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Research article

Different GARCH model analysis on returns and volatility in Bitcoin

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Abstract: The aim of this study was to examine the returns and volatility of Bitcoin. The study uses the daily closing price of Bitcoin from October 1, 2013 to July 31, 2020 as the sample data, which include 2496 observations. About the methodology, the paper describes the utilisation of GARCH models to analyse Bitcoin's returns and volatility. First, the data were tested by using the augmented Dickey-Fuller test to verify the stability and diagram tests sequence. After that, the lag order and determination results of the mean value equation show that the Lag 4 period is the best. Additionally, the paper describes an autocorrelation test of the residual series, which revealed that there is no significant autocorrelation in the residual term for the Bitcoin returns, but that the residual squared has significant autocorrelation. In addition, a linear graph of squared residuals was formulated and the ARCH-LM test was used to find the data that are suitable for modelling with GARCH models since the data have a strong ARCH effect. As result, a GARCH (1,1) model was used; the findings indicated that the returns and volatility of Bitcoin have clustering characteristics, and that the returns and volatility of Bitcoin constitute a persistent process although the effects gradually reduce over time. Because of the limitations of the GARCH (1,1) model and researching asymmetry of the returns and volatility of Bitcoin, TARCH and EGARCH models were adopted; the findings indicated that the returns and volatility of Bitcoin are without a "leverage effect". To further explain this special phenomenon, safe-property is quoted in this research. In the end, this paper demonstrates that Bitcoin, as a safe-haven property, can hedge financial risks in times of economic depression. Besides, Bitcoin has a revised asymmetric effect between positive and negative shocks that makes it a viable asset to add to the portfolios of investors.

Keywords: Bitcoin; returns; volatility; GARCH models; asymmetry

JEL Codes: C22, G11, G15

1. Introduction

Since the publication of Bitcoin (BTC) in October 2008, the digital and decentralised currency has attracted the attention of many researchers. BTC is one of the most famous and important cryptocurrencies, and it is based on blockchain technology with cryptology. Its transaction assumes the peer-to-peer (P2P) method. Notably, mining BTC is the most important way to get more coins, and owing to the calculations of a special algorithm, BTC does not depend on any currency institutions for issuance. Instead, it uses a decentralised transaction system and distributed ledger, which combines with many nodes in the BTC internet to record each trade information unit for every node. Besides, it uses cryptology to protect the safety of the decentralised system during BTC transactions. In addition, there are only about 21 million bitcoins that can be mined on the BTC internet. However, owing to the calculation speed now, the BTC system currently releases some BTC to miners every 10 minutes once. Nonetheless, in the future, more precisely by 2140, the number of mining bitcoins will be maximum.

To study BTC, it is important to understand blockchain technology, which is the core technology of BTC. The technology involves recording a series of trade information units, also called a block, and sending them from one account to another. Besides, every block is encrypted by cryptography, which can effectively protect the transaction information of every block during the process of transmission. As a new method of application of computer technology, blockchain technology includes aspects such as the storage of distributed data, P2P transmission, an encryption algorithm and a consensus mechanism. In addition, blockchains, an essential technology of BTC, has a lot of new advantages in different aspects. For example, a blockchain is a decentralised system, which makes it different from traditional currencies' transaction systems. In a normal system, there is a centre to control and collect all information and data from all transactions. As a result, this characteristic of blockchains can effectively improve the safety of a system since there is no centre in this system and all nodes act as the centre for the whole system. Besides, this aspect enhances the security of the system since every node takes part in recording transaction information and every node can use the distributed ledger to monitor the safety of the decentralised system and avoid tampering by hackers. Therefore, committing crimes in this decentralised system is too difficult amidst a continuous threat from hackers. Furthermore, information transferring in the blockchain is irreversible. In this system, when people trade with others via blockchain technology, the process of the transferring information to the next point cannot be changed again because of BTC's special algorithm. As a result, every trade information unit is stored forever when the information is recorded and verified to the blockchain once. Modification of the database is invalid on a single node unless more than 51% of the nodes can be controlled at the same time in the system. Thus, the stability and reliability of data within the blockchain are extremely high.

Blockchain systems also tend to be open, but also have privacy. A portion of the data of the blockchain is open to everyone, but the private information of all parties and individual transaction information are encrypted with secret keys. The open attribute of blockchain means that anyone can check and query the data in the blockchain system through the open interface. In this respect, the information of the whole system is highly transparent. More related, consensus-based specifications and protocols are adopted by blockchains, such as a set of open and transparent algorithms. This implies that data can be freely and safely exchanged between all nodes throughout the whole system in a distrustful environment, which makes the trust of people change to the trust of machines, and no artificial intervention can work. Besides, blockchains are also highly effective at preserving anonymity. The rationale is that all transactions between every node follow a fixed algorithm, and that the interaction between the data does not need to be trusted because the program rules in the blockchain will judge whether the activity is effective or not by themselves. This means that the counterparty does not need to let the other party generate trust by revealing its identity, which is very helpful for the accumulation of credit. Hence, the reason why a lot of people focus on BTC is due to such advantages.

BTC's functions and characteristics make it different from other virtual currencies of online gaming communities. Notably, it is often viewed as a new and creative digital currency with cryptology, which is remarkable in this development of the currency. Due to the specifics of BTC, many people tend to overestimate it. Consequently, the virtual currency market has seen huge growth in a great number of new currencies and the prices of cryptocurrencies, and now people invest more money in cryptocurrencies with a high frequency of transactions. When more people started to focus on cryptocurrencies, their prices rapidly increased over the past several years. During this period, its price has always been up and down, which means it has high volatility. There have been a great number of people whose emotions follows its price. Gradually, BTC has become more likely to be an asset due to this trend, despite its volatility being more frequent than traditional currencies.

Although financial creativities are conducive to achieving developments in the finance industry, they bring some new problems. New turmoil in the financial markets shows enormous opportunities and challenges for governments, economists, financial institutions and entrepreneurs. For example, BTC improves financial development, but there are a great number of criminals who want to commit crimes using BTC, such as money laundering and swindling. Therefore, the governments of various countries should impose laws and policies with actions to protect investors' properties and the stability of the financial market. Generally, BTC not only brings new creativities, but it also brings new turmoil. To avoid risks, governments should strengthen the supervision and institutions of Initial Coin Offerings (ICO), and cryptocurrencies should be more transparent.

There is vast academic literature on the returns and volatility of BTC, but asymmetric research is still insufficient. Precisely, there is scarce research on the use of different generalised autoregressive conditional heteroskedasticity (GARCH) models to further analyse BTC's returns and volatility. In this respect, different GARCH models were used in this study to analyse sample times that are longer than other studies; the characteristics of BTC were found and the safe-haven property and revised asymmetry were quoted. The aim was to explain why the returns and volatility of BTC do not have a "leverage effect", which is rare in this area of study. It is also expected that the findings of this study will be of great help to investors who want to make strategic investment decisions on how to hedge financial risks.

