Investigating the nexus between Volatilities of Bitcoin, Gold, and American Stock Markets during the COVID-19 Pandemic: Evidence from ARMA-DCC-GARCH and NAR-NN Models

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Abstract

The spread of the coronavirus has reduced the value of stock indexes, depressed commodity prices like oil, and caused financial instability in financial markets around the world. Due to this situation, investors should consider investing in more secure assets, such as cash, and crypto assets are gaining more attention than traditional investments. The study compared the Bitcoin market, gold market, and American stock indexes (S&P500, Nasdaq, and Dow Jones) before and during the COVID-19 pandemic. For this purpose, we use the dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model to estimate the DCC coefficient and compare this model with a nonlinear autoregressive neural network (NAR-NN) approach to predict volatility and correlation of assets. Our empirical findings show a substantial dynamic conditional correlation between Bitcoin, gold, and stock markets. In particular, we observe that Bitcoin offers better opportunities for diversification to reduce risks in key stock markets during the COVID-19 period. Research has practical impacts on risk management and portfolio diversification.

Keywords: Bitcoin Market, Gold Market, American Stock Markets, COVID-19 Pandemic, ARMA-DCC-GARCH Model, NAR-NN Model.

JEL Codes: C22, C58, G17

1. Introduction

Today, the financial markets play such an important role in the development of a country that its boom directly affects its development. A major concern for those considering entering the financial markets is losing capital and reducing asset values. Thus, reducing financial risks and risks that may threaten capital has always been an area of concern for traders and investors (Toque and Terraza, 2011; Toque and Terraza, 2014). The recent spread of the COVID-19 virus in the world has created a big shock in the economies of the world. This shock was accompanied by a fall in the value of stock market indexes and oil prices as well as other financial assets. In response to this pandemic crisis, governments have decided on extensive shutdowns and heavy restrictions which have enhanced instability in the financial markets and sustained the crisis phenomenon. During financial crises, investors search for more secure assets to invest in. In particular, they tend to prefer investing in more cash and available assets. In recent years, the development of cryptocurrencies has recently gained the attention of investors in particular to enhance portfolio returns (Makarov and Schoar, 2020) and to improve the risk and return profile of a well-diversified portfolio (Briere et al, 2015).

In terms of asset classes, the stock market is one of the most important financial markets. An index's change reflects the performance of the market and the boom or bust of a country's economy. There are different ways in which stock market activity can affect a country's economy. The stock market is a constituent part of the financial markets and one of the main arteries of financing in an economy. A strong stock market plays such an important role in a country's economy that some economists believe the difference between developed and underdeveloped countries lies not in the presence of advanced technology but rather in the presence of an integrated and active stock market (Kyrtsou and Terraza, 2000; Göçken et al., 2016; Rounaghi and Nasirzadeh, 2016; Göçken et al., 2019; Abbaszadeh et al., 2020; Arashi and Rounaghi, 2022).

In addition to the stock market, investors are also interested in investing in gold to maximize profit and minimize risk. Gold has maintained its value for many years, making it popular among investors. The gold market protects the value of the investor's property over time and protects them from inflation risks. Investing in gold depends on several factors at the same time, just like investing in other investments. The right decision requires an analysis of past trends and a thorough examination of the current state of the global market, as well as the determination of how to invest based on the data and the current situation. Investing in this type of asset has the advantages of high long-term profit and quick liquidity.

There is a difference in the situation when it comes to the Bitcoin market. Bitcoin is a relatively new investment market that has only entered the market in the last few years. There are active Bitcoin markets 24 hours a day, 7 days a week, and understanding Bitcoin's capabilities are crucial for financial market participants (Ciaian et al., 2016; Stensas et al., 2019; Nasir et al., 2019; Kim et al., 2019; Hakim das Neves, 2020; Ante, 2020; Mizerka et al., 2020; Kristoufek, 2020; Lahiani et al., 2021; Malladi and Dheeriya, 2021; Kwon, 2021; Li et al., 2022; Lorenzo and Arroyo, 2022). Among the digital currencies that have emerged in the last decade are Bitcoin, LiteCoin, PeerCoin, AuroraCoin, DogeCoin, and Ripple. Among them, Bitcoin stands out due to its price volatility and outstanding growth. Several studies have shown that Bitcoin is a highly innovative and attractive digital currency (Brandvold et al., 2015; Shaikh, 2020; Giudici et al., 2020; Kayal and Rohilla, 2021; Ma and Tanizaki, 2022).

Investments in gold and Bitcoin generated big profits during the COVID-19 pandemic (Jin et al,2019; Bouri et al 2020) and there is still debate about whether Bitcoin can replace gold in times of financial crisis. However, the first thing to understand about Bitcoin is that it is an asset, not a currency. This means that a rapid decline in price or volatility makes it difficult to use this asset as a real currency in transactions. Because investors who intend to invest in safe markets are interested in determining the degree of uncertainty of the financial markets during times of financial crises, we investigate the dynamic nexus between Bitcoin, gold, and stock markets during the COVID-19 pandemic. The main finding of this paper is to show how different asset classes contribute to improving the risk-adjusted returns of an investment portfolio and how Bitcoin investment can improve portfolio diversification during crises.

The paper is organized as follows: Section 2 discusses the stock markets, gold markets, and Bitcoin markets, as well as different aspects of their financial behavior. We compare the trends of these markets before and during the COVID-19 pandemic in section 3. Section 4 of this paper explains our methodology and discusses the results. In this study, we use a multivariate GARCH model to take into account the time-varying effect of covariation between markets, and we compare the results of this methodology with those obtained by a NAR-NN method. The last section concludes the paper given the limits of our study and making some suggestions for future research.

