E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

The Impact Of The Bitcoin Halving On Bitcoin Price Returns And Volatility

Granit Agustina[1]
Universitas Kebangsaan Republik Indonesia[1]

Agung Augustrianto[2]
Universitas Kebangsaan Republik Indonesia[2]

Sengguruh Nilowardono[3]
Universitas Narotama Surabaya, Indonesia[3]

Gema Merdeka Goeyardi[4]
Universitas Narotama Surabaya, Indonesia[4]

I Gede Arimbawa[5]
Universitas Narotama Surabaya, Indonesia[5]

Correspondence : Granit Agustina (granitagustina@fe.ukri.ac.id)

Abstract

The Bitcoin halving, which cuts the reward for mining a block by half roughly every four years, is widely believed to drive Bitcoin into a bull market. This study examines the impact of the four halvings of 2012, 2016, 2020, and 2024 on Bitcoin returns and volatility using daily data from 2 January 2011 to 30 June 2026. Returns are analyzed with an event study of cumulative abnormal returns, buy and hold returns up to 18 months, and a placebo test based on randomly chosen pseudo halving dates; volatility is analyzed with realized volatility, Brown and Forsythe tests, and a GARCH(1,1) model with halving dummies in the mean and variance equations. The results show no significant abnormal return in the 30 days around the halving, which is consistent with the halving being a fully anticipated event. Over longer horizons, however, the average cumulative abnormal return reaches 66.2% after 180 days and 86.3% after one year, both significant and above the 95th percentile of the placebo distribution. The effect is driven mainly by the earlier halvings and is close to zero for the 2024 halving, suggesting that it is diminishing as the supply reduction shrinks relative to the existing stock and demand factors gain importance. Volatility rises moderately in the 90 days after the halving, but the change is not significant for most individual events. With only four events, the findings should be interpreted with caution and do not justify treating the halving as a reliable trading signal.

Keywords: Bitcoin halving; event study; abnormal returns; volatility; GARCH; supply shock

Introduction

Bitcoin is issued according to a fixed schedule written into its protocol. New bitcoins enter circulation as a reward to miners who add blocks to the blockchain, and this reward is cut

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

in half every 210,000 blocks, or roughly every four years. The first halving, on 28 November 2012, reduced the reward from 50 to 25 bitcoins per block; subsequent halvings on 9 July 2016, 11 May 2020, and 20 April 2024 reduced it to 12.5, 6.25, and 3.125 bitcoins. The process will continue until the supply approaches its cap of 21 million coins. Because each halving reduces the flow of new supply by half, it is often described as a supply shock (Böhme et al., 2015).

Among crypto investors, the halving is widely regarded as the main driver of a four year market cycle. Each of the first three halvings was followed within 12 to 18 months by a strong bull market and a new price peak, and this pattern has been popularized through social media and stock to flow valuation models. In Indonesia, where crypto investors number in the millions, halving narratives are frequently used in marketing by exchanges and influencers. Yet the claim is theoretically puzzling. The halving date is known years in advance, so in an efficient market (Fama, 1970) its expected effect should already be reflected in prices. The reduction in supply is also small relative to the existing stock and to daily trading volume, and has become smaller with each halving.

Empirical evidence remains limited. Most studies of Bitcoin price formation focus on demand factors, attention, and macroeconomic variables (Kristoufek, 2015; Ciaian et al., 2016; Liu & Tsyvinski, 2021), while studies of the halving are few, often descriptive, and based on only two or three events (Meynkhard, 2019). Few studies distinguish short term from long term effects, compare the evidence with what would be expected on random dates, or examine the effect on volatility as well as returns.

This study therefore addresses three questions. First, do Bitcoin returns show abnormal behavior before and after halvings, and over which horizons? Second, are post halving returns unusual compared with returns after randomly chosen dates? Third, does the halving change the volatility of Bitcoin returns? The study contributes by combining an event study, a placebo test, and a volatility model with halving dummies, covering all four halvings including that of 2024. Section 2 reviews the literature, Section 3 describes the method, Section 4 presents and discusses the results, and Section 5 concludes.