2. Literature review

2.1. Bitcoin with blockchain

Originally, BTC and blockchain were first published by Satoshi Nakamoto in the Bitcoin White Book in October of 2008. Generally, a decentralised system and cryptography are essential technologies of cryptocurrencies, as they help digital assets to facilitate security, improve the efficiency of transactions and create additional asset. Macroscopically, blockchain technology is a cutting-edge technology that combines cryptology and computer technology via distributed computing and P2P transferring to yield a distributed system. In the BTC system, every block is a storage space to store the trading information and data between nodes that are interconnected by chains to achieve point-to-point communication and share information and data (Nakamoto, 2008). The framework of BTC was largely designed by locking its protocol. With blockchain being the essential technology of BTC, there is no clear alternative to keeping installed BTC software and maintaining compatibility with intermediary systems. Furthermore, instant transaction validation seems to require an equally fundamental change. In this respect, it will be hard for BTC to adjust (Bohme et al., 2015). With cryptocurrency continuing to become increasingly famous every day, different types of cryptocurrencies, such as Ethereum, Litecoin and Tron, have emerged over time. Nowadays, several innovative digital currencies are waiting in the wings. For example, Litecoin can confirm and read information four times in the same amount of time, making it faster than BTC. This improved functionality potentially facilitates retail payments and other time-sensitive transactions. The electronic and computational burden of mining BTC is reduced in NXT cryptocurrency by replacing work-proof mining with equity proof and allocating the responsibilities of the blockchain according to the proportion of bitcoins held. Besides, Zerocash can improve the protection of privacy by hiding identifiers in the public transaction history, and Peercoin allows the supply of money to slightly grow by 1% a year (Ben-Sasson et al., 2014). Although there are a lot of different cryptocurrencies, they are all founded on the concept of decentralisation and a distributed ledger. Blockchains and distributed ledgers improve the safety of systems since every block connects with each other, which means that there is no centre, or that all points are centred in the system. If hackers want to change any data, they must change over 50% of the points in this system. This means that the cost of tampering with data is higher than that for a traditional currency system with a data centre. Apart from this, Satoshi Nakamoto found that his team set up an electronic trading system that does not rely on trust. The system relies on digital signatures and cryptology, which provide strong supervision over ownership, although this is still not a way to prevent repeat consumption. The pioneers of BTC proposed a point-to-point network that uses the idea of a working proof to record the history of common trading information to solve this problem. If honest nodes cannot control most of the CPU power, an attacker can quickly change the unrealistic history of computing for these transactions. The unstructured simplicity of the network is robust because nodes in this system simultaneously work with little coordination. Besides, the nodes do not need to be verified and identified by the centre because the message is not routed to any particular location, as it is just delivered as best as possible. Nodes can leave and join the network again, accepting the working-proof chain as proof of what happened when they left. Furthermore, nodes vote with their CPU power, extend valid blocks to indicate that they accept valid blocks and reject invalid blocks by refusing to process invalid blocks. Through this consensus mechanism, any necessary rules and incentives can be implemented (Nakamoto, 2008).

2.2. Valuation of Bitcoin

Due to the maximum availability of only 21 million bitcoins and the premium of blockchain technology, the BTC price has increased more than 700 times over the last five years. Currently, there are at least 35 BTC exchange markets where BTC prices are quoted in standard currencies. These exchange markets trade with a daily transaction volume of over 1 million dollars. With more people focusing on cryptocurrencies, some cryptocurrencies have grown faster recently, with examples being

BTC, Ethereum, Litecoin and Ripple. However, there are a lot of discussions about whether cryptocurrencies and BTC, in particular, should be classified as currencies, assets or investment vehicles or not. As Chu et al. (2017) found, that their analysis assumes that we are looking at cryptocurrency transactions in the form of financial assets that most users use for investment purposes, either as long-term investments in new technologies or as short-term profits. Studying the fluctuations of cryptocurrencies is an important hedging or pricing tool in financial investment. As such, these results will be particularly useful in terms of portfolio and risk management, and can help others make better-informed decisions about financial investments and the potential benefits and pitfalls of using cryptocurrencies (Chu et al., 2017). In addition, to provide their design decisions with competitiveness, alternative digital currencies need to firstly gain confidence in their adoption and valuation. Services of BTC are beneficial for BTC to receive early enthusiasm of positive media coverage and buyers and sellers on the Silk Road. This combination of advantages will be hard to achieve with alternatives to virtual currencies, but few of them are willing to convert traditional currencies into a competition without good expectations of growth. Whether or not BTC evolves as its supporters imagine, it will provide researchers with an excellent experiment, a laboratory and an attractive means of trading for some traders and consumers (Bohme et al., 2015). BTC is intended as a currency to exchange, but it can also be used as an asset to invest in. Baur et al. (2015) found that the returns attributes of BTC are unlike those of traditional assets, as they afford significant diversification of investments. Through an analysis of the BTC public ledger, researchers found that a third of all bitcoins are held by investors (Baur et al., 2015). For instance, some investors receive bitcoins and they never send them to others. A small number of users, both numerically and in BTC balances, seem to be using BTC as a medium of exchange. This phenomenon shows that BTC is mainly being held as an asset for investment purposes, but not as a currency for trading. Whether BTC volatility leads to investment rather than currency, and thus to a medium of exchange, is a question for future research. Since the scale of BTC investments and transactions is relatively small as compared to other assets, there are no direct risks or even threats to the stability of finance or currency. However, it is important to stress that this conclusion is based on its size. A significant increase in the global acceptance of using BTC or similar virtual currencies to trade could influence the behaviours of consumers and producers, thus changing relative monetary policies. Furthermore, owing to the global dispersion of BTC and its independence from any central bank or supranational institution, regulation will be difficult and challengeable (Baur et al., 2015). An article by Koutmos (2018) examines the link between the returns and transaction activities of BTC. The literature so far has concluded that the price of BTC is unexplainable based on economic factors. The article highlights the importance of using microstructural variables to explain the returns of BTC. The binary value-at-risk model was used here to show a high correlation between the returns of BTC and its activities of trading, although returns can somewhat explain the changes in trading activities, rather than the other way around. To understand BTC, more empirical work is needed. As people can see here, researchers engaged in this sort of work might pay more attention to the microstructure and new variables of BTC instead of the usual economic variables that explain the returns on traditional assets (Dimitrios, 2018). From a market linkages perspective, Klein et al. (2018) used different models to portray that BTC is different from gold, especially in times of downturns. When financial markets fall under similar shocks, BTC drops and shows a positive coupling effect, unlike with gold. In a portfolio application, this point suggests that BTC is not a hedged equity investment. However, the scale of their sample was limited and they were only looking at a small fraction of these recessions. Given the relative youth of the market, this result should be tested again when the cryptocurrency markets are mature. Now, BTC as an asset is unlike any traditional asset from an econometric point of view.

In the early days, most scholars conducted studies about BTC technologies and development, but currently, people are doing more research on finance. On one hand, Popper (2015) considered BTC as a digital gold for cryptocurrencies. Similar views were shared by Bouri et al. (2017), who emphasised that BTC is a valuable investment in a financial crisis, and that it can be a necessary asset in a portfolio investment. On the other hand, Yermack (2013) argued that BTC facilitates economic transactions to finish in the capitalisation of markets, making it more of a speculative investment than traditional currencies. The author concluded that the volatility of BTC has adverse influences on the stability of BTC as a currency. After these studies, there was some comprehensive literature, which is as follows. Kristoufek (2014) argued that BTC, a special and new asset, shows two characteristics: asset and currency. Besides, research by Anne HD (2016) showed that BTC combines some advantages of traditional currencies, such as gold and the RMB and USD, in financial markets. Therefore, it can be a useful tool for market sentiment analysis, risk analysis and portfolio management. Both Kristoufek (2014) and Anne HD (2016) thought that BTC not only has features of a currency, but also has features of an asset. Furthermore, some researchers started to study the returns and volatility of BTC with BTC price fluctuation. Over the past five years, the price of BTC has changed rapidly. The highest price was 19783 USD in November of 2017, but the lowest price was 3122 USD after a crazy increase in December of 2018 (https://www.coindesk.com/price/bitcoin). Obviously, the volatility and returns of BTC has exhibited a huge change over time, which means that the returns-volatility of BTC has fluctuated over time.

Figure 1. Daily price of BTC (USD).