2. Literature and theoretical background

We analyze the behavior of the Bitcoin, gold, and stock markets. As gold and stock markets are traditional markets that investors are familiar with, we will cover only Bitcoin's characteristics, since it is a newly emerging market, and compare studies about Bitcoin, gold, and the stock market.

The inventor of Bitcoin is known as Satoshi Nakamoto. Bitcoins do not have banknotes or coins like other currencies like the dollar or euro. Bitcoin is a virtual currency that can be bought, sold, ordered online, and traded like a stock. However, it is based on computer code, so it follows its own rules. The production and distribution of Bitcoin are not controlled by any government, group, or organization.

Bitcoin comes from solving complex mathematical problems. To do this, mining calculators test different numbers in a mathematical function called the hash function, so that they can predict the output. Bitcoin will be awarded to the first person who solves the problem and finds the correct function. More technically about the nature of these blocks, we can say that the Bitcoin system is based on a concept called a "blockchain". In this advanced database architecture model, users can record data simultaneously without disrupting the network or altering its integrity due to interference from other users. The current situation makes it harder for individuals to collect Bitcoins individually, rather, they join a mining pool, where everyone connects their devices to an integrated network called an "extraction pool," and this network solves problems and rewards miners by providing them with more processing power. Following that, the rewards are distributed according to the processing power of the participants.

Halving, or halving the reward for Bitcoin mining, is a predesigned program for organizing Bitcoin mining. This is very important for investors and miners of this cryptocurrency, because, in addition to mining, it also has a great impact on the price of Bitcoin. Halving Bitcoin in 2012 caused its value to increase 80 times, and halving Bitcoin in 2016 added 300 percent to its value.

Bitcoin prices are generally determined by supply and demand factors. But in more detail, several factors can affect it. For example, legislation banning Bitcoin mining or trading in one of the major economies could affect its price. Development situations, developers' decisions, important and expected events, and happenings are other factors that can influence the price of Bitcoin. Some of the factors mentioned above can have a positive effect on the price of Bitcoin. For example, offering more financial products such as futures contracts and ETFs can attract the attention of many investors. Positive legislation in this area could also benefit Bitcoin. On the other hand, this digital currency was the source of the financial crisis of 2008. Due to this, any situation that contributes to global economic instability will attract attention to Bitcoin.

Recent years have seen much research conducted on Bitcoin's price behavior. Kapar and Olmo (2019) analyzed the price discovery between Bitcoin futures and spot markets. They discovered that a common component drives both prices, which is provided by a weighted combination of futures and spot markets. They also demonstrated that deviations from the equilibrium condition equating the futures and spot log price can predict the return on the Bitcoin spot price but not the futures price. Philippas et al. (2019) proposed a dual-process diffusion model to investigate whether Bitcoin prices respond to informative signals with jumps obtained from Twitter and Google trends. The empirical findings suggest that Bitcoin prices are influenced in part by social media attention, implying a sentimental appetite for information demand.

Additionally, many researchers have compared different aspects of Bitcoin, gold, and stock markets before and during the COVID-19 pandemic that influenced the decision of investors and policymakers of businesses and governments. These studies are listed in Table 1. Among them, Al-Yahyaee et al. (2018) in their study compared the three markets and concluded that Bitcoin has the strongest long-memory and multifractality features, and it is also the least efficient. More interesting results of some studies concern the diversification benefits of cryptocurrencies. The benefits of incorporating Bitcoin in a traditional benchmark portfolio of stocks and bonds were investigated by Platanakis and Urquhart (2019). According to their findings, investors should incorporate Bitcoin in their portfolio because it provides significantly higher risk-adjusted returns. Complementary, Shahzad et al. (2020) compared the hedging characteristics of gold, Bitcoin, and G7 stock markets. Their findings indicate that gold offers comparatively higher and more stable conditional diversification benefits than Bitcoin for stock investments in G7 markets. According to some studies, Bitcoin has a lower dependence on other asset classes. In particular, Bouri et al. (2020) demonstrated that Bitcoin, gold, commodities, and stocks are all weakly dependent at different time scales, with Bitcoin being the least dependent and outperforming gold and commodities. Baur et al. (2018) analyzed the relationship between Bitcoin, gold, and the US dollar, and their results show that Bitcoin returns, volatility, and correlation characteristics are distinctively different compared to gold and the US dollar. Kwon (2020) expanded this investigation to a value-at-risk analysis examining Bitcoin's tail behavior with the dollar, gold, and stock market index. Based on the contemporaneous correlation, Bitcoin and the dollar, and the stock market index exhibit similar tail behavior.

Several empirical studies have been used to investigate risk spillovers and estimate correlations between asset market returns. Two perspectives have concerned risk analysis: the relationship of COVID- 19 metrics with stock market performance and economic uncertainty and the transmission volatility during the COVID- 19 crisis. Kakinuma (2021) investigated the nexus between Southeast Asian stock markets, Bitcoin, and gold before and during the COVID-19 pandemic. According to the results, Southeast Asian stocks, Bitcoin, and gold appear to be increasingly interdependent during pandemics. Matkovskyy and Jalan (2019) investigated the contagion effect of Bitcoin markets and their results show, that there is evidence of an increased contagion effect from financial to Bitcoin markets after the launch of Bitcoin futures. After the launch of Bitcoin futures and bearish time, risk-averse investors avoided USD/GBP Bitcoin markets, choosing instead NASDAQ and NIKKEI. Jiang et al. (2022) investigated the volatility spillover mechanism between the financial market and Bitcoin. According to their findings, Bitcoin acts as a hedge in the financial system rather than a haven. Moreover, they observe that shifts in external market attention across various markets are more likely to cause overall volatility spillovers.