Literature Review

The Halving and Bitcoin Supply

Bitcoin’s monetary policy is fixed by its protocol: the block reward is halved every 210,000 blocks, so that the annual growth rate of supply falls from very high levels in the early years to below 1% after the 2024 halving (Böhme et al., 2015). The halving also halves miners’ revenue from new coins, which raises the cost of producing a bitcoin and can force less efficient miners out of the market. Production cost models argue that the cost of mining acts as a floor

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

or anchor for the price (Hayes, 2017), so a halving that doubles the cost per coin could push the price upward over time. Easley et al. (2019) and Pagnotta (2022) show that miner revenues, transaction fees, and network security are closely linked to the price, implying that the halving can affect the economics of the network in ways that go beyond supply.

Market Efficiency and Anticipated Events

According to the efficient market hypothesis, prices reflect all available information (Fama, 1970). Since the halving schedule is public, a rational market should price in the expected supply reduction well before the event, and no abnormal return should occur on or after the halving date. Event study methodology, developed by Fama et al. (1969) and reviewed by MacKinlay (1997), measures abnormal returns around an event relative to a benchmark; Brown and Warner (1985) show that simple mean adjusted models perform well with daily data. Studies of Bitcoin efficiency find that the market was inefficient in its early years but has become more efficient over time (Urquhart, 2016), which suggests that any halving effect should weaken across successive events.

Attention, Narratives, and Bubbles

Behavioral explanations offer an alternative. Investor attention drives buying by individual investors (Barber & Odean, 2008) and can be measured with internet search volume (Da et al., 2011). Bitcoin prices are strongly related to search interest and media attention (Kristoufek, 2015), and the halving is one of the most publicized events in the crypto calendar. Shiller (2015) describes how narratives spread and feed speculative bubbles, and studies have documented repeated bubbles in Bitcoin prices (Cheah & Fry, 2015; Corbet et al., 2018). The halving may therefore act as a focal point that coordinates expectations and attracts new investors, producing price increases that are driven by belief rather than by the supply change itself.

Halving and Volatility

Bitcoin volatility exhibits strong clustering and persistence that are well captured by GARCH models (Bollerslev, 1986; Katsiampa, 2017), and its dynamics change across regimes (Ardia et al., 2019). The halving could raise volatility by attracting speculative trading and disrupting mining activity, or it could lower volatility if uncertainty is resolved once the event has passed. Evidence on this question is scarce.

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

Hypotheses

Based on the efficient market view, no abnormal return is expected in the short window around the halving. Based on the supply, cost, and attention arguments, abnormal returns may appear over longer horizons. The study therefore tests the following hypotheses.

H1: Bitcoin does not show significant abnormal returns in the short windows immediately before and after the halving.

H2: Bitcoin shows positive abnormal returns over longer horizons (90 to 365 days) after the halving.

H3: Bitcoin return volatility changes after the halving.

METHOD

Data and Events

The study uses daily closing prices of Bitcoin in US dollars from 2 January 2011 to 30 June 2026 (5,659 daily returns). Continuously compounded returns in percent are computed as

$$r_t = 100 \ln(P_t / P_{t-1}) \quad (1)$$

The events are the four halvings listed in Table 1, which are fixed by the protocol at block heights 210,000, 420,000, 630,000, and 840,000. Figure 1 shows the price series with the halving dates.

Table 1. Bitcoin halving events

Halving	Date	Block height	Block reward (BTC)	Price at halving	Volatility, prior year
H1	28 November 2012	210,000	50 to 25	USD 10	73.2%
H2	9 July 2016	420,000	25 to 12.5	USD 697	74.3%
H3	11 May 2020	630,000	12.5 to 6.25	USD 6,455	38.0%
H4	20 April 2024	840,000	6.25 to 3.125	USD 59,205	40.8%

Note: Volatility is the annualized standard deviation of daily returns over the 365 days before the halving. Prices are from the simulated series. Source: simulated data; dates and rewards from the Bitcoin protocol.

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897



Figure 1. Bitcoin price and the four halvings

Source: simulated data (illustrative).