2.3. Returns and volatility of Bitcoin

Regarding the returns and volatility of BTC, Balcilar et al. (2017) concluded that BTC's volume can be used to predict returns, but it is too hard to use it to forecast BTC volatility. In addition, research by Ciaian et al. (2016) paid attention to the determinants of the volatility of BTC prices. The paper shows that several supply-side variables have a smaller impact on the price of BTC than a unique number of BTC daily transactions as a demand-side variable. However, cryptocurrencies are still a relatively unexplored area of research, and there are few studies that investigate the volatility of BTC price. As cryptocurrencies seem to gain legitimacy and profits, it is important to understand the driving forces behind market movements, especially with the creation of derivative markets. Conrad et al. (2018) tried to tease out drivers of the long-term volatility of BTC. They found that the volatility of the S&P 500 has a very significant negative impact on the long-term volatility of BTC, and that the volatility risk premium of the S&P 500 has a significant positive impact on the long-term volatility of BTC. In addition, they found a strong positive correlation between the Baltic Dry Freight index and the long-term volatility of BTC; they reported a significant negative correlation between BTC trading volumes. It is worth noting that the set of data they considered—such as those related to crime—does not seem to explain BTC's volatility, despite extensive media coverage of the topic. They also tested the escape security index proposed by Engle et al. (2012) and found that the long-term fluctuation of BTC tended to decrease during the escape security period. This result is consistent with the author's finding of a negative correlation between BTC volatility and USA stock market risk (Conrad et al., 2018). Besides, Aalborg et al. (2019) found that the quantity of BTC that uses a unique address in the BTC network has a positive relationship with the daily returns of BTC. The author demonstrated that forecasting BTC's returns and volatility may be determined by a series of BTC available. However, sometimes some returns cannot be explained. For instance, BTC's price, like the other prices of assets, cannot be predicted. More importantly, the trading volume of BTC improving is positive for forecasting its volatility. Except in finance, BTC is used to trade energy. For example, the paper by Efthymia and Konstantinos (2018) indicated that there is significant return spillover from energy and technology stocks to BTC. Short-term volatility spillover from technology companies to BTC and the volatility of BTC impact energy companies for a long time via asymmetric impact spillover between BTC and stocks. Finally, Efthymia and Konstantinos (2018) demonstrated the implications and benefits of portfolio management from the perspective of the low dependence of BTC on the stock index. From a geopolitical view, Ahemet et al. (2019) indicated that BTC is a viable tool to hedge geopolitical risks, for example, in conflicts between different countries. Precisely, Ahemet et al. (2019) found that, if they implement a Bayesian Graphical Structural Vector Autoregressive (BGSVAR) estimation procedure, there is predictive power for the price volatility and the returns of BTC, which change in the global GPR index. Klein et al. (2018) illustrated that cryptocurrencies will remain highly volatile with the coming recession, and stated that it is still very unclear whether they will continue to exhibit huge developments in both directions. Important price changes in passwords depend on several factors. First, investors will continue to make profits at peaks of BTC price movements as other cryptocurrencies continue to sharply drop. Second, investor behaviours will be strongly impacted by regulatory decisions. Regulators still put pressure on the legal framework for cryptocurrencies. Third, the cryptocurrency ecosystem has to enhance its standards of propriety to be accepted by traditional investors because of repeated network attacks, such as MtGox and Instawallet.

2.4. Applications of different GARCH models to the returns and volatility of Bitcoin

After predicting the returns and volatility of BTC, researchers started to use different models to find the returns and volatility of BTC. The volatility of the price was investigated in financial markets early, but the reports on the volatility of the price of BTC are not sufficient. Because BTC prices rapidly change, now more researchers are gradually focusing on this area. Therefore, the excessive volatility of BTC and how to correctly judge it have not been studied enough, leaving a wide research gap. However, BTC price volatility remains a major concern among investors, as numerous studies have shown. For instance, Jamal and Refk (2015) conducted a study that was aimed at providing a discussion of BTC's price fluctuations by using several extensions of the optimal GARCH model. In this case, the results of their study suggested extreme volatility in the price of BTC. Precisely, their findings indicated that conditional variances followed a long memory process between December of 2010 and June of 2015. In this respect, Jamal and Refk (2015) noted that there was a less volatile period of persistence and clustering between January and June of 2015, but that this appeared to be temporary. It is worth noting that, from the two substages under consideration, the BTC volatility process seems to be significantly more affected by negative news than by positive shocks. Not surprisingly, the BTC market is highly motivated by self-fulfilling expectations. It is caused by the behaviour of non-professional noise traders, which may lead to the serious bubble behaviour of BTC and increase the volatility of the price. While BTC users were known primarily as technocrats, liberals and criminals (Yermack, 2013), today users are predominantly individual noise traders and speculators. This has always highlighted how far the BTC market is from maturing. The lack of regulation and transparency adds to the uncertainty surrounding the cryptography market. Therefore, it is hard to predict the future of the currency. However, despite uncertainties and price volatility, it is apparent that the technology behind cryptocurrency is at a point of no technical return. Its philosophy is also not to be outdone by seeing cryptocurrencies in general and related electronic technology transactions. As technology becomes more integrated into our daily lives, it is clear that cryptocurrencies such as BTC will continue to grow, and that BTC may be replaced by better currencies (Jamal and Refk, 2015). Methodologically, the time series of BTC price is substantially more volatile than those of the EUR or USD exchange rates, as its market bubbles and crashes are relatively abundant. Substantial arbitrage opportunities are available for USD or EUR currency pairs involving RMB currency. The HARRVJ model well captures the dynamics of daily realised volatility as aggregated on a 5-minute grid (Lukáš and Taisei, 2017). The time-series model is an essential model of volatility research, but there are fewer variables in this model, so more researchers have used GARCH models to improve the integrality of the tests. Ardia et al. (2019) found that BTC daily log returns have regime changes in their volatility dynamics when treated with the Markov-switch GARCH model. Notably, the Markov-switch GARCH model shows better in-sample performance than standard single-regime GARCH models. When comparing different GARCH models, Katsiampa (2017) found that the AR-CGARCH model is optimal because of its best goodness-of-fit to data, which means that the AR-CGARCH model is the best model to research the volatility and returns of BTC. Furthermore, Beneki et al. (2019) used a bivariate diagonal BEKK-GARCH (1,1) model that allows the modelling of the variance with the covariance, as well as the application of the impulse response analysis in a Value at Risk (VAR) framework to research the volatility of BTC and Ethereum. The delayed response of BTC volatility to shocks in Ethereum's returns demonstrated the inefficiencies of the BTC market, as shocks take time to affect the full price. Notably, this provides room for a lot of profit and speculation in the most frequently traded cryptocurrency. This can help traders build profit strategies in the derivatives market. This is crucial for traders who are reluctant to include weak cryptocurrencies in their portfolios. As a result, holding BTC at a time of weak demand in the BTC and Ethereum markets may yield exceptional returns for investors, but it does not prove beneficial as a haven (Beneki et al., 2019). The argument can be affirmed by findings by Conrad et al. (2018), which indicated that the prediction of BTC volatility using the GARCH-MIDAS model is superior to the prediction based on a simple GARCH model. For example, when constructing portfolios of BTC and other assets, such as stocks and bonds, their results can be used to improve the time-varying portfolio weights. The results by Beneki et al. (2019) may also be useful for the pricing of BTC futures, as they predicted changes in BTC volatility over a longer period. Finally, simulating BTC fluctuations using the GARCH-MIDAS model can be effectively applied for global economic activity or alternative scenarios based on USA stock market developments. Beneki et al. (2019) suggested that these possibilities be explored in future research. However, they emphasised that all of their results are based on a relatively short sample period. It will be interesting to see if their results hold for longer samples, and when BTC becomes more mature. Chu et al. (2017) found that, in modelling, IGARCH and GJRGARCH models show the best fit for the volatility of the most popular and largest cryptocurrencies. The IGARCH model implements the standard GARCH framework and contains a conditional wave process, which is highly persistent (with unlimited memory), as shown in the literature (Caporale et al., 2003). However, while the conventionally innovative IGARCH (1,1) seems well suited to many users of cryptocurrency, it has been shown that this may be due to structural changes in the data, which may not be explained by variables such as policy changes (Caporale et al., 2003). Therefore, further analysis of the data set may require confirmation or rejection of possible structural changes. The future work will include fitting the multivariable GARCH model to describe the combined behaviour of the model on BTC, Dash, Dogecoin, Litecoin, Maidsafecoin, Monero and Ripple exchange rates. Such a study will require methodological and empirical development. In addition, the value at risk was used in the current study because it is the most popular measure of risk in finance. However, the transfer of the value at risk highlights the inadequacy of Basel III expectations (see Kinateder and Wagner (2014)). Therefore, another future endeavor will involve using the expected shortages rather than the VAR model (Chu et al., 2017).