Table 1. Studies about Bitcoin, gold, and stock markets before the COVID-19 pandemic and during the COVID-19 pandemic

Authors	Bitcoin Market	Gold Market	Stock Markets
Al-Yahyaee et al. (2018)	✓	✓	✓
Das et al. (2019)	✓	✓	
Vardar and Aydogan (2019)	✓		✓
Hoon Kang et al. (2019)	✓		✓
Kwon (2020)	✓	✓	✓
Shahzad et al. (2020)	✓	✓	✓
Mokni et al. (2020)	✓		✓
Zhang and Wang(2020)	✓	✓	✓
Owusu Junior et al. (2020)	✓	✓	
Jareno et al. (2020)	✓	✓	
Grobys (2021)	✓		✓
Wang et al. (2021)	✓		✓
Kakinuma (2021)	✓	✓	✓
Kyriazis (2021)		✓	✓
Singh (2021)	✓	✓	✓
Jeribi and Ghorbel (2021)	✓	✓	✓
Chkili et al. (2021)	✓		✓
Derbali et al. (2021)	✓	✓	
Guo et al. (2021)	✓		✓
Yarovaya et al. (2022)	✓	✓	✓
Özdemir (2022)	✓		✓

Evidence from studies suggests that the diversification benefits of cryptocurrencies are not robust geographically and across markets. To the best of our knowledge, this is the first attempt in our study to test whether adding Bitcoin into a portfolio of traditional assets may enhance the risk/reward relationship during a crisis period and then contribute to one still incipient literature on the diversification benefits of cryptocurrencies in the COVID-19 period. The existing literature contends that prediction accuracy can be increased even further by looking for newer information sources including investor attitudes, economic conditions, and sentiments on social media. Despite an increase in accuracy, prediction is still a challenging process in Bitcoin, gold, and stock markets. Therefore, the motivation behind this paper is to get better prediction results for Bitcoin, gold, and stock markets using fewer input data and a more straightforward model structure.

3. Financial behavior of Bitcoin market, gold market, and stock markets before COVID-19 pandemic and during COVID-19 pandemic

Coronavirus was first identified in late 2019 and outbroke globally in early 2020. COVID-19 has swept into many countries and has been announced as a global pandemic by World Health Organization (WHO) on March 11, 2020 (Guo et al., 2021). Like any other industry, the Bitcoin, gold, and stock markets are affected by the COVID-19 pandemic (Chen et al., 2020; Yousaf and Ali, 2020; Sikiru and Salisu, 2021; Arif et al., 2021; Shahzad et al., 2021; Youssef et al., 2021; Wang and Liu, 2022; Hui and Chan, 2022).

However, the virus provided more opportunities for some financial assets, especially crypto-assets. Since Bitcoin was created, there has always been an expectation that this digital currency is a safe investment. In other words, with the stock market crashing, investors can take refuge in Bitcoin and virtual currencies. It is the same relationship that exists between the stock market and precious metals.

Many studies have examined whether cryptocurrencies (especially Bitcoin) can act as hedges and safe havens. . Jareno et al. (2020) found the existence of positive and statistically significant connectedness between Bitcoin and Gold. A study by Bahloul et al (2021) examined whether the Morgan Stanley Capital International all-country world index, Islamic index, gold, and Bitcoin could be used as hedges or safe-haven assets against world conventional stock markets from April 30, 2015, to March 27, 2020. In the sub-period of COVID-19, empirical findings suggest that gold is only a weak safe asset, while Bitcoin is more of a weak hedge than a safe-haven asset. Będowska-Sójka and Kliber (2021) obtained the same properties which are that cryptocurrencies can play a role of weak safe-havens in the European market. During the four months following the World Health Organization's official designation of COVID-19 as a global pandemic, Diniz-Maganini et al. (2021) looked at the price efficiency and net cross-correlations of Bitcoin, gold, a US dollar index, and the Morgan Stanley Capital International World Index (MSCI World). Based on their results, they suggest that the time scale plays a significant role in their conclusions. It seems that when the time is greater than two months, gold can be considered a haven for investors holding the MSCI world and US dollar indexes and when the time scale exceeds three months, Bitcoin can be considered a haven for the MSCI World index.

Despite the similarities between Bitcoin and gold as a hedge and a diversifier during the COVID-19 crisis found in the above-mentioned studies, Chemkha et al. (2021) demonstrated that gold is not a safe-haven for the assets considered during COVID-19, but Bitcoin cannot provide shelter due to its increased volatility. Omane-Adjepong and Paul Alagidede (2021) examined the COVID-19 effects on the Bitcoin market, gold market, and Africa's stock markets. According to their findings, neither traditional safe havens nor Bitcoin can provide a haven for Africa's emerging stock markets. Palladium and gold, however, provide a more stable environment for small-sized equity markets than the other candidates. Gold and Bitcoin were compared as safe havens during the COVID-19 outbreak by Shehzad et al. (2021). An approach based on wavelets found that gold has more robust safe-haven properties than Bitcoin during COVID-19.

It appears that there is no consensus regarding the safe-haven properties of Bitcoin during COVID-19. Therefore, the current study contributes to the literature by examining Bitcoin volatility before and during COVID-19.

