The correlation between the stock market and Bitcoin during COVID-19 and other uncertainty periods

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A R T I C L E   I N F O

A B S T R A C T

This research examined the impact of the stock market on Bitcoin during COVID-19 and other uncertainty periods. Based on the quantile regression results, during periods of high uncertainty, such as COVID-19, the S&P 500 returns significantly affected Bitcoin returns. Moreover, this research applied the VAR (1)–GARCH (1, 1) model to investigate the spillover effect from the stock market to Bitcoin. According to the findings, the shocks from the stock market also influenced Bitcoin's volatility during COVID-19 and other periods of turmoil.

1. Introduction

Cryptocurrencies are becoming increasingly popular as an investment product with incredible returns and high risks. They have also inspired research on portfolio diversification, hedging, and safe haven for other financial assets (Bouri et al., 2017b; Shahzad et al., 2019; Smales, 2019). Some previous studies have pointed to Bitcoin as a hedge asset against the S&P 500 stock market (Bouri et al., 2017a; Tiwari et al., 2019). However, due to the arrival of COVID-19, an important question has emerged regarding how the relationship between Bitcoin and other investment assets has changed during this period of turmoil. Conlon and MacGee(2020) indicated that Bitcoin was not a safe haven for securities because it increased portfolio risk during a high uncertainty period. Thus, in this research, we will examine the relationship between the stock market and Bitcoin during COVID-19 and other uncertainty periods.

For this purpose, this research uses quantile regression to estimate Bitcoin returns on the S&P 500 market during low, medium, and high uncertainty periods. In order to investigate the conditional Bitcoin volatility, we apply the ARCH (1)–GARCH (1, 1) model, introduced by Ling and McAleer (2003), which is advantageous for observing the spillover effect from the stock market to Bitcoin. This method was also used by Chan et al. (2005), Hammoudeh et al. (2009), and Arouri et al. (2011) to inspect the interdependencies between other markets and the stock market. It is hoped that the findings will contribute to the literature on the effectiveness of safe-haven assets in portfolios.

The remainder of the paper is as follows. Section 2 explains the methodology, while Section 3 displays the data and statistic descriptions. Then, Section 4 presents the empirical results. Finally, Section 5 presents the conclusion.

2. Methodology

This research used Eq. (1) given below to examine the stock market's impact on Bitcoin returns. In this equation, R^{BTC}_t is the return

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of Bitcoin at time t, U is the uncertainty index, and R^{SP} is the return of the S&P 500 index. The lagged error term (u_{t-1}) and the lagged returns (R^{BTC}_{t-1}, R^{BTC}_{t-2}) are also included in the model. We ran a quantile regression based on the three-group uncertainty index (low, medium, and high) to assess how the stock market impacted Bitcoin returns in each period. In addition, we compared this effect between the time periods with and without COVID-19, respectively.

$$R^{BTC}t = \alpha_{0+} \alpha_1\left(R^{SP}_{t-1}\right) + \alpha_2 U_t + \alpha 3\left(R^{BTC}_{t-1}\right) + \alpha_4\left(R^{BTC}_{t-2}\right) + \alpha_5 u_{t-1} + \varepsilon_t \tag{1}$$

Moreover, the VAR (1) - GARCH (1,1) model, proposed by Ling and McAleer (2003), was used to evaluate how volatility was transmitted from the stock market to Bitcoin. The system of equations is as follows:

$$R_t = c + \mu R_{t-1} + e_t \tag{2a}$$

$$e_t = h_t^{1/2} n_t \tag{2b}$$

where $R_t = (R^{BTC}_t, R^{SP}_t)$' with R^{BTC}_t, and R^{SP}_t are the returns at time t of Bitcoin and S&P 500, respectively; $e_t = (e^{BTC}_t, e^{SP}_t)$' with e^{BTC}_t, and e^{SP}_t are the residuals from the Eq. (2a) of Bitcoin and S&P 500 returns, respectively; $n_t = (n^{BTC}_t, n^{SP}_t)$' is the vector of independently and identically distributed errors; and $h_t^{1/2} = diag\left((h^{BTC}_t)^{1/2}, (h^{SP}_t)^{1/2}\right)$ with h^{BTC}_t, and h^{SP}_t are the conditional variances of Bitcoin and S&P 500 returns that are given by