3. Data

3.1. Data selection

For this study, the closing price of BTC from Coindesk, a platform famous for BTC exchange all over the world, was selected as the research data; it spanned the period of October 1, 2013 to July 31, 2020. Precisely, the study included 2496 observations, which were all drawn from the database. By using Eviews 6.0, the data could be visually presented in a graph, as shown in Figure 2. The figure illustrates that the daily closing price of BTC increased to reach USD 1139.331 by December 5, 2013. The increment was highly associated with the European sovereign debt crisis (ESDC), which happened between 2010 and 2013. During this period, the financial crisis made investors scared of investing in financial products such as stocks, bonds and futures. However, the research found that they were willing to put their money in traditional and high-growth currencies such as gold, silver and cryptocurrencies, such as BTC, Ethereum and Litecoin during economic downtrends (Bouri et al., 2017). After that, the daily closing prices of BTC slightly changed from the beginning of 2014 to the end of 2015. In addition, BTC’s closing price rapidly increased during 2016–2017. Its closing price suddenly reached a historical peak at USD 20000, which is 23 times more than one year prior to that time, although there were several fluctuations in 2017. There are some reasons why the daily closing price of BTC increased as it was observed. First, due to global financial markets crashing in September 2016, investors went to hedge negative shocks of the financial crisis, leading to investing in currencies, which included traditional currencies and digital currencies. The rationale as that traditional and digital currencies were still at low prices and their premiums were normal, or even undervalued. As a result, those currencies emerged or served as safe-haven properties at that time. Second, some countries, such as Australia, India, Pakistan and Venezuela, opened their markets to reform their currency system and relevant laws to avoid risks and hedging. Consequently, more investors and media started to pay attention to BTC. Third, according to BTC's algorithm mechanism, when bitcoins were mined to half its original quantity in 2016–2017, BTC's harsh calculation were be hard than before.

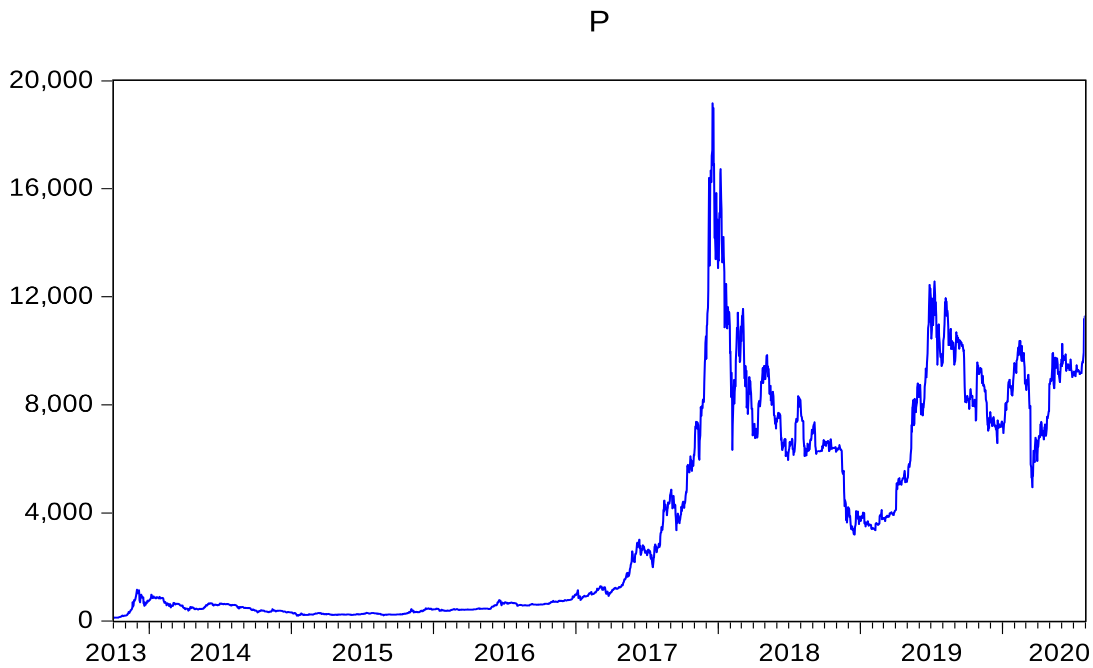


Figure 2. Daily closing price of BTC (USD).

However, as the BTC price continued to increase as investors became increasingly more terrified, a sudden drop in price occurred from USD 20000 to USD 13000. In response, there were a great number of investors who sold their BTC, but the BTC price returned to USD 17000 within 2 months. From September to December of 2017, most people guessed that BTC would overtake the historical peak again, but, unfortunately, BTC's closing price fell a cliff from USD 17000 to USD 6000 during the period of December 2017 to February 2018. After that, investors gradually started to sell a great number of bitcoins and change their investment ways. On one hand, BTC's price was overvalued and overheated at that time, so it lost real valuation and fewer investors were using it to invest, opting to instead speculate on its price increasing over time. On the other hand, global financial trends slowly recovered, so more investors were willing to put their money into undervalued assets because they could earn more money from undervalued assets than from overvalued assets. After a volatile period, the BTC closing price continued to dramatically decrease to USD 6000 with some fluctuations. Beginning in October of 2018, BTC's closing price crashed to

USD 3800 in January 2019. There are some reasons that are associated with the continued price decline. First, cryptocurrency bubbles were broken by the survival of the fittest. There were a lot of bad cryptocurrencies to be weeded out by the market. Second, Coindesk, the biggest cryptocurrency exchange platform in Japan, was attacked by hackers, which led investors to lose a lot of money, so they lost their enthusiasm in cryptocurrency markets. More importantly, some countries started to reinforce limitations and supervision regarding the trade of cryptocurrencies to avoid money laundering and other financial crimes. Besides, some countries banned the trade of cryptocurrencies, such as China and South Korea. After four months, the closing price of BTC rapidly grew to USD 11000 again. The main reason was that the quantity of available BTC halved again, which means that it became harder to mine than before, so investors focused on it again and thought it would be more valuable. After another volatile time, the closing price of BTC gradually change to a downtrend. Until July 2020, BTC's daily price kept fluctuating with a mean of USD 8000.

P_t is the closing price of BTC on Day *t*. For the estimation process, the daily rate of return is considered to be a variable that can be easily observed. In order to reduce errors during this process, a natural logarithm was applied to treat the daily rate of return; this means that the daily return of BTC is expressed as a logarithmic first-order difference between the closing prices of the next two days. The formula of BTC returns is

$$r = \log\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

All analysis of the data of the research was performed using Eviews 6.0 and Microsoft Excel.

3.2. Statistical analysis

Figures 2 and 3 show the descriptive statistics for BTC's daily return rate.