Several aspects of Bitcoin's volatility can be analyzed to better understand its dynamics and capabilities as a financial asset. Examining assets' trends is the first step to understanding how volatility changes over time. The evolution of Bitcoin's price between 2015 and 2020 is represented in Figure 1, while Figure 2 shows Bitcoin's price performance during the COVID-19 pandemic. We observe a sustained upward trend from 2015 to 2018, with a peak at over 19000 $ in December 2017. However, the trend is reversing in 2018 with news of the hacking of Bitcoin exchanges, as well as pessimistic opinions of governments and some major personalities in the financial and investment sector. This general negative atmosphere continued with a decrease in 2019 to start up again during the COVID-19 crisis. During this period, Bitcoin went from 7149.44 $ at the end of 2019 to 65930.54 $ at the end of 2021, which represents an increase of 822%.

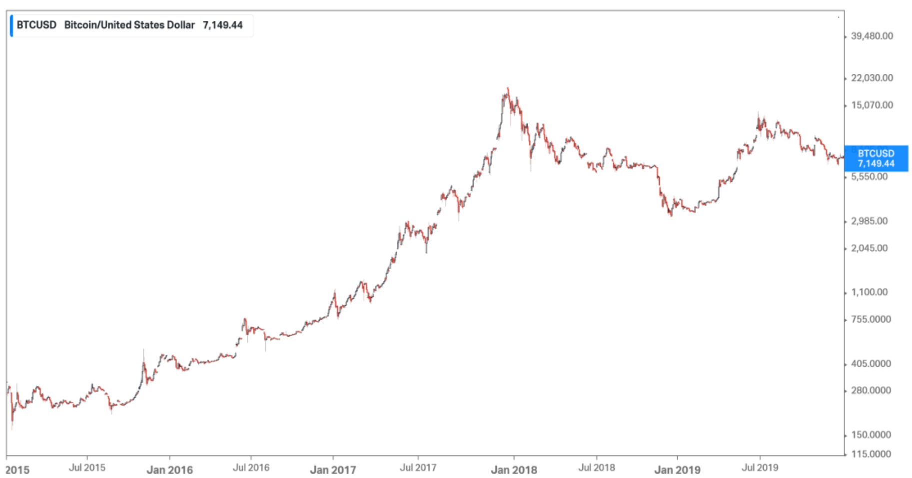

Fig 1. Bitcoin trend (2015-2020)
Source: https://www.koyfin.com.

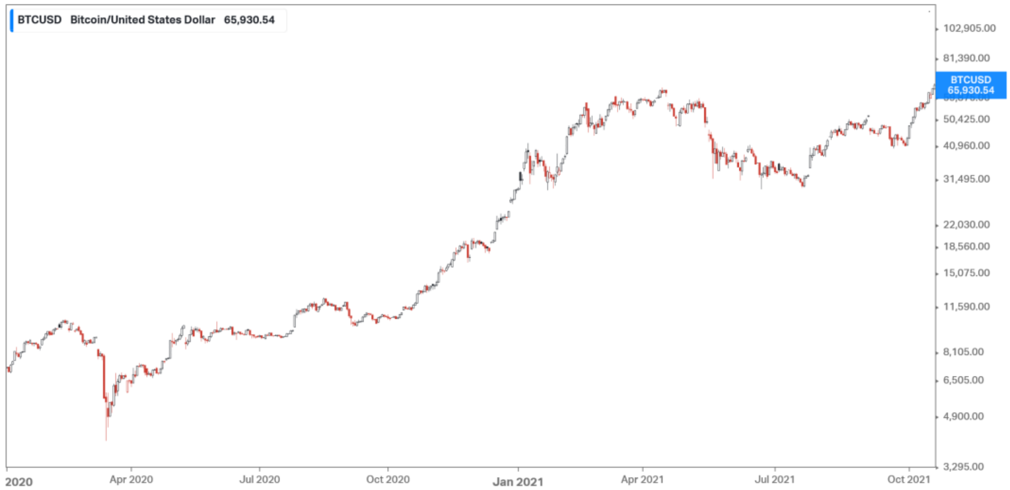

Fig 2. Bitcoin and COVID-19 pandemic
Source: https://www.koyfin.com.

To better understand these trends, it could be helpful to observe the evolution of Bitcoin mining's geographical distribution. In Figure 3, we compare the Cambridge Bitcoin Electricity Consumption Index (CBECI) at the end of 2019 with the index at the end of 2021. With 73,46% of the average monthly hashrate share, China dominated this technology until the end of 2019. However, this share fell to 19,14% in 2021 and China's major player is gradually ceasing its mining activities for political, energy, and economic reasons. On contrary, the share of the United States rose from 3,87% to 37,45.%, placing it in first place in 2021. As a result of the pandemic crisis coupled with a weak dollar, big financial companies shifted to cryptocurrency and Bitcoin has seen a significant rise in its price.

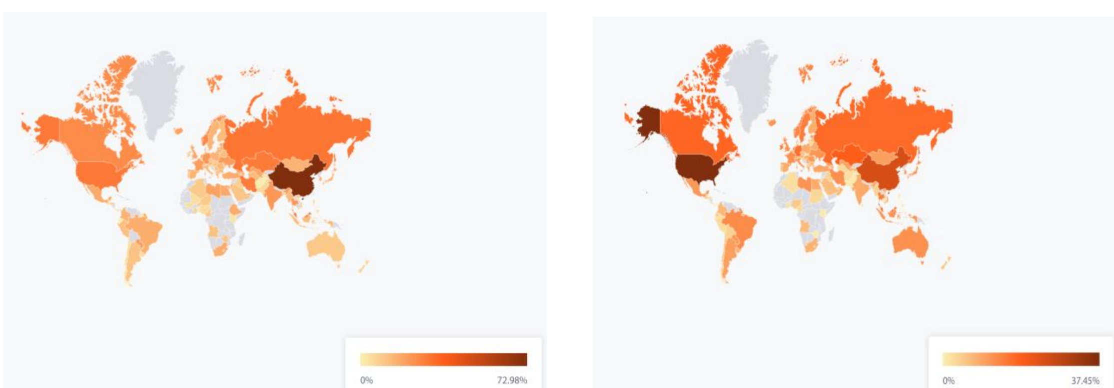

Fig 3. Comparison of the Cambridge Bitcoin Electricity Consumption Index for the periods 2019 and 2021

The pandemic crisis has caused the economy to become more digital, explaining recently how the cost of energy is driving Bitcoin's geographical redeployment. The debate surrounding Bitcoin's insatiable appetite for electricity has gathered momentum and ignited a global debate about reducing carbon emissions based on cryptocurrencies.