$$h^{BTC}_t = \alpha_{BTC} + \beta_1\left(e^{BTC}_{t-1}\right)^2 + \beta_2 h^{BTC}_{t-1} + \beta_3\left(e^{SP}_{t-1}\right)^2 + \beta_4 h^{SP}_{t-1} \tag{3}$$

$$h^{SP}_t = \alpha_{SP} + \beta_5\left(e^{BTC}_{t-1}\right)^2 + \beta_6 h^{BTC}_{t-1} + \beta_7\left(e^{SP}_{t-1}\right)^2 + \beta_8 h^{SP}_{t-1} \tag{4}$$

Similarly, we ran a quantile regression for Eqs. (3) and (4) to determine how the spillover effect from the stock market to Bitcoin differed in each period. As shown in Eq. (3), the Bitcoin variances are conditional on previous information (e^{BTC}_{t-1}, h^{BTC}_{t-1}) and the shock transmission from the stock market (e^{SP}_{t-1}, h^{SP}_{t-1}).

3. Data

This research employed the weekly time-series data of Bitcoin and the S&P 500 Index from January 1, 2016 to January 1, 2021, i.e., 262 weeks of observations. The Bitcoin price was extracted from www.coingecko.com. The uncertainty index was also obtained over the same period from the Economic Policy Uncertainty Index suggested by Baker et al. (2016). Figs. 1(a) and 1(b) illustrate the price of Bitcoin and the S&P 500 over time. Notably, they moved quite similarly after the appearance of COVID-19 (marked by the vertical red line). Their returns also plummeted and gradually recovered, as shown in Figs. 1(c) and 1(d). However, the uncertainty index and its changing level (the first difference of uncertainty) sharply increased when the pandemic began and then declined (see Figs. 1(e) and 1(f)).

Table 1 displays the statistical results of Bitcoin, stock returns, uncertainty, and the first difference of uncertainty. In Panel A, the
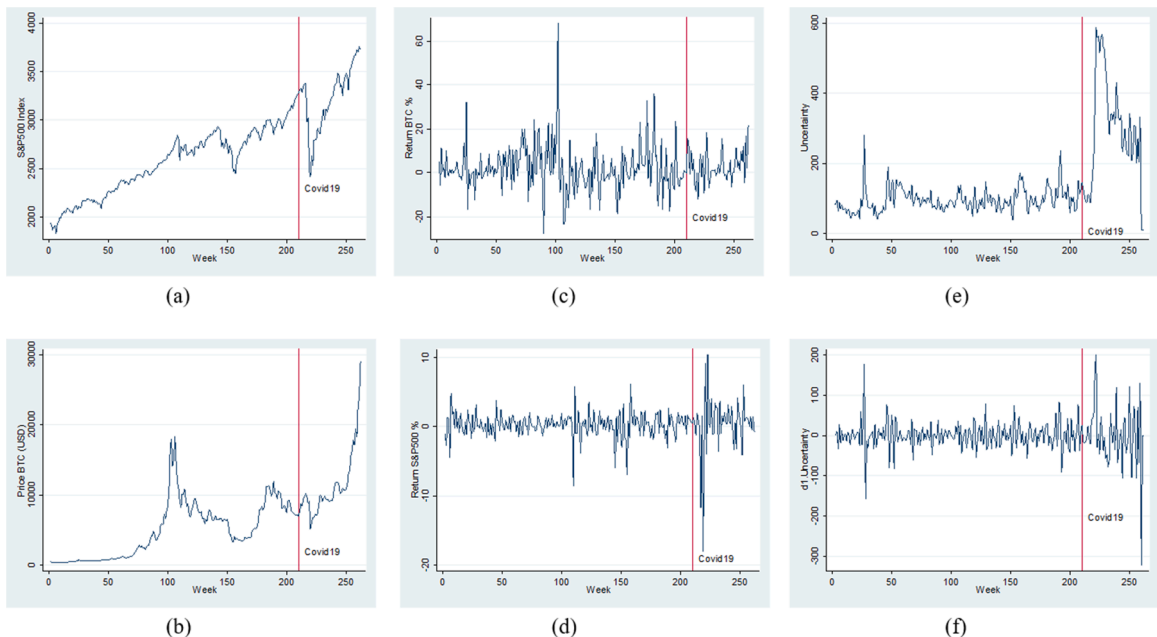