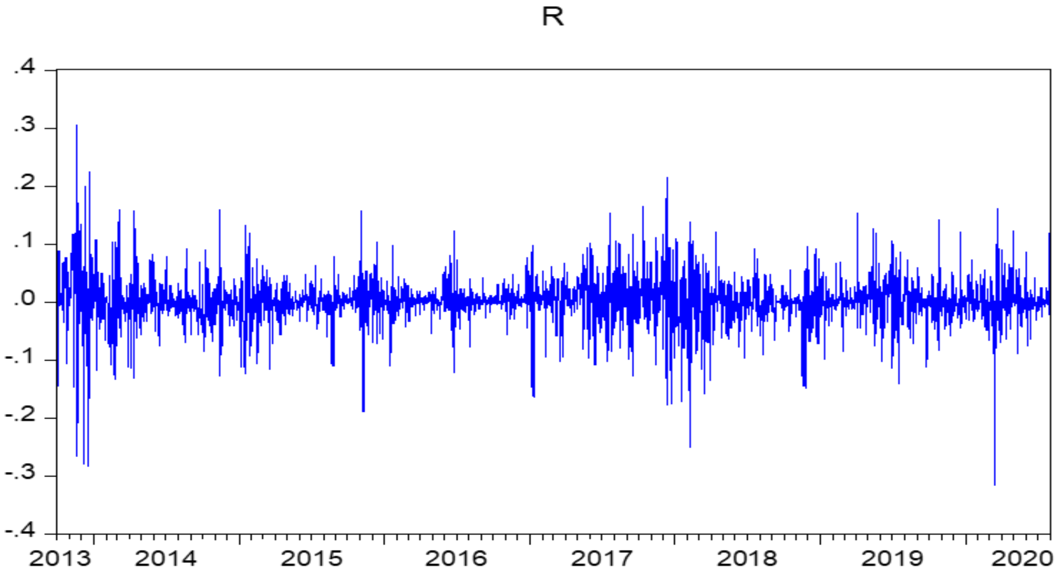


Figure 3. BTC daily rate of return (*r*) volatility graph.

Figure 3 is a volatility diagram of the daily rate of return (*r*) for BTC. The figure illustrates that fluctuation of the daily rate of return (*r*) reveals obvious time-varying, clustering and unpredictable characteristics. From the figure, it can be clearly seen that BTC's daily return in 2013 had strong volatility. This is because, in 2013, the ESDC brought a financial crisis, so people paid attention to currency that was not overvalued as a safe-haven property. Apart from this, the volatility of the daily return in 2013 was the strongest for the whole sample period. After that period, the volatility gradually reduced, and then it suddenly grew during the period of January 2014 to January 2015. However, until mid-2015, the volatility slowly decreased. Then, the volatility repeatedly fluctuated again from the beginning of 2015 to the end of 2016. Interestingly, the volatilities crowded in 2017–2018. Analysis of Figures 2 and 3 together shows that BTC's daily price changed frequently between 2017 and 2018. Because of the available BTC quantity halving (and other reasons), there was a great number of investors who focused on it and invested in it, leading to daily returns enormously changing over time. The volatility of the returns of BTC first rose in 2017, but it quickly decreased in 2018. After that, the volatility kept fluctuating in 2019. Especially, because of COVID-19 and a trade war between China and the USA in 2020, the global economy showed a downtrend tendency. Therefore, BTC is still a safe-haven asset to hedge against negative shocks.

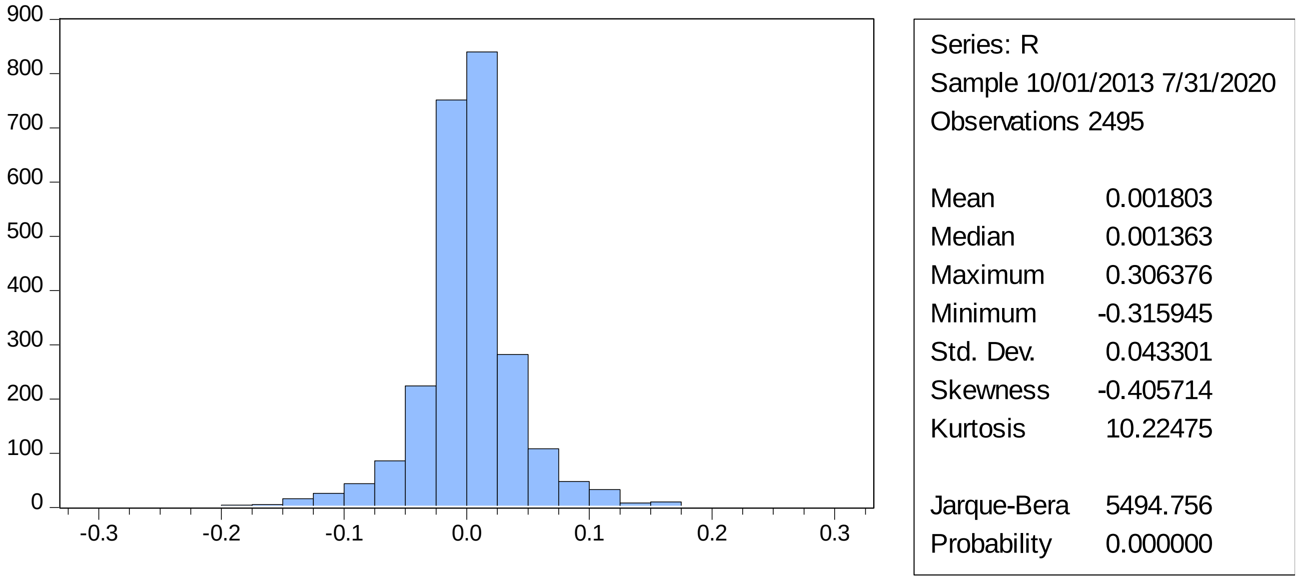


Figure 4. Histogram of BTC's return rate (*r*).

It can be seen from Figure 4 that, during the sample period, the average value of the BTC daily return (*r*) was 0.1803%, standard deviation was 4.3301% and skewness was −0.405714; and, the left skew kurtosis of 10.22475 was much higher than the normal distribution of kurtosis 3. The daily rate of return (*r*) results exhibited a sharp peak and thick tail characteristic. The sharp peak and thick tail feature were confirmed via a normality test. Besides, the Jarque-Bera (J-B) statistic was 5494.756. The rate of return (*r*) was significantly different from the normal distribution on a very small level, that is, when the sequence used the F test or all of the test methods based on the normal distribution statistical method could not test the return sequence.

3.3. Stability test of Bitcoin return rate series

The unit root method, the most common method in stationarity testing, was proposed by two American statisticians, Dickey and Fuller, in the 1970s. It judges whether the autocorrelation coefficient is equal to 1. After nearly 30 years of academic research, this method was finally summarised as the ADF test method.

From the above descriptive statistical analysis, it is apparent that the return rate series fluctuates around the mean, and that there is no trend (R mean = 0.001803). Therefore, the ADF unit root test was performed on the sequence, and four lags were selected, with an intercept term and a no-trend term. The test results are as follows.

Table 1. Stability test results for the rate of returns.

Null Hypothesis: R has a unit root			
Exogenous: Constant			
Lag Length: 4 (Fixed)			
		t-Statistic	Probability*
ADF test statistic		−20.736	0.000
Test critical values:	1% level	−3.433	
	5% level	−2.863	
	10% level	−2.567	
*MacKinnon (1996) one-sided p-values.			

From the unit root test results, it can be seen that the t value of the BTC return rate series was −20.736, which was much smaller than −3.433 at the 1% level. Thus, H_0 was rejected, indicating that the BTC return rate *r* obeys the I (0) process, that is, there is no unit root in a stationary time series.