In Figures 4 to 5, we compare the trend of the Bitcoin market with the gold market and the stock market, before the COVID-19 pandemic and during the COVID-19 pandemic. Before the pandemic, Bitcoin was in general disconnected from traditional financial markets. However, when COVID-19 emerged, Bitcoin rose significantly, and the question was raised about the correlation structure and its evolution between all markets.

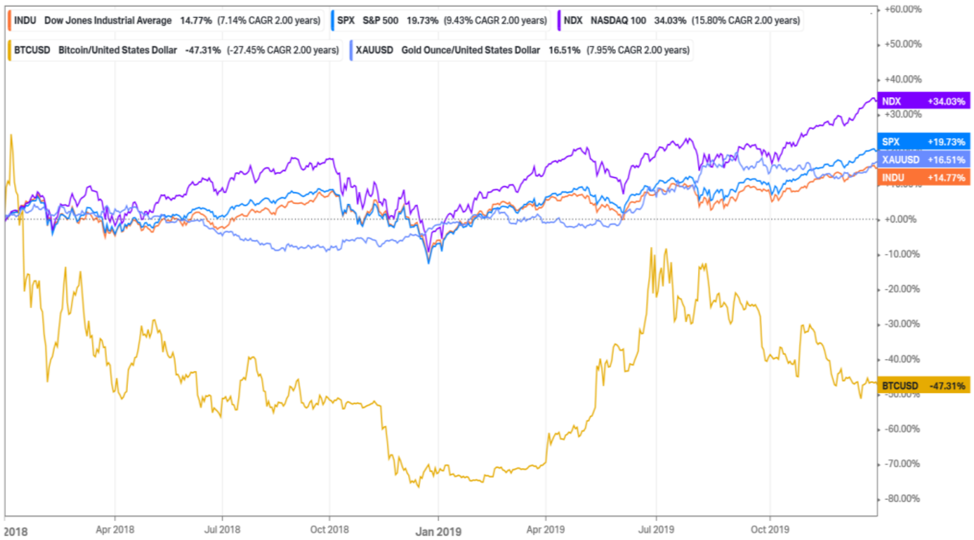

Fig 4. Fluctuates of Bitcoin market in comparison with gold market and stock markets before the COVID-19 pandemic (2018-2019)
Source: https://www.koyfin.com.

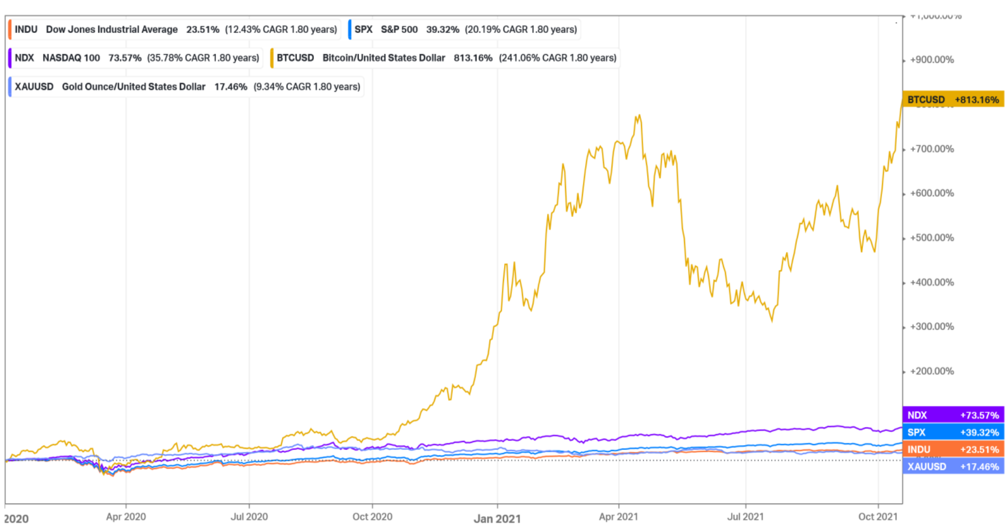

Fig 5. Fluctuates of Bitcoin market in comparison with gold market and stock markets during the COVID-19 pandemic (2020-2021)
Source: https://www.koyfin.com.

Consequently, in our study, we investigate the dynamic relationship between Bitcoin, gold, and stock markets before the COVID-19 pandemic outbreak and we ask the question: Have Bitcoin, gold, and American stock markets been independent before the COVID-19 pandemic? Additionally, our study examines the dynamic nexus between Bitcoin, gold, and the stock market during the outbreak of the COVID-19 pandemic, verifying the following hypothesis: Have Bitcoin, gold, and the stock market become interdependent during the outbreak of the COVID-19 pandemic?