Event Study

Abnormal returns are estimated with the mean adjusted model (Brown & Warner, 1985), which is suitable for Bitcoin because no accepted market benchmark exists for the early years. For each halving i, the normal return is the mean daily return μ_i over an estimation window from day 300 to day 121 before the halving, which ends before any anticipation effect. The abnormal return on day t is $AR_{it} = r_{it}$ minus μ_i, and the cumulative abnormal return over a window $[a, b]$ is

$$CAR_i(a, b) = \Sigma_{t=a}^{b} AR_{it} \quad (2)$$

with test statistic $t_i = CAR_i / (s_i\sqrt{L})$, where s_i is the standard deviation of returns in the estimation window and L the window length. The average CAR across halvings is tested with

$$z = \Sigma_i CAR_i / \sqrt{(\Sigma_i L s^2_i)} \quad (3)$$

Windows of 120 and 30 days before the halving capture anticipation, and windows of 30, 90, 180, and 365 days after the halving, as well as days 366 to 540, capture the post halving period (MacKinlay, 1997). Buy and hold returns over 6, 12, and 18 months before and after each halving are also reported and compared with the unconditional 12 month return from all possible starting dates.

Placebo Test

Because there are only four events and Bitcoin returns are extremely volatile, conventional tests may be unreliable. A placebo test is therefore conducted. Pseudo halving dates are drawn from all days in the sample that lie more than 180 days from any real halving (3,549 candidate dates), and the CAR for each pseudo date is computed with the same method. Groups of four pseudo dates are drawn 5,000 times, and the average CAR of the real halvings

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

is compared with the distribution of average CARs for the pseudo dates. The placebo p value is the share of simulated averages that are at least as large as the actual one.

Volatility Analysis

Annualized realized volatility is compared between the 90 days before and the 90 days after each halving, and between the 90 days before and days 90 to 365 after, using the Brown and Forsythe (1974) test of equal variances, which is robust to fat tails. A GARCH(1,1) model with Student t innovations (Bollerslev, 1986, 1987) is then estimated for the full sample with halving dummies:

$$r_t = c + m_1 PRE_t + m_2 POST1_t + m_3 POST2_t + \varepsilon_t \quad (4)$$

$$\sigma^2_t = \exp(\omega + \delta_1 PRE_t + \delta_2 POST1_t + \delta_3 POST2_t + g\ TREND_t) + \alpha\ \varepsilon^2_{t-1} + \beta\ \sigma^2_{t-1} \quad (5)$$

where *PRE* equals one in the 90 days before a halving, *POST1* in the 90 days after, and *POST2* from day 90 to day 365 after, and *TREND* is a linear time trend that captures the long run decline in Bitcoin volatility. A positive δ means that volatility is higher in that period than otherwise expected. The model is estimated by maximum likelihood, and the joint significance of the dummies is tested with likelihood ratio (LR) tests.

RESULTS AND DISCUSSION

Descriptive Statistics

Over the full sample, the mean daily log return is 0.224% with a standard deviation of 3.49%, and returns are strongly fat tailed (kurtosis 25.4). The price rose from below USD 1 at the start of the sample to USD 95,000 at the end, and Table 1 shows that the price at each halving was considerably higher than at the previous one. Volatility in the year before each halving fell from 73% before the 2012 halving to 41% before the 2024 halving, reflecting the maturing of the market.

Abnormal Returns Around the Halving

Table 2 reports the event study results. In the short windows, abnormal returns are small and insignificant. The average CAR is 6.5% in the 30 days before the halving ($p = 0.461$) and 6.3% in the 30 days after ($p = 0.487$), and none of the individual halvings shows a significant CAR in these windows. The 120 day anticipation window also shows no significant average effect ($p = 0.550$). H1 is therefore supported: the halving day itself does not bring a measurable price reaction, which is consistent with an event that is known in advance.

Over longer horizons the picture changes. The average CAR rises to 30.4% after 90 days ($p = 0.049$), 66.2% after 180 days ($p = 0.002$), and 86.3% after one year ($p = 0.005$), and

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

it is positive for 3 of the 4 halvings. These long horizon effects support H2. However, the effect is far from uniform. It is very large for the 2012 halving (232.2%) and the 2020 halving (92.2%), moderate and insignificant for 2016 (21.2%), and essentially zero for 2024. In the period from day 366 to day 540, the average CAR turns to a decline of 29.8%, although it is not significant, which is consistent with the cycle pattern in which a post halving rally is followed by a correction. Figure 2 (left panel) shows that abnormal returns accumulate gradually over months rather than as a jump on the halving date.