4. Methodology

4.1. ARCH model

In econometrics, the autoregressive conditional heteroscedasticity (ARCH) model, a statistical model for time-series data, describes the variance of the current error term or innovation as a function of the actual sizes of the previous periods' error terms. Normally, the variance is related to the squares of the previous innovations. The ARCH model is appropriate when the error variance in a time series follows an autoregressive (AR) model. ARCH models are commonly employed to model financial time series that exhibit time-varying volatility and volatility clustering, such as periods of swings interspersed among periods of relative calm. ARCH-type models are sometimes considered to be in the family of stochastic volatility models, although this is technically incorrect since, at time *t*, the volatility is completely pre-determined (deterministic) given previous cues.

Using an ARCH model to model a time series, ϵ_t expresses the returns or residuals of returns and σ_t, a time-dependent standard deviation, characterises the typical scale of the terms. In addition,

z_t is a random variable with a strong white-noise process.

$$\epsilon_t = \sigma_t z_t \tag{2}$$

The series σ_t^2 is modelled by

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 \epsilon_{t-2}^2 + \cdots + \alpha_{q-1} \epsilon_{t-q-1}^2 + \alpha_q \epsilon_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 \tag{3}$$

where > 0 and $\alpha_i \geq 0$, $i > 0$.

4.2. GARCH models

4.2.1. GARCH and ARMA models

The GARCH model transforms from an AR moving average (ARMA) model when the ARMA model is assumed for the error variance.

A GARCH (p, q) model is a normal GARCH model. p is the order of the GARCH terms. α^2 and q denote the order of the ARCH terms ϵ^2.

The equation for a GARCH (p, q) model is

$$y_t = x_t' b + \epsilon_t \tag{4}$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \cdots + \alpha_q \epsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \cdots + \beta_p \sigma_{t-p}^2 = \omega + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{5}$$

4.2.2. GARCH (1,1) model

The nonlinear asymmetric GARCH (1,1) model is a model with the following specifications:

$$\sigma_t^2 = \omega + \alpha(\epsilon_{t-1} - \theta\sigma_{t-1})^2 + \beta\sigma_{t-1}^2 \tag{6}$$

$\alpha > 0$, $\beta \geq 0$, $\omega > 0$ and $\alpha(1 + \theta^2) + \beta < 1$, which ensures the non-negativity and stationarity of the variance process. This model reflects a phenomenon commonly referred to as the "leverage effect", as it signifies that negative return increases future volatility by a larger amount than positive returns of the same magnitude.

4.2.3. EGARCH model

The exponential GARCH (EGARCH) model is another form of the GARCH model. Formally, an EGARCH (p, q) model is expressed as follows:

$$log\sigma_t^2 = \omega + \sum_{k=1}^{q} \beta_k\, g(Z_{t-k}) + \sum_{l=1}^{p} \alpha_k\, log\alpha_{t-k}^2 \tag{7}$$

where $g(Z_t) = \theta Z_t + \lambda(|Z_t| - E(|Z_t|))$, the conditional variance is σ_t^2, α, θ and λ are coefficients, a standard normal variable or come from a generalised error distribution is Z_t. The equation for $g(Z_t)$

allows the sign and the magnitude of Z_t to have separate effects on the volatility. Since $\log\sigma_t^2$ may be negative, there are no sign restrictions for the parameters.

4.2.4. Asymmetry

Regarding asymmetry, there are a lot of sufficient pieces of evidence to show that negative shocks generate more effects than positive shocks in the stock market (Glosten et al., 1993; Bollerslev et al., 1986). There are two theories that have been used to illustrate these negative return and volatility relationship inequities. First, volatility feedback is one of the theories (Campbell and Hentschel, 1992). This theory shows that the expected increase in volatility increases the required return on equity, leading to a fall in equity prices. In other words, a positive shock to volatility leads first to lower equity returns, which in turn increases the time-varying risk premium. However, the negative change of expected return tends to be more severe than the positive change of expected return, which leads to the phenomenon of asymmetric volatility. The aspect can also be explained via the leverage hypothesis. The leverage hypothesis states that, when the ratio of stock to the valuation of a company decreases but the ratio of debt to the valuation of the company increases, there is a risk that the company stock will rise in the dropping valuation of a company. This negative relation leads to a spike in stock volatility (Black, 1976; Duffee, 1995).

Unlike stocks, the volatility of gold returns has the opposite reaction to negative shocks, which means that positive shocks of the same degree produce more volatility than negative shocks (Baur, 2012). Baur (2012), while also citing Bollerslev et al. (1986), further argued that, for a commodity such as gold, such a positive return-volatility relationship cannot be properly explained by the leverage effect or volatility feedback, as it is related to a safe-haven asset. When the price of gold rises during the downward movement of the market, investors interpret it as an increase in the uncertainty of the macroeconomic environment, which consequently transfers the uncertainty and volatility of the stock market to the gold market. In contrast, if gold prices fall during a stock market rally, this uncertainty of volatility is also transmitted to the gold market by investors. With the Commodity Futures Trading Commission (CFTC) accepting BTC as a commodity, any evidence of a positive reaction-volatility relationship in the BTC market is likely to point to a safe-haven property. This evidence can be used to expand the usefulness of BTC as a hedge against stock market turbulence.

5. Results

5.1. ARCH effect test

5.1.1. Selection of lag order and determination of mean value equation

A time series approach was used in this study; thus, the equation for BTC's return rate (*r*) took the following form:

$$r_t = c_0 + \sum_{i=1}^{n} c_i r_{t-1} + \varepsilon_t \tag{8}$$

Regression was independently performed on Lags 1, 2, 3 and 4, and the results are shown in Table 2.

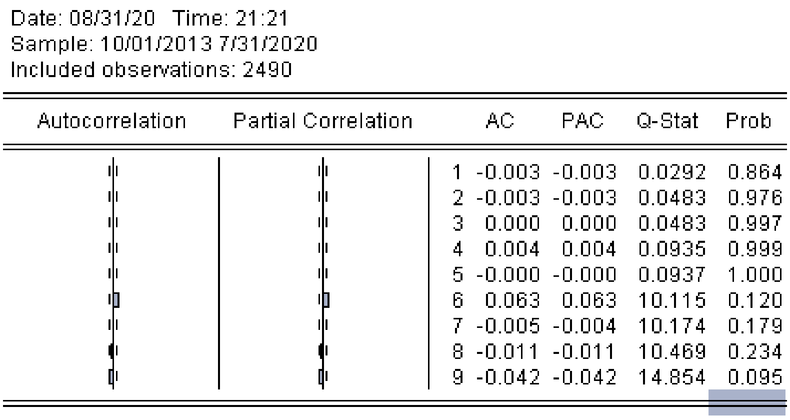
Table 2. Selection of AR order.