4. Data and empirical methodology

4.1. Data

To investigate the effect of the COVID-19 pandemic on the Bitcoin, gold, and stock markets, we collect two sample data for each asset class: Before the COVID-19 pandemic (2018-2019) and during the COVID-19 pandemic (2020-2021). The daily closing prices are collected from Yahoo Finance. As closing price series are non-stationary, the series are transformed into returns series.

4.1.1. Descriptive statistics of the returns

Table 2 and Table 3 demonstrate the descriptive statistics of the returns of the Bitcoin, gold, and stock markets over a period from 2018-to 2019 (before the COVID-19 pandemic), and from 2020 to 2021 (during the COVID-19 pandemic).

Table 2. Descriptive statistics of the returns of the data (before the COVID-19 pandemic, 2018-2019)

	Bitcoin Market	Gold Market	Nasdaq Stock Market	S&P Stock Market	Dow Jones Stock Market
Minimum	-0.2411	-0.0164	-0.0453	-0.0418	-0.0471
Median	0.0006	-0.0003	0.0003	0.0004	0.0006
Mean	-0.0055	-0.0001	-0.0003	-0.0004	-0.0004
Maximum	0.1312	0.0190	0.0606	0.0569	0.0600
Standard deviation	0.0510	0.0058	0.0134	0.0110	0.0116
Skewness	-0.7189	0.0116	-0.2854	-0.2472	-0.2532
Kurtosis	2.2387	0.4030	2.3852	4.0562	4.0940

Table 3. Descriptive statistics of the returns of the data (during the COVID-19 pandemic, 2020-2021)

	Bitcoin Market	Gold Market	Nasdaq Stock Market	S&P Stock Market	Dow Jones Stock Market
Minimum	-0.4686	-0.0540	-0.1315	-0.1277	-0.1384
Median	0.0047	0.0005	0.0022	0.0017	0.0012
Mean	0.0049	0.0003	0.0012	0.0008	0.0005
Maximum	0.1957	0.0679	0.0893	0.0897	0.1076

Standard deviation	0.0514	0.0107	0.0186	0.0173	0.0182
Skewness	-1.7859	0.0035	-1.0080	-1.0424	-1.0268
Kurtosis	16.4078	5.4137	9.8756	13.8120	15.4353

When comparing the average return over both periods for all investments, the return is higher over the second period. In particular, we observe that Bitcoin returns are higher compared to other investments, even if its return reaches more values that are negative over the second period. Except for Bitcoin, the return volatilities are substantially the same for all investments with the lower variability for gold.

The difference between the maximum and minimum returns for Bitcoin is the highest, suggesting that Bitcoin has experienced more significant fluctuations relative to other markets. Indeed, Bitcoin exhibits the greatest variability for the two periods. During the COVID-19 pandemic, Bitcoin appears to be the riskiest asset with more negative extremes.

4.1.2. Nonlinearity of the data and autocorrelation of the data

Before modeling, it is necessary to determine the presence of non-linear components in our data sets. We report the results of the BDS tests for all the returns series, considering the embedding dimension of [2] and [3], (The tables are given in Appendix A), and we test autocorrelation in the returns using the Ljung Box test (The tables are given in Appendix B).

For US stock markets, the calculated probability values are above 5%, and the non-linearity hypothesis is accepted regardless of the period. The results are different according to the periods for the gold. Before the COVID-19 pandemic, we reject the hypothesis of non-linearity, while during the COVID-19 pandemic, the test accepts the hypothesis of non-linearity in the returns. Concerning Bitcoin, the non-linearity is rejected for the two periods.

There is autocorrelation in the squared of the returns (see the results of the Lagrange Multiplier test in Appendix C). Then, a model of conditional volatility is required for all assets.

Another stage of the econometric analysis is to test the interdependence of the markets. In particular, to see the impact of the COVID-19 pandemic on the dynamics of market correlations.

4.2. Empirical methodology

To demonstrate the effect of the COVID-19 pandemic on the Bitcoin, gold, and stock markets, two approaches are considered. First, the dynamic connectedness between the markets is investigated by employing the class of the ARMA-DCC-GARCH models and a dynamic network model (the NAR-NN) is explained. A second time, these models will be used for the comparison of future predicted values.

4.2.1. ARMA-DCC-GARCH model

Originally, GARCH models propose to model conditional variance for individual assets or indexes to take into account the sensitivity and persistence of a volatility shock itself. In this study, we are interested in a specific model analyzing the various relationships between the assets. Indeed, volatility moves together more or less closely over time across assets and markets. GARCH multivariate models (MVGARCH) allow for analyzing volatility transmission between different assets and the introduction of DCC-GARCH models enables the analysis of interdependence among markets by estimating time-varying conditional correlations (Engle, 2002).

Previously, we have shown autocorrelation in the returns series suggesting using ARMA linear processes in the mean equation. We compare the different specifications of ARMA models, and then we select an appropriate model based on Akaike Information Criteria (see tables B3-B12 in the Annex which report the estimation of ARMA processes in the returns of the series for both periods). After adding ARMA (p, q) model to the DCC-GARCH model, it is possible to catch the presence of autocorrelation of returns or autocorrelation of random disturbance using the ARMA-DCC GARCH model.

The general ARMA(p,q)-DCC-GARCH model can be written as follows:

$$(1 - \Phi_1 B - \ldots - \Phi_p B^p) Y_t = c + (1 + \theta_1 B + \ldots + \theta_q B^q)\epsilon_t \quad (1)$$

$$\varepsilon_t \equiv N(0, D_t R_t D_t) \quad (2)$$

In the mean equation, $Y_t = (Y_1, Y_2, \ldots\ldots, Y_{nt})$ is the vector of the returns, Φ, Θ the parameters of the ARMA(p,q) processes, and c, the vector of constant.