Fig. 1. Bitcoin, the S&P 500, and uncertainty over time.

skewness and kurtosis statistics show that the time series are asymmetric and leptokurtic. Also, as all of the Jarque–Bera values are statistically significant, the data are not normally distributed. In Panel B, we present the value of the uncertainty in three levels. Moreover, we sort the time-based uncertainty before and after the appearance of COVID-19. The statistics indicate that uncertainty is also high during the COVID-19 period. In Table 2, we test whether the data is stationary by applying unit-root testing. Both the Augmented Dickey–Fuller and Phillips–Perron tests confirm that the weekly returns of Bitcoin and S&P 500 are stationary. After taking the first difference of uncertainty, d1.uncertainty also becomes stationary.

4. Empirical results

Table 3 presents the mean regression results of Bitcoin returns, by applying the ARIMA (1,0,2) model, while column *All* displays the regression results for all of the observations. Evidently, the S&P 500 returns in the previous week had a statistically significant impact on Bitcoin returns, at approximately 0.585%. However, when we conducted the quantile regression according to the uncertainty level (low, medium, and high), this effect was only found when the uncertainty was high. It became stronger at 0.698% and significantly stronger. Likewise, when comparing the periods with and without COVID-19, the stock market's influence was higher at 0.774%. Nevertheless, in the period before COVID-19 (or during low and medium uncertainty), this effect was indifferent from zero. In addition, the significant coefficients of AR (1) indicate that the previous returns also influenced its return.

Table 4 presents the regression results of the conditional Bitcoin variance at time t (h^{BTC}_t) on information variables at time t-1, by applying the VAR (1)–GARCH (1, 1) model. Strikingly, the error terms (e^{SP}_{t-1})^2, which reflected the unexpected shocks in the stock market, were statistically significant during the COVID-19 period and during the high uncertainty period. The findings confirm the volatility spillover effect from the S&P 500 to Bitcoin during these periods. However, there was no evidence to suggest the effect of the S&P 500 variance (h^{SP}_{t-1}) at any time. Moreover, as the coefficients of (e^{BTC}_{t-1})^2 and (h^{BTC}_{t-1}) were both highly significant, the previous information of Bitcoin plays an important role in explaining its variance. This research also regressed the conditional S&P 500 variance. However, we did not find any effect of the volatility spillover effect from Bitcoin to the stock market. The results are plausible as cryptocurrency is trivial when compared to the stock market.

The findings also suggest that COVID-19 is a circumstance in which the level of uncertainty escalates. Evidently, when the financial market experiences periods of high uncertainty, the stock market tends to impact Bitcoin's return and volatility. However, this effect was not found in the low and medium uncertainty periods. The results remind investors to pay attention to high uncertainty periods in the future in order to optimize their portfolios.

5. Conclusion

This research aimed to find the effect of the stock market on Bitcoin during periods of turmoil. Based on the quantile regression results, the stock market's return in the previous week significantly impacted Bitcoin returns during the high uncertainty periods and after the appearance of COVID-19. This research also applied the VAR (1)–GARCH (1, 1) model to investigate the conditional Bitcoin variance. It found a volatility spillover effect from the stock market to Bitcoin during the COVID-19 period and during other periods of high uncertainty. Therefore, the stock market and cryptocurrency are more correlated during periods of high uncertainty.

Table 1
Panel A: Descriptive statistics for variables.

