = \rho_{12,t}\sqrt{\sigma^2_{1,t}\sigma^2_{2,t}}$$

Equation 2 shows the analysis of covariance. Thus, the covariance is the product of the linear correlation coefficient $\rho_{12,t}$ and the conditional standard deviations $\sigma_{1,t}$ and $\sigma_{1,t}$ In his paper, Engle (22) also states that under the assumption that the correlation matrix R is constant ($R_t = R$), the linear correlation coefficients are equal, i.e., $\rho_{21,t} = \rho_{12}$. This model of constant conditional correlations (the CCC-GARCH model) was the first of this type introduced by Bollerslev in 1990 (23). It assumes that the dynamics of the covariance are determined only by the dynamics of the two conditional variances, but not by those of their correlations.

Engle and Sheppard introduced the DCC-GARCH model (18), a continuation of the CCC-GARCH model, for which the conditional correlation matrix is designed to vary over time. Two requirements must be considered when specifying the form R_t. The first is that H_t must be positive, and the second is that all correlation matrix elements must be equal to or less than 1.

$$3)\ \ R_t = (1 - \theta_1 - \theta_2)\, R + \theta_1 S_{t-1} + \theta_2 R_{t-1}$$

Equation 3 represents a positive correlation matrix R, with unit values on the main diagonal assuming it is constant throughout the optimization period. Here, θ_1 and θ_2 are negative scalars; R_{t-1} is a matrix from the previous period; and S_{t-1} is the correlation matrix of all previous standardized errors (7). If the null hypothesis is accepted, this would mean that the negative scalars are equal to zero, so the DCC (1,1) model reduces to the CCC (1,1) model.

In addition, Engle has defined a modified DCC (1,1) model (24), according to which the following equations describe the dynamics of the conditional correlation matrix:

$$4)\ \ R_t = (diag Q_t)^{-1/2}\ \ Q_t (diag Q_t)^{-1/2}$$

$$5)\ \ Q_t = (1 - \theta_1 - \theta_2)\, \bar{Q} + \theta_1 (u_{t-1} u^{\tau}_{t-1}) + \theta_2 Q_{t-1}$$

$$6)\ \ \bar{Q} = [\rho_{12}] = \frac{1}{T} \sum_{t=1}^{T} u_t u_t^{\tau}$$

The dynamics of the conditional correlation matrix R_t (Equation 4) are determined by a matrix Q_t that depends on the conditional variance and covariance matrix of the standardized relations u_t and their unconditional covariance matrix $\bar{Q}$ (representing a correlation ρ_{12}). Equation 5 defines a matrix Q_t within which the scalar θ_1 is positive and θ_2 negative and the relation $\theta_1 + \theta_2 < 1$ constrains it. Arnerić and Mateljan (7) explain that conditional correlations are not defined as a weighted sum of correlation matrices conditioned on past information, but the matrix Q_t. The components described by univariate GARCH (1,1) models are transformed into a correlation matrix. In conducting statistical tests, we set the level of statistical significance at $P < 0.001$ and $P < 0.05$.

Results

Cryptocurrency trading takes place daily, while stock trading does not take place on weekends. Accordingly, we first harmonised the data to prepare it for analysis. We then examined the characteristics of both markets before evaluating the model.

If weekly prices are analysed (**Table 1**), the range of changes in value from the minimum to the maximum is most pronounced for Bitcoin, whose lowest value in the observed period was USD 199.60, while the highest value was USD 61,195.30. This is confirmed by the coefficient of variation, which is 0.22 for S&P500 and 1.62 for Bitcoin.

Table 1. Descriptive statistics of the weekly price of the observed variables (in USD for the period January 5, 2014, to April 4, 2021)*

Variable	No.	Mean	SD	Min	Max	V
Bitcoin	382	6,552.63	10,630.81	199.60	61,195.30	1.62
S&P500	382	2,556.03	557.71	1 782.59	4,182.47	0.22

*Abbreviations: max – maximum, min – minimum, SD – standard deviation, V – coefficient of variation.