Lag	AIC	F-statistic
1	−3.44017	1.184208
2	−3.444386	1.266232
3	−3.445114	0.025164
4	−3.446444	4.118333

According to Table 2, because smaller Akaike Information Criterion (AIC) can avoid overfitting and bigger F-statistics means coefficient is better, AIC is the smallest and F-statistics is the biggest item in lag 4. Thus, Table 2 clearly shows that the lag 4 period was the best, so the lag order was selected as 4. Thus, the formula can be written as

$$r_t = c_0 + c_1 r_{t-1} + c_2 r_{t-2} + c_3 r_{t-3} + c_4 r_{t-4} + \varepsilon_t \quad (9)$$

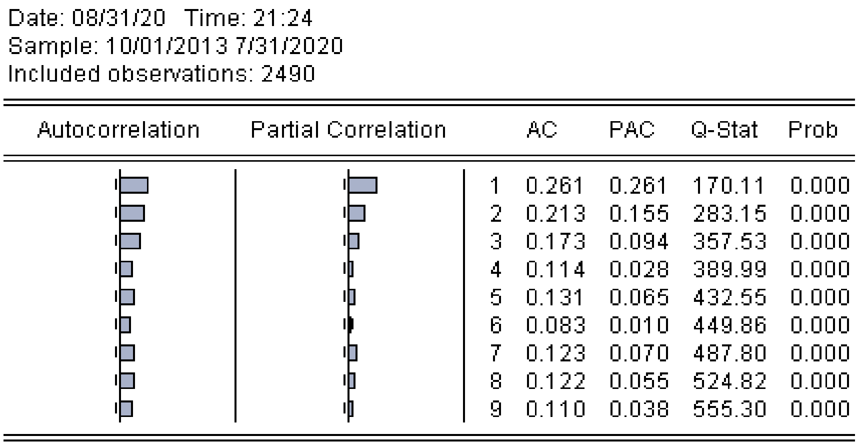
5.1.2. Autocorrelation test for residual series



Date: 08/31/20 Time: 21:21
Sample: 10/01/2013 7/31/2020
Included observations: 2490

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.003	-0.003	0.0292	0.864
		2	-0.003	-0.003	0.0483	0.976
		3	0.000	0.000	0.0483	0.997
		4	0.004	0.004	0.0935	0.999
		5	-0.000	-0.000	0.0937	1.000
		6	0.063	0.063	10.115	0.120
		7	-0.005	-0.004	10.174	0.179
		8	-0.011	-0.011	10.469	0.234
		9	-0.042	-0.042	14.854	0.095

Figure 5. Autocorrelation (AC) and partial autocorrelation (PAC) values for the AC coefficient for the residual term of BTC returns (*r*).



Date: 08/31/20 Time: 21:24
Sample: 10/01/2013 7/31/2020
Included observations: 2490

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.261	0.261	170.11	0.000
		2	0.213	0.155	283.15	0.000
		3	0.173	0.094	357.53	0.000
		4	0.114	0.028	389.99	0.000
		5	0.131	0.065	432.55	0.000
		6	0.083	0.010	449.86	0.000
		7	0.123	0.070	487.80	0.000
		8	0.122	0.055	524.82	0.000
		9	0.110	0.038	555.30	0.000

Figure 6. AC coefficient, AC and PAC results for the residual square of the BTC returns (*r*).

Sequence residuals and the residual squared autocorrelation graphs were drawn. From Figures 4 and 5, the results show that there was no significant autocorrelation in the residual term of the BTC return (*r*), but the residual squared had significant autocorrelation.

5.1.3. Linear graph of the squared residuals

A line graph of the squared residuals was drawn. It can be seen from the figure that the fluctuation of the residual ε_t^2 of the regression equation exhibited the phenomenon of grouping; particularly, fluctuations were very small in some longer periods and larger in other longer periods, demonstrating obvious temporal variability and clustering. This shows that the residual sequence had a high-order ARCH effect, which is suitable for modelling with GARCH models. The graph shows that the residuals ε_t^2 in 2013–2014 crowded together with high volatilities, which means that there were a great number of people investing in BTC based on emotions during that period of the time. Apart from this, the grouping phenomenon suddenly came up again in 2017–2018. It can be explained by the halving of quantity of BTC that resulted in overvaluation of BTC and a BTC bubble that led investors to rapidly sell their bitcoins, which caused the volume of transactions of BTC to be really large. In 2020, although the grouping phenomenon was not very obvious, the volatility remained at a high level. To sum up, the mean volatility of BTC always remained at a high level and there was culminant buying and selling of BTC during a period of time.

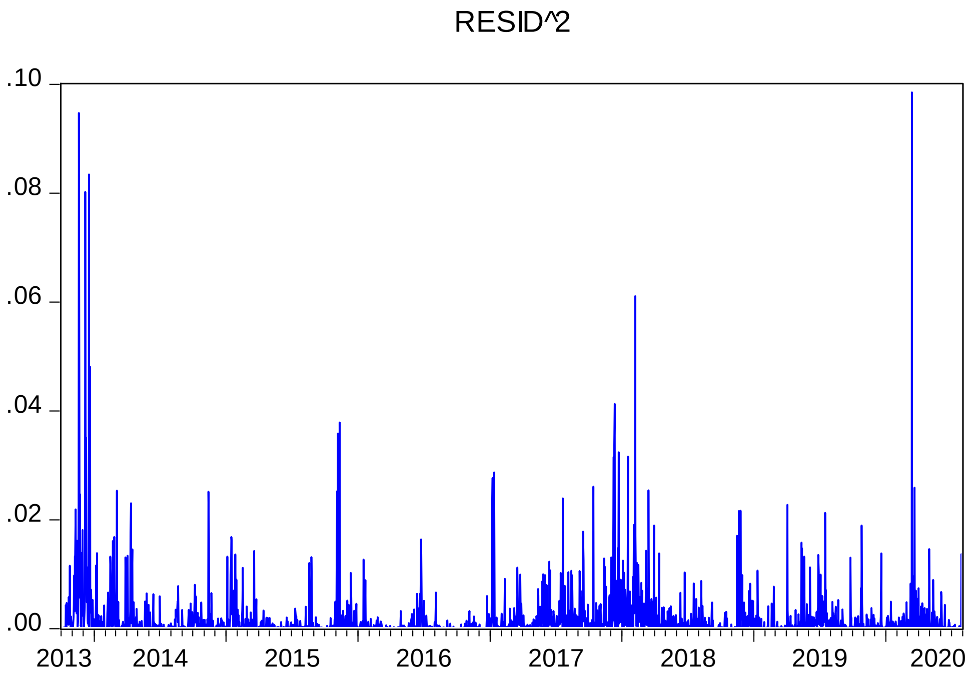


Figure 7. BTC returns (*r*) residual square line graph.

5.1.4. ARCH-LM test for the residual (9th-order lag)

ARCH-LM testing, the standard test to detect autoregressive conditional heteroscedasticity, was first be presented by Engle in 1982. ARCH-LM testing was performed on the residuals of serial linear regression, and the object of the F test was the joint significance of the squared residuals of all of the lags. The Obs*R statistic is the LM test statistic, which is the number of observations multiplied by the test regression R. Given the significance level α = 0.05 and a degree of freedom of 9, the value of LM was 284.1393, which is greater than the critical value of 16.9190, and the concomitant probability P was 0.0000, which is less than 0.05. The null hypothesis was rejected. This shows that there was obvious heteroscedasticity in the return sequence, and that the residual had a strong ARCH effect. Therefore, it is reasonable that the GARCH model was selected to simulate the data for BTC's returns rate.

Table 3. ARCH-LM test for the residual of the BTC return.

Heteroskedasticity Test: ARCH			
F-statistic	35.50890	Pro. F (9,2472)	0.0000
Obs*R-squared	284.1393	Pro. Chi-Square (9)	0.0000

5.2. ARCH effect test

5.2.1. Research on the volatility of Bitcoin returns

The estimation results for the GARCH (1,1) model are shown in Table 4.

Table 4. GARCH (1, 1) model estimation results.

Dependent Variable: R
Method: ML-ARCH (Marquardt)–Normal distribution
Sample (adjusted): 10/03/2013–7/31/2020
Included observations: 2491 after adjustments
Convergence achieved after 21 iterations

	Coefficient	Standard Error	z-Statistic	Probability
C	0.001034	0.000666	1.554104	0.1202
R (-4)	−0.008808	0.020909	−0.421273	0.6736
Variance Equation				
C	0.000076	0.00000553	13.74898	0.0000
RESID (-1) ^2	0.189179	0.013256	14.27126	0.0000
GARCH (-1)	0.785817	0.012448	63.12982	0.0000

$$r_t = 0.001034 - 0.008808\gamma \tag{10}$$

$$(1.554) \quad (-0.421)$$

$$\sigma_t^2 = 7.6\times10^{-5} + 0.189179\varepsilon_{t-1}^2 + 0.785817\sigma_{t-1}^2 \tag{11}$$

$$(13.749) \quad (14.271) \quad (63.130)$$

The results are as follows: log likelihood = 4731.619, AIC = −3.795 and SC = −3.783.