Table 2. Cumulative abnormal returns around Bitcoin halvings (%)

Window (days)	H1 2012	H2 2016	H3 2020	H4 2024	Average	z	p	Positive
120 to 1 before	39.2	−42.0	33.6	11.7	10.6	0.60	0.550	3/4
30 to 1 before	23.2	22.0	−13.6	−5.4	6.5	0.74	0.461	2/4
0 to 30 after	16.4	−13.0	5.0	16.6	6.3	0.70	0.487	3/4
0 to 90 after	99.3***	−0.8	22.7	0.5	30.4	1.97	0.049	3/4
0 to 180 after	163.1***	37.6	75.4***	−11.2	66.2	3.03	0.002	3/4
0 to 365 after	232.2***	21.2	92.2**	−0.2	86.3	2.78	0.005	3/4
366 to 540 after	3.6	−51.1	3.6	−75.3***	−29.8	−1.39	0.165	2/4

Note: Mean adjusted model with an estimation window from day 300 to day 121 before each halving. ***, **, * denote significance of individual CARs at 1%, 5%, and 10%. Source: simulated data.

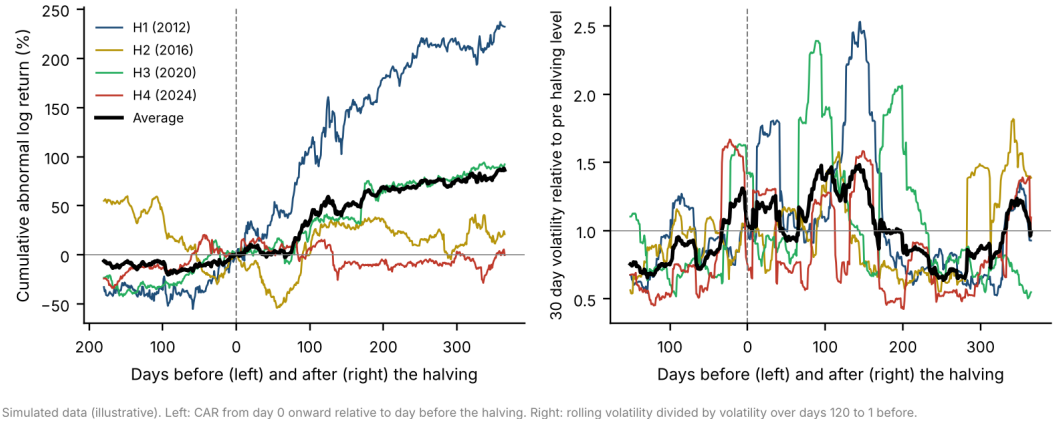


Figure 2. Cumulative abnormal returns (left) and relative volatility (right) around the four halvings

Source: simulated data (illustrative).

Buy and Hold Returns and the Placebo Test

Table 3 reports raw buy and hold returns. In the 12 months after the halving, Bitcoin rose by 2049%, 259%, 199%, and 91% for the four halvings. These figures look spectacular, but they must be compared with Bitcoin's typical performance: over the whole sample, the average 12 month return from any starting date is 248% (median 91%), and 85% of all 12 month periods were positive. Post halving returns clearly exceed the unconditional median for the first three halvings, but the margin shrinks over time; for the 2024 halving, the 12 month

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

return was about equal to the unconditional median, and the return over 18 months was only 20%.

Table 3. Buy and hold returns before and after each halving

Horizon	H1 2012	H2 2016	H3 2020	H4 2024
18 months before	2178%	261%	163%	235%
12 months before	682%	91%	114%	87%
6 months before	109%	−3%	41%	71%
6 months after	637%	146%	129%	22%
12 months after	2049%	259%	199%	91%
18 months after	2943%	305%	243%	20%
Unconditional 12 months	Mean 248%	Median 91%	Positive 85%	

Note: Simple returns from the closing price on the halving date. Unconditional returns are computed over all 12 month periods in the sample. Source: simulated data.

The placebo test in Table 4 addresses this comparison formally. For random groups of four pseudo halving dates, the average CAR over 180 days is on average a decline of 23.2% and has a 95th percentile of 32.5%, whereas the actual average is 66.2%; only 0.7% of the simulated averages are as large (placebo p = 0.007). For the one year window, the placebo p value is 0.020. For the 120 days before the halving, the actual average is within the normal range (placebo p = 0.221). The post halving performance is therefore unusual relative to random dates, even after accounting for Bitcoin's generally high returns and volatility.