$\epsilon_t = (\epsilon_1 , \epsilon_{2t} , \ldots\ldots\ldots, \epsilon_{nt})$ is the vector of standardized residuals.

$D_t = diag\,(\sqrt{h_{11,t}}, \sqrt{h_{22,t}}, \ldots \ldots , \sqrt{h_{nn,t}})$ is a diagonal matrix of standards deviations for each of the returns series obtained from estimating a univariate GARCH (1,1) process formulated by the following equation:

$$h_{ii,t} = \omega_i + \alpha_i \epsilon^2_{i,t-1} + \beta_i h_{t-1} \quad (3)$$

with $h_{ii,t}$, the conditional variance which depends on the unknown parameters ω_i (the constant), α_i, (the coefficient of the ARCH part of the process), β_i (the coefficient of the GARCH part of the process) to be estimated.

$R_t = ((Q_t))^{-1/2}\, Q_t\, (diag(Q_t))^{-1/2}$ represents the time-varying conditional correlation matrix.

Q_t is (n × n) variance-covariance matrix of standardized residuals, defined by:

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

with

$$\bar{Q} = cov(\varepsilon_t \varepsilon'_t) = E(\varepsilon_t \varepsilon'_t) \quad (5)$$

$\bar{Q}$: the unconditional covariance of the standardized residuals obtained by the univariate GARCH model.

α, and β are parameters to be estimated. The sum of these coefficients must be less than one to respect the positivity of the matrix Q_t.

To ensure that the matrix H_t is defined as positive it is necessary to verify that:

$$\alpha_{DCC} \geq 0 \; ; \; \beta_{DCC} \geq 0 \text{ and } \alpha_{DCC} + \beta_{DCC} < 1 \quad (6)$$

In the DCC-GARCH models, one estimates individual GARCH-type processes (which could differ for each asset) and then used the GARCH models to standardize the individual residuals. A second time, the correlation dynamics of these standardized residuals can be specified.

4.2.2. NAR-NN model

Artificial Intelligence modeling has recently attracted much attention as a new technology in finance and economic forecasting. In this paper, we use an alternative approach that relies on an artificial neural network (ANN) to capture the nonlinear relationships between market volatility. In prediction, ANN is a strong competitor to regression and time series. ANN is well suited to modeling problems with unknown variables. ANN is also appropriate when static circumstances or other conditions make traditional techniques ineffective, and applying time series is difficult. ANNs are made up of attributes that lead to good solutions in cases where we need to learn linear or nonlinear mapping. As a result of these attributes, ANNs would be able to tackle complicated problems precisely and flexibly (Azadeh, Ghaderi, and Sohrabkhani, 2007). One of the dynamic networks is the nonlinear autoregressive neural network (NAR-NN) model, which can learn to predict a time series based on its past values. In time series forecasting, dynamic neural networks are more powerful because of their memory and ability to learn time-varying patterns.

The NAR-NN model is based on the feed-forward back propagation method introduced by Rumelhart, Hinton, and Williams (1986). Before using data to create a nonlinear autoregressive neural network (NAR-NN), it is pre-processed to remove all the blank lines. Then, min-max normalization is used to normalize the two datasets. It normalizes the values of the attribute X by their minimum and maximum values, X_{min} and X_{max}, respectively. It normalizes the values of the attribute X by their minimum and maximum values, X_{min} and X_{max}, respectively. It computed the following to convert a value v_i $(i = 1, 2, \dots, n)$ of attribute X to v_i' in the predefined range $[new\_X_{min}, new\_X_{max}]$ (Pan et al., 2016). new_X_{max} and new_X_{min} are determined as 0 and 1, respectively.

$$v_i' = \frac{v_i - X_{min}}{X_{max} - X_{min}}(new\_X_{max} - new\_X_{min}) + new\_X_{min} \tag{7}$$

The NAR-NN is a recurrent dynamic network with feedback links that are based on a linear autoregressive model. It predicts future values by using past values from the actual time series (Benmouiza and Cheknane, 2013). It is created using Equation (8).

$$y(t) = f(y(t-1) + y(t-2) + \cdots + y(t-d)) \tag{8}$$

$y(t)$ is a series and the time delay parameter is denoted by d. t is a unit of time $(t = 1,2, \dots, n)$. In addition, the NAR-NN method is precisely specified in Equation (5) (Benrhmach et al., 2020).

$$y(t) = \alpha_0 + \sum_{j=1}^{k} \alpha_j \emptyset\left(\sum_{i=1}^{a} \beta_{ij} y_{t-i} + \beta_{0j}\right) + \varepsilon_t \tag{9}$$

The number of entries is denoted by the letter a. The hidden layer number is k and the activation function is $\emptyset$. The weight of the connection between the input unit i and the hidden unit j is represented by the parameter β_{ij}. The weight of the connection between the hidden unit j and the output unit is denoted by the letter α_j. The constants β_{0j} and α_0 correspond to the hidden unit j and the output unit, respectively. At time t, ε_t is a random error. Dataset is randomly split into a training set (70%), validation set (10%), and testing set (20%) in the proposed NAR-NN. The number of delays is determined as two. The number of a neuron is determined as 10 and the training algorithm is selected as Levenberg–Marquardt algorithm.

The general structure of the proposed NAR-NN is given in Figure 6 and Figure 7.