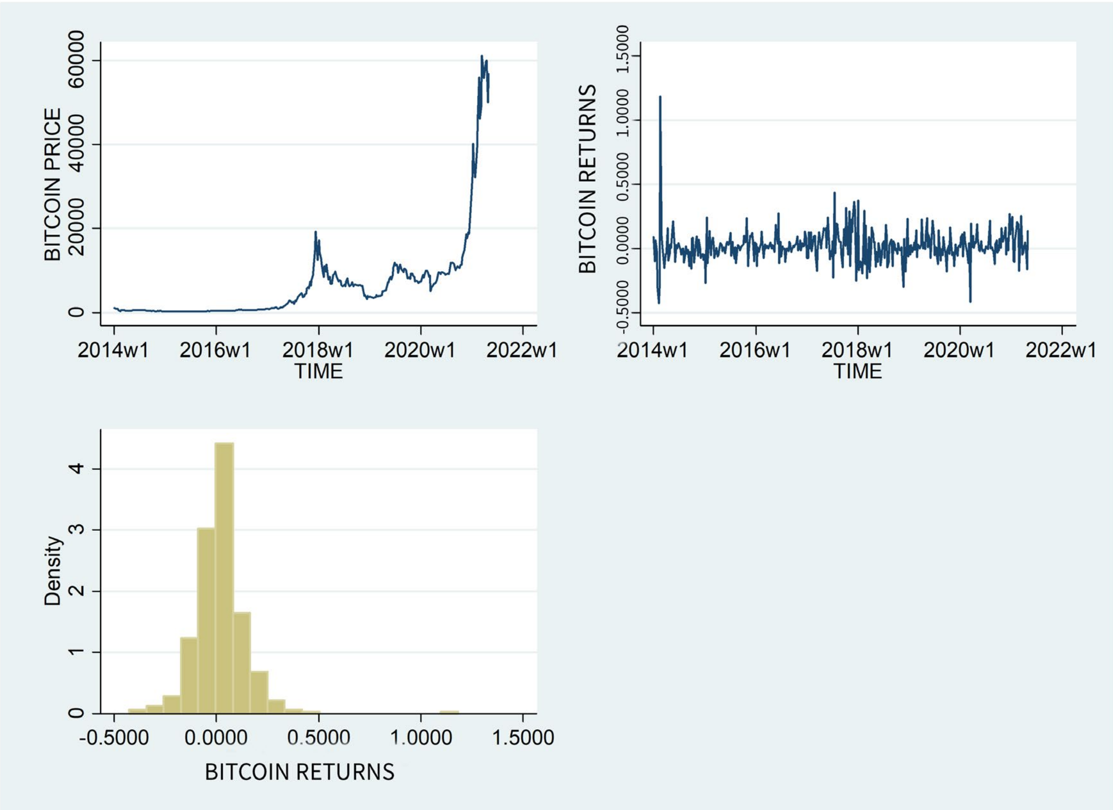

Figure 1. Prices (top left), return (top right), and return distribution (bottom left) of Bitcoin.

The Bitcoin price trend can be divided into three periods (**Figure 1**). The first period covered the years 2014 to 2017, when the distribution had a uniform shape. The period of the following two years, i.e., until the onset of the COVID-19 pandemic, is characterized by an exponential upward and downward trend. In the third period, the exponential upward trend continues. Meanwhile, the movement of the S&P500 can be divided into two periods separated by the pandemic in 2020 (**Figure 2**). Before the pandemic, linear growth with occasional fluctuations can be seen. In contrast, after the pandemic, there is a sharp decline in value and a steep rise to the highest level within the observed period.