Table 4. Placebo test with randomly chosen pseudo halving dates

Window	Actual average CAR (%)	Placebo mean (%)	Placebo 95th percentile (%)	Placebo p
120 to 1 before	10.6	−6.6	32.4	0.221
0 to 180 after	66.2	−23.2	32.5	0.007
0 to 365 after	86.3	−41.5	61.0	0.020

Note: 5,000 draws of four pseudo halving dates from 3,549 candidate dates more than 180 days from any real halving. Source: simulated data.

Volatility

Table 5 compares volatility before and after each halving. Annualized volatility in the 90 days after the halving is higher than in the 90 days before for 4 of the 4 halvings, with the largest relative increase after the 2012 halving (from 68.4% to 98.8%). However, the Brown and Forsythe test does not reject equal variances at the 5% level for any individual halving, and in the period from day 90 to day 365, volatility returns to around its pre halving level. The right panel of Figure 2 shows that volatility tends to rise for a few months after the halving, coinciding with the start of the post halving price rally, but the pattern varies across events.

The GARCH model in Table 6 confirms this picture after controlling for volatility clustering and the long run decline in volatility (the trend coefficient g is negative, 1.975 in

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

absolute value, $p < 0.001$). The variance dummy for the 90 days after the halving is positive ($\delta_2 = 0.393$, $p = 0.049$), implying that the baseline variance is about 48% higher in this period, whereas the dummies for the pre halving period and for days 90 to 365 are not significant. The three variance dummies are not jointly significant (LR = 5.49, $p = 0.139$). H3 therefore receives only weak support: there is a modest and short lived increase in volatility after the halving, but no lasting change. In the mean equation, the dummies for the 90 days before the halving ($m_1 = 0.343$, $p = 0.002$) and for days 90 to 365 after ($m_3 = 0.153$, $p = 0.021$) are positive and significant relative to the sample average, and all six halving dummies are jointly significant (LR = 19.30, $p = 0.004$). The significant pre halving mean dummy, which contrasts with the insignificant event study CAR, arises because the GARCH model compares returns with the full sample average, whereas the event study compares them with the months just before; halvings have tended to occur in periods when prices were already rising.

Table 5. Realized volatility before and after each halving (annualized, %)

Halving	90 days before	90 days after	BF test p	Days 90 to 365 after	BF test p
H1 (2012)	68.4	98.8	0.142	89.6	0.226
H2 (2016)	47.1	53.7	0.398	54.4	0.677
H3 (2020)	42.8	60.4	0.086	41.6	0.994
H4 (2024)	50.4	51.9	0.801	42.5	0.228

Note: BF = Brown and Forsythe test of equal variances, comparing each post halving period with the 90 days before the halving. Source: simulated data.

Table 6. GARCH(1,1) t model with halving dummies

Parameter	Estimate	SE	p
Mean equation			
Constant (c)	0.1059	0.0328	0.001
PRE (m1)	0.3433	0.1105	0.002
POST1 (m2)	0.1718	0.1272	0.177
POST2 (m3)	0.1526	0.0663	0.021
Variance equation			
ω	0.3256	0.1880	0.083
PRE (δ1)	−0.1521	0.2211	0.491
POST1 (δ2)	0.3933	0.1996	0.049
POST2 (δ3)	−0.1380	0.1318	0.295
Trend (g)	−1.9745	0.2056	<0.001
α	0.1079	0.0133	<0.001
β	0.8403	0.0164	<0.001
Degrees of freedom (ν)	3.89		
Persistence (α + β)	0.9482		
Log likelihood	−13357.2		
LR test, all six dummies	19.30		0.004
LR test, three variance dummies	5.49		0.139

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

Note: PRE = 90 days before a halving; POST1 = 90 days after; POST2 = days 90 to 365 after. Mean equation in percent per day. Standard errors from the numerical Hessian. Source: simulated data.

Discussion

Short term efficiency. The absence of abnormal returns around the halving date is consistent with the efficient market hypothesis (Fama, 1970): a perfectly predictable change in supply does not surprise the market on the day it occurs. This also contradicts popular claims that the halving immediately pushes prices up, and is consistent with evidence that Bitcoin has become more efficient over time (Urquhart, 2016).