	Return BTC	Return S&P 500	Uncertainty	d1. Uncertainty
Obs.	261	261	261	260
Mean	2.31	0.28	134.93	−0.28
Min	−27.64	−17.97	10.92	−321.93
Max	68.17	10.40	587.63	200.76
Std. Dev.	10.05	2.41	108.70	45.27
Variance	101.03	5.81	11,814.69	2049.42
Skewness	1.33	−1.91	2.35	−0.68
Kurtosis	10.32	19.08	8.39	15.34
Jarque–Bera	658.8***	2972***	1670***	556.4***

| Panel B: Descriptive statistics for uncertainty groups | | | | | |
Uncertainty	*Low*	*Medium*	*High*	*COVID-19*	*No COVID-19*
Obs.	87	87	87	52	209
Mean	65.61	98.00	241.17	292.91	95.62
Std. Dev.	14.90	9.02	133.25	154.71	33.28
Variance	222.07	81.37	17,755.75	23,936.03	1107.27
Skewness	−1.82	0.12	1.14	0.14	1.54
Kurtosis	7.09	1.95	3.29	2.39	7.90

The Jarque–Bera statistic is for testing normality. *** p-value < 0.01.

Table 2

Unit-root test for stationary data.

Unit-Root test	Augmented Dickey–Fuller		Phillips-Perron	
	Z(t)	p-value	Z(t)	p-value
Return BTC	−6.85	0.000	−13.751	0.000
Return S&P 500	−9.062	0.000	−18.765	0.000
Uncertainty	−2.475	0.122	−3.000	0.035
d1 .Uncertainty	−6.95	0.000	−19.184	0.000

Table 3

Empirical results of the ARIMA (2,0,1) model.

Return BTC	All	Low	Medium	High	COVID-19	No COVID-19
d1.Uncertainty	−0.0133	−0.0652*	0.0638	−0.0133	−0.0199	−0.00271
	(0.00995)	(0.0271)	(0.0387)	(0.0112)	(0.0154)	(0.0154)
Return S&P 500 t-1	0.585***	−0.0523	0.234	0.698***	0.774***	0.32
	(0.166)	(0.231)	(0.596)	(0.1)	(0.104)	(0.39)
_cons	2.138**	2.046	1.571	1.580**	2.950*	2.026*
	(0.733)	(1.204)	(1.127)	(0.542)	(1.202)	(0.894)
ARMA						
AR (1)	−0.751***	−0.0317	−0.764***	0.738*	−0.572***	−0.760***
	(0.0813)	(0.408)	(0.174)	(0.34)	(0.154)	(0.086)
AR (2)	0.179*	−0.351	0.123	−0.478***	0.278	0.185*
	(0.0783)	(0.362)	(0.141)	(0.136)	(0.176)	(0.087)
MA (1)	0.882***	1.000***	0.758***	−1.777	0.783***	0.898***
	(0.0541)	(0.000)	(0.093)	(1.152)	(0.11)	(0.0525)
Sigma						
Cons	9.721***	8.172***	10.29***	4.023	6.042***	10.39***
	(0.93)	(0.786)	(0.924)	(2.805)	(0.612)	(1.067)
N	260	87	86	87	52	208

Standard error is in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4

Empirical results of the conditional variance of Bitcoin on its previous information and the S&P 500.

h^{BTC}_t	All	Low	Medium	High	COVID-19	No COVID-19
$(e^{BTC}_{t-1})^2$	0.252***	0.252***	0.252***	0.251***	0.253***	0.252***
	(0.000363)	(0.000202)	(0.000977)	(0.00204)	(0.000812)	(0.000347)
h^{BTC}_{t-1}	0.659***	0.670***	0.655***	0.672***	0.655***	0.659***
	(0.00799)	(0.0033)	(0.00941)	(0.00461)	(0.00489)	(0.00818)
h^{SP}_{t-1}	−0.00894	0.0194	0.0474	0.00144	−0.000619	0.0211
	(0.00834)	(0.0342)	(0.0865)	(0.00294)	(0.00192)	(0.0425)
$(e^{SP}_{t-1})^2$	0.0026	0.00684	0.0371	0.00137*	0.00148***	0.027
	(0.00307)	(0.0121)	(0.024)	(0.000571)	(0.000337)	(0.0192)
_cons	11.59***	10.68***	11.75***	10 44***	11.38***	11.53***
	(0.738)	(0.159)	(1.003)	(0.348)	(0.251)	(0.747)
N	259	87	85	87	52	207

Standard error is in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Authors statement

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Declaration of Competing Interest

The author declared no potential conflicts of interest concerning the research, authorship, or publication of this article.

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