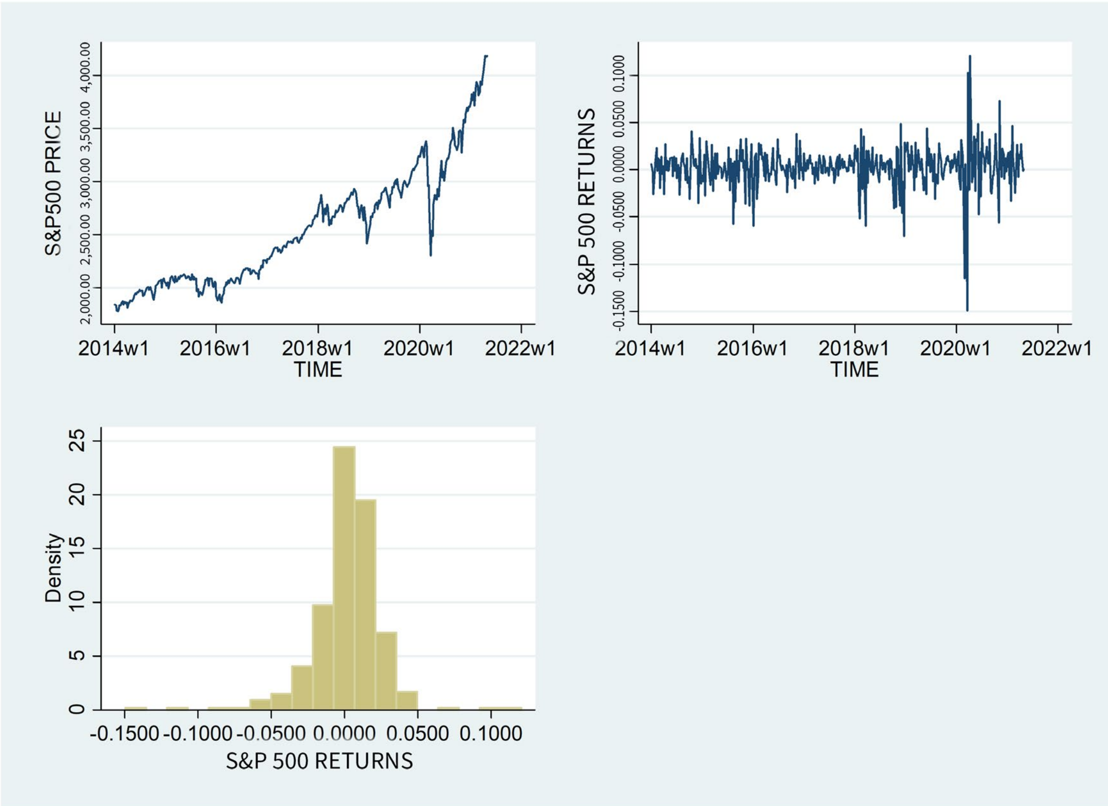

Figure 2. Prices (top left), return (top right), and return distribution (bottom left) of S&P500.

Table 2. Descriptive statistics of Bitcoin and S&P500 returns*

Variable	x̄	SD	Min	Max	ADF	LB (1)	LM (2)	JB
Bitcoin return	0.0182	0.1271	−0.4280	1.1808	-19.253†	0.02605	9.216†	0
S&P500 return	0.0024	0.0229	−0.1498	0.1210	-21.392†	4.2306	56.716†	0

*Abbreviations: ADF – augmented Dickey-Filler test, JB – Jarque-Berra test, LB – Ljung-Box test, LM – Lagrange multiplier test, max – maximum, min – minimum, SD – standard deviation, x¯ – mean.
†P < 0.001.

Table 2 provides summary statistics, including the Dickey-Fuller generalized least-squares unit root tests, the Jarque-Bera (JB) test, and the Ljung-Box (LB) test. The average weekly growth rate of Bitcoin was 1.82%, while that of S&P500 was 0.24%. In particular, the weekly return of Bitcoin ranged from −42.8% to 118.1%, which is a significantly high interval compared to the range of the S&P500 (−14.9% to 12.1%). Bitcoin's standard deviation is almost six times higher than that of the stock index, which is 2.29%. Thus, we see that the standard deviations of the two instruments are normally distributed, which was further confirmed by the JB test. Moreover, the augmented Dickey-Fuller unit roots test showed that the time series is stationary, while the LB test showed that the returns are not in autocorrelation. Finally, a Lagrange multiplier test shows that the variance of the returns is heteroskedastic.