From this model, it can be seen that, in the conditional variance equation for BTC's return rate, both the ARCH and GARCH terms are highly significant. This significance indicates that the volatility of the return rate series had clustering characteristics. Additionally, the dependent variable was R and the sample time was from October 6, 2013 to July 31, 2020, which included 2491 observations after adjustments. Besides, convergence was achieved after 21 iterations. The sum of the ARCH term and the GARCH term for the BTC rate of return was 0.974996 < 1, which meets the constraints on the parameters. But, since the sum of the two coefficients (0.974996) is very close to 1, it can be ascertained that the impact of the shock on the conditional variance was not transient, as it is a permanent process. Then, the impact can be inferred from this feature to play an important role in future predictions, so GARCH (1,1) modelling is a smooth process. However, the conditional variance shows that the influence of past fluctuations is limited, and that its influence on the future tends to gradually attenuate to 0, which is called mean-reversion.

5.2.2. Research on the asymmetry of Bitcoin returns

The estimation results for the Threshold ARCH (TARCH) model are shown in the following table.

Table 5. TARCH model estimation results.

Dependent Variable: R
Method: ML-ARCH (Marquardt) – Normal distribution
Sample (adjusted): 10/06/2013 7/31/2020
Included observations: 2491 after adjustments
Convergence achieved after 25 iterations

	Coefficient	Standard Error	z-Statistic	Probability
C	0.001039	0.000724	1.434527	0.1514
R (-4)	−0.00876	0.021361	−0.4101	0.6817
Variance Equation				
C	7.6E−05	5.56E−06	13.67519	0.0000
RESID (-1) ^2	0.18969	0.016727	11.34065	0.0000
ARCH (1) * (RESID (-1) < 0)	−0.001122	0.015673	−0.071609	0.9429
GARCH (-1)	0.78587	0.012451	63.11544	0.0000

$$r_t = 0.001039 - 0.00876\gamma \tag{12}$$

(4.435) (-0.410)

$$\sigma_t^2 = 7.60\times10^{-5} + 0.18969\varepsilon_{t-1}^2 - 0.001122\varepsilon_{t-1}^2 d_{t-1} + 0.78587\sigma_{t-1}^2 \tag{13}$$

(13.675) (11.340) (-0.072) (63.115)

The results were as follows: log likelihood = 473.620, AIC = −3.794 and SC = −3.780.

Table 5 shows that the dependent variable was R and sample time spanned October 6, 2013 to July 31, 2020, which included 2491 observations after adjustments. In the TARCH model, the leverage effect term is described by (RESID < 0) * ARCH (1). The coefficient estimate of the ARCH (1)*(RESID (−1) < 0) (i.e., the $\varepsilon_{t-1}^2 d_{t-1}$ in the model) term is negative and not significant (β = −0.001122, p > 0), which shows that the special price fluctuation did not exhibit a leverage effect.

The estimation results for the EGARCH model are shown in the following table.

Table 6. EGARCH (1, 1) model estimation results.

Dependent Variable: R				
Method: ML-ARCH (Marquardt) – Normal distribution				
Sample (adjusted): 10/06/2013 7/31/2020				
Included observations: 2491 after adjustments				
Convergence achieved after 37 iterations				
	Coefficient	Standard Error	z−Statistic	Probability
C	0.001052	0.000646	1.629147	0.1033
R (-4)	−0.025538	0.020908	−1.221422	0.2219
Variance Equation				
C	−0.691107	0.03877	−17.8256	0.0000
ABS (RESID (-1)/@SQRT (GARCH (-1)))	0.336807	0.017652	19.08078	0.0000
RESID (-1)/SQRT (GARCH (-1))	−0.001903	0.008307	−0.229028	0.8188
LOG (GARCH (-1))	0.930196	0.004365	213.0794	0.0000

$$r_t = 0.001052 - 0.025538\gamma \quad (14)$$

$$(1.629) \quad (-1.221)$$

$$Log\ (\sigma_t^2) = -0.691107 + 0.336807\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - 0.001903\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + 0.9682\, log(\sigma_{t-1}^2) \quad (15)$$

$$(-17.826) \quad (19.081) \quad (-0.229) \quad (213.079)$$

As is notable from the above table, the dependent variable was R and the sample time spanned October 6, 2013 to July 31, 2020, which included 2491 observations after adjustments. In the EGARCH model, the coefficient for the asymmetric term RESID (-1)/@SQRT(GARCH (−1)) was significantly less than zero ($\beta = -0.001903$, $p > 0.05$), indicating that BTC during the sample period was no leverage effect in the rate of return. Whether there were negative shocks or positive shocks, the shocks only brought an impact of $\alpha = 0.336807$.

6. Conclusions

To sum up, the GARCH (1,1) model results show that the returns and volatility of BTC have clustering characteristics. Figures 7 and 8 show that the BTC returns and volatility sharply increased from 2013 to 2014, 2017 to 2018 and 2019 to 2020. The ESDC happened in 2013–2014, a trade war between China and the USA started in 2017–2018 and the COVID-19 pandemic arose in 2019–2020, all amounting to famous financial crises. Interestingly, financial market returns declined during the financial crash, but the returns of BTC rose. This phenomenon can be explained by a reduction in interest rates and monetary excessing. Because the central banks of countries across the world issued more of their currency to hedge risks of economic depression with a low interest rate, people had more money. However, they wanted to minimise inflation, so investments were helpful. Due to the issuance of more currencies, BTC can be a low valuation asset for investment; thus, it is a concern of capital for every country. This is why BTC returns and volatility exhibited a clustering feature during several periods. Besides, the findings associated with the GARCH (1,1) model indicate that the shocks affecting conditional variance are a part of a long-term process, so this finding can be used to predict the returns and volatility of BTC in the future. However, because conditional variance is limited to influencing the future returns and volatility of BTC, its effect gradually decreases; this can effectively explain why BTC's returns and volatility decrease after financial crises and crashes.

Furthermore, ARCH and EGARCH models were used for analysis because the GARCH (1,1) model cannot explain the leverage effect, which is an asymmetric effect observable in returns and volatility research. The results drawn from the TARCH and EGARCH models illustrate that BTC's returns and volatility do not exhibit the leverage effect, which means that the returns and volatility of BTC have asymmetric relations. But, the figure for returns and volatility understandably showed an asymmetric effect between positive and negative shocks; for example, when negative shock in light of COVID-19 came up in 2019–2020, BTC's returns and volatility sharply increased. But, before COVID-19 happened, a positive shock brought a smaller change in its returns and volatility. As an asset, BTC should exhibit characteristics similar to other assets, such as stocks, bonds and gold. However, it demonstrated a revised phenomenon as compared with stock. Similarly, gold returns and volatility appeared to resemble trends. In addition, the CFTC accepted BTC as a commodity in October of 2015. Besides, gold and BTC have a significant correlation, so the revised asymmetry of BTC cannot be easily explained by the leverage effect. Based on this critical thinking, the conception of a safe-haven property was discussed. A safe-haven property is an asset that can offer defence protection to hedge risk during a financial crisis. Between 2013 and 2014, 2017 and 2018 and 2019 and 2020, BTC played the role of a safe-haven property, so financial institutions and other investors were able to add BTC to their investment portfolios to efficiently avoid and hedge financial risk.

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Conflict of interest

The authors declare no conflicts of interest in this study.

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