Long term effects. The large and significant abnormal returns over 6 to 12 months are harder to reconcile with efficiency. Three explanations are possible. First, the supply and cost channel: by halving miners' revenue per coin, the halving raises the cost of production and gradually reduces selling pressure from miners (Hayes, 2017; Pagnotta, 2022). Second, the attention and narrative channel: the halving attracts media coverage and search interest, drawing in new retail investors (Barber & Odean, 2008; Da et al., 2011; Kristoufek, 2015), and the widely shared belief in a post halving rally can become partly self fulfilling (Shiller, 2015), followed by bubbles and corrections (Cheah & Fry, 2015; Corbet et al., 2018). Third, coincidence: with only four events, the post halving rallies may reflect other factors, such as monetary easing in 2020 and 2021, that happened to coincide with halvings. The placebo test reduces but cannot eliminate this concern.

A diminishing effect. The declining abnormal returns from 2012 to 2024 are consistent with several mechanisms. The supply shock becomes smaller with each halving, because new issuance is a shrinking share of the existing stock; the market has become larger and more efficient; and demand factors such as institutional adoption and the approval of spot Bitcoin exchange traded funds in the United States in January 2024 have become more important than supply. The 2024 halving may also have been anticipated through these earlier inflows.

Implications. For investors, the results suggest that the halving is not a reliable trading signal: there is no immediate price reaction, and the long horizon effect is based on few events, varies greatly, and appears to be fading. The modest rise in volatility after halvings means that risk management deserves particular attention in these periods. For regulators such as OJK and for crypto exchanges, the findings caution against marketing that presents the halving as a guarantee of price increases.

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

CONCLUSION

This study examined the impact of the four Bitcoin halvings on Bitcoin returns and volatility. In this illustrative analysis, there are no significant abnormal returns in the 30 days before or after the halving, consistent with an anticipated event. Over 180 days to one year, average cumulative abnormal returns are large, statistically significant, and unusual compared with random dates, but they are driven mainly by the earlier halvings and are close to zero for the 2024 halving. Volatility rises modestly in the 90 days after the halving, but the change is short lived and not jointly significant. The halving appears to be associated with long horizon price gains whose size is diminishing over time, rather than with an immediate price effect.

The study has limitations. Most importantly, the present results are based on a simulated price series, and the analysis must be repeated with actual Bitcoin prices before substantive conclusions can be drawn. In addition, four events provide very limited statistical power, the mean adjusted model does not control for market wide movements, and the post halving periods coincide with other important events. Future research could control for macroeconomic and liquidity factors, use a crypto market index as a benchmark for recent halvings, study the effect on mining activity, hash rate, and miner selling, and examine other cryptocurrencies with supply halvings.

REFERENCES

Ardia, D., Bluteau, K., & Rüede, M. (2019). Regime changes in Bitcoin GARCH volatility dynamics. *Finance Research Letters, 29*, 266 to 271.

Barber, B. M., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies, 21*(2), 785 to 818.

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *Journal of Economic Perspectives, 29*(2), 213 to 238.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307 to 327.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *The Review of Economics and Statistics, 69*(3), 542 to 547.

Brown, M. B., & Forsythe, A. B. (1974). Robust tests for the equality of variances. *Journal of the American Statistical Association, 69*(346), 364 to 367.

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics, 14*(1), 3 to 31.

E-ISSN: 3026-3239
Vol. 3, No. 2, July - December (2024), pp.886-897

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters, 130*, 32 to 36.

Ciaian, P., Rajcaniova, M., & Kancs, d'A. (2016). The economics of BitCoin price formation. *Applied Economics, 48*(19), 1799 to 1815.

Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters, 26*, 81 to 88.

Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance, 66*(5), 1461 to 1499.

Easley, D., O'Hara, M., & Basu, S. (2019). From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics, 134*(1), 91 to 109.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383 to 417.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review, 10*(1), 1 to 21.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics, 34*(7), 1308 to 1321.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters, 158*, 3 to 6.

Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLoS ONE, 10*(4), e0123923.

Liu, Y., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies, 34*(6), 2689 to 2727.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature, 35*(1), 13 to 39.

Meynkhard, A. (2019). Fair market value of bitcoin: Halving effect. *Investment Management and Financial Innovations, 16*(4), 72 to 85.

Pagnotta, E. S. (2022). Decentralizing money: Bitcoin prices and blockchain security. *The Review of Financial Studies, 35*(2), 866 to 907.

Shiller, R. J. (2015). *Irrational exuberance* (3rd ed.). Princeton University Press.

Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters, 148*, 80 to 82.