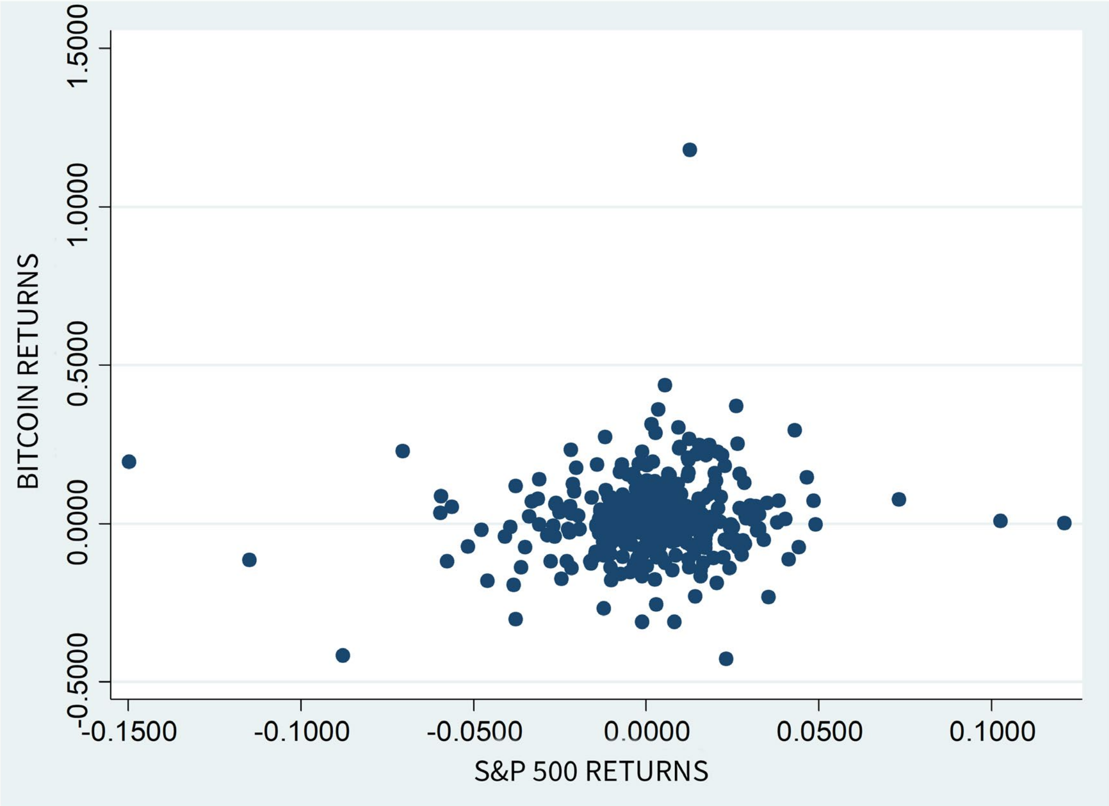

Figure 3. Scatter diagram – correlation of S&P500 and Bitcoin returns.

Figure 3 shows the scatter diagram without signs of covariance, meaning that the values are not correlated. However, it cannot be ignored that the returns of Bitcoin and S&P500 fluctuated during the observed period, which was influenced by the COVID-19 pandemic.

The results of the DCC model (1, 1) are shown in **Table 3**. We can see that all parameters are statistically significant except for θ_1 and θ_2. The value of the unconditional correlation coefficient ρ_{12} is significant, suggesting that there is a correlation between S&P500 and Bitcoin returns. Non-significant parameter values for θ_1 and θ_2 indicate that the correlations are not constant over time, thus accepting a null hypothesis based on the Wald test. Diagnostic testing of the standardized residuals and their squares of each GARCH (1, 1) model indicates that neither do the autoregressive conditional heteroskedasticity (ARCH) effects remain at 5 and 10 lags, and that there is no autocorrelation at five lags as well. The JB test confirms the normality of the standardized residuals. This means that the DCC (1, 1) model, estimated by the two-step ML method, satisfies all assumptions and is precisely specified. The data on the sum of $\alpha_1 + \beta_1$ are essential. Namely, the variances are persistent, implying a trend in value volatility.

Table 3. Dynamic conditional correlation model estimates*

Maximum likelihood†				
GARCH (1,1)	S&P500	Bitcoin	Engel's model DCC (1,1)	
M	0.0029 (0.0008)‡	0.0143 (0.0052)‡	ρ12	0.1316 (0.0559)§
α0	0.00003 (0.00001)‡	0.0024 (0.0008)‡	θ1	0.0795 (0.0841)
α1	0.3466 (0.0700)‡	0.3311 (0.0788)‡	θ2	0.2616 (0.2916)
β1	0.6422 (0.0534)‡	0.5298 (0.9939)‡		
Diagnostic tests				
GARCH (1,1)	S&P500	Bitcoin	Engel's model DCC (1,1)	
α1 + β1	0.9888	0.8610	θ1+ θ2	0.3411
LB (5)	-0.0436	0.0498	logL	1 286.367
LM (5)	3.4640	3.5240	AIC	-2,600.00
LM (10)	3.7250	2.9430	BIC	-2,500.00
JB	0.0000	0.0000	Wald test	2.5600

*Abbreviations: AIC – Akaike information criterion, JB – Jarque-Berra test, BIC - Bayesian information criterion, DCC – dynamic conditional correlation model, LB – Ljung-Box test, LM – Lagrange multiplier test.
†The first part of the table lists the parameter estimates for Engle's DCC model (1, 1), with standard errors in parentheses.
‡P < 0.001.
§P < 0.05.

The variance of the S&P500 was defined as 0.642 values from the previous period and 0.347 errors due to disturbances from the previous period. In comparison, Bitcoin's variance was defined as 0.530 values from the last period and 0.331 errors caused by disturbances from the previous period. These values are essential for this research because they confirm that volatility is higher in certain turbulent periods such as crises than in stable periods. In addition, the values of the Akaike information criterion, the Bayesian information criterion, and the likelihood function *logL* (**Table 2**) suggest that the model is appropriate .

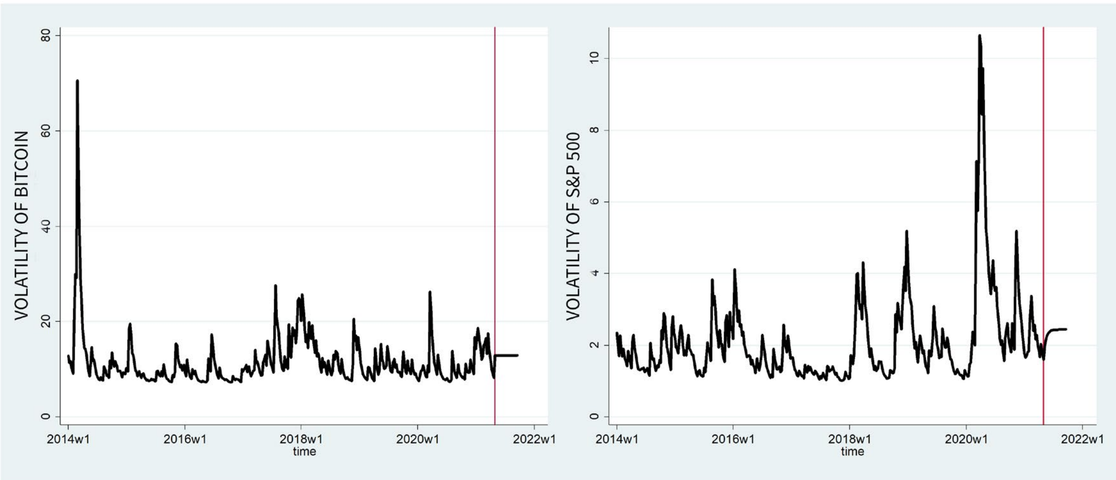

Figure 4. Conditional standard deviations of Bitcoin returns (left) and S&P500 returns (right).

Figure 4 shows an estimate of the volatility of the sample, both in-sample and out-of-sample, for 20 weeks ahead. The out-of-sample values are predictive content that converges over time. In particular, Bitcoin volatility is expected to be around 15%, while the S&P500 is just above 2%. The results also complement previous claims that Bitcoin fluctuates significantly over time. The stock market index strives to maintain its stability.

Discussion

The COVID-19 pandemic acted as a catalyst for a digital transformation and impacted investment and portfolio strategies related to Bitcoin in turbulent times. Using weekly data on Bitcoin and S&P500 for the period that included the COVID-19 pandemic, we wanted to examine if Bitcoin can serve as a safe haven for portfolio managers during the downturn in times of crisis. By analysing the underlying data and using the DCC GARCH model, we found that the fluctuation range of weekly prices for Bitcoin in the observed period was significantly higher compared to the S&P500. Moreover, due to the wide fluctuation of weekly prices, the standard deviation of Bitcoin was 6% higher than that of the S&P500, reflecting its extreme volatility. Our primary result suggests that Bitcoin cannot serve as a safe haven during times of crisis. This means that, due to the strong and positive correlation between Bitcoin and the S&P500 return, an investment in the former does not minimize the risk in the portfolio in periods of crisis.

The result is in line with the study by Fidrmuc, Kapounek, and Junge (*15*), who showed that Bitcoin is most inefficient in crises, which was also suggested by Khaki et al. (*17*) who found that Bitcoin does not contribute significantly to portfolio diversification during economic turmoil. The results are also in line with Ghorbel and Jeribi (*16*) and Corbet, Larkin, and Lucey (*14*) who showed that Bitcoin is not a safe haven in times of crisis. Thus, our results support the notion that Bitcoin cannot serve as a safe haven during the crisis period because it behaves the opposite of gold, as shown by Klein, Hien, and Walther (*13*).

This study has its limitations, the first being the analysed period. Namely, the sample period was from 17 September 2014 to 29 April 2021. In the meantime, Bitcoin's value has significantly dropped after peaking at around USD 69,000.00 in November 2021, stabilizing at between USD 20,000.00 and 30,000.00 (*25*). Therefore, more up-to-date analyses might provide different results than shown here. Another limitation relates to the frequency of Bitcoin trading, as it is traded 24/7, while the traditional stock market is traded from Monday to Friday. Still, as the sampling interval of the stock market was weekly, this resulted in a relatively short time series. This might have infringed on the robustness of our results, as relevant results should be applied to daily data.

Future analyses should consider the rest of the COVID-19 pandemic and the post-pandemic period. Conducting analyses over such a longer period may provide better quality results and therefore lead to more robust conclusions. Also, separating the analysed period into two sub-periods, one before the COVID-19 crisis and the one that includes only the COVID-19 crisis, might provide valuable results that can be compared with current ones. Besides, the relationship between Bitcoin and other traditional investment classes such as commodities could be included in the analyses. Additionally, other types of cryptocurrencies such as stablecoins could be analysed, as they have been developed to resolve some of the shortcomings of Bitcoin, such as price volatility. Therefore, stablecoins may represent a new possible safe haven for investors as they are, in contrast to Bitcoin, less susceptible to price fluctuations, providing investors with a sense of security and limited financial risk, making them a reliable store of value.

Due to extreme volatility, Bitcoin is a high-risk asset, which makes it speculative and unpredictable in terms of price trends. According to our findings, it cannot be used as safe haven in times of crisis. Therefore, investment in Bitcoin is not recommended for risk-averse investors and conservative portfolio managers, as it is a rather speculative investment that does not generate steady cash flow or dividends and an asset without a fair value. Still, in January 2024, the US Securities and Exchange Commission approved exchange-traded funds for Bitcoin providing an additional boost to its price (*26*). Nevertheless, it should be recognized that Bitcoin has been characterized by significant volatility, making it riskier for small investors.

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ORCID

Josip Visković https://orcid.org/0000-0002-8797-1496

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