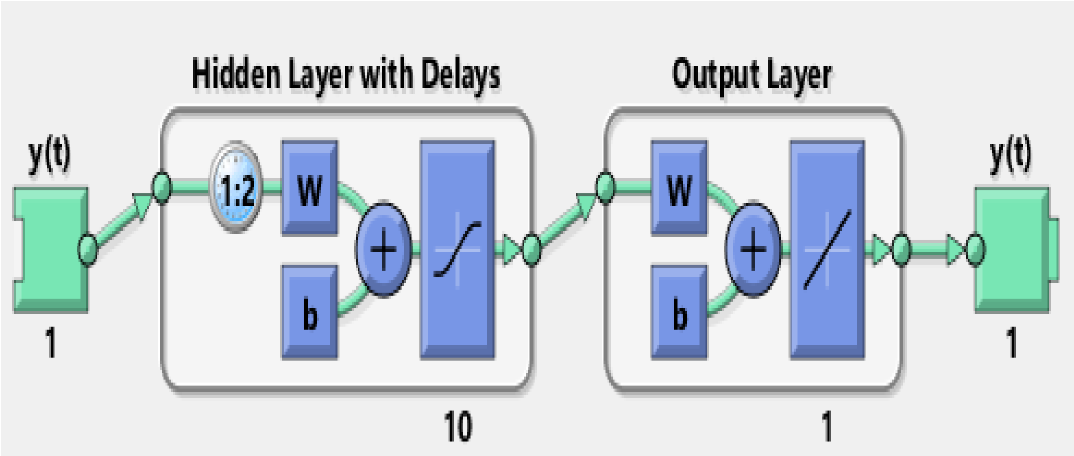

Fig 6. The general structure of the proposed trained NAR-NN

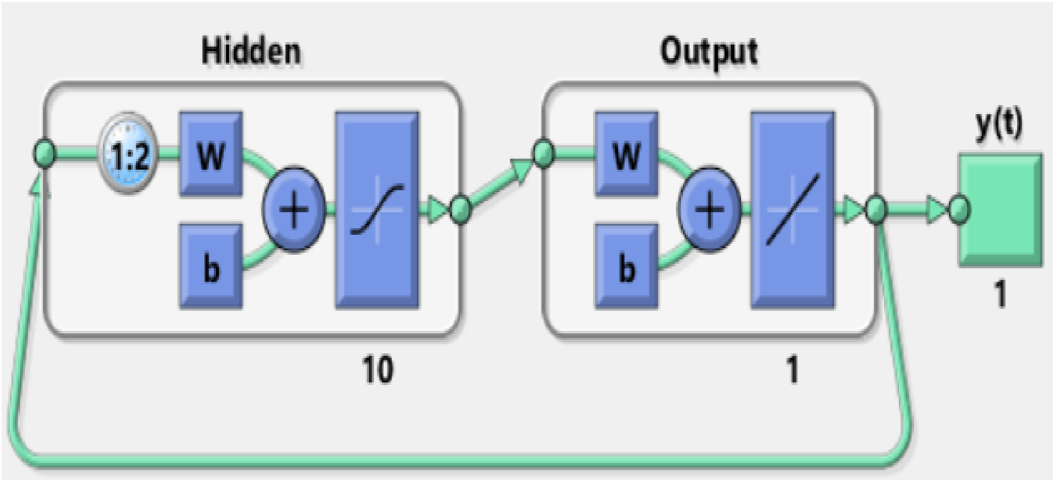

Fig 7. The general structure of the proposed closed-loop NAR-NN

5. Results

5.1. Results of the ARMA-DCC-GARCH model

The estimation results of the model are given in Table4 and Table5.

Table 4. The performance measures of the ARMA-DCC-GARCH model (period1: before the COVID-19 pandemic)

DCC-GARCH model Period1	Estimate	Std.Error	t value	Pr(>|t|)
[BITCOIN].mu	-0.004452	0.002535	-1.756023	0.079084
[BITCOIN].ar1	-0.831733	0.107726	-7.720797	0.000000*
[BITCOIN].ma1	0.742991	0.124881	5.949583	0.000000*
[BITCOIN].omega	0.000085	0.000073	1.175613	0.239750
[BITCOIN].alpha1	0.083757	0.042217	1.983961	0.047260*
[BITCOIN].beta1	0.882216	0.047436	18.597977	0.000000*
[GOLD].mu	-0.000055	0.000425	-0.128511	0.897745
[GOLD].ma1	0.230065	0.096502	2.384047	0.017123*
[GOLD].alpha1	0.083660	0.070406	1.188242	0.234738
[GOLD].beta1	0.553767	0.258345	2.143523	0.032071*
[NASDAQ].mu	0.001020	0.002431	0.419440	0.674894
[NASDAQ].omega	0.000007	0.000101	0.070848	0.943519
[NASDAQ].alpha1	0.222051	0.677325	0.327834	0.743037
[NASDAQ].beta1	0.770086	0.422417	1.823044	0.068297*
[SP500].mu	0.000790	0.001112	0.710040	0.477679
[SP500].omega	0.000006	0.000010	0.563699	0.572959
[SP500].alpha1	0.235821	0.118447	1.990936	0.046488*
[SP500].beta1	0.751966	0.086697	8.673543	0.000000*
[DJIA].mu	0.000152	0.000058	2.632067	0.008487*
[DJIA].ar1	0.966830	0.039284	24.611204	0.000000*
[DJIA].ma1	-1.000000	0.001502	-665.765969	0.000000*
[DJIA].omega	0.000005	0.000025	0.199738	0.841685
[DJIA].alpha1	0.171164	0.075944	2.253811	0.024208*
[DJIA].beta1	0.811312	0.200133	4.053872	0.000050*
[Joint]dcca1	0.054099	0.013006	4.159529	0.000032*
[Joint]dccb1	0.892190	0.016000	55.760188	0.000000*

*significant parameters at 5%

Table 5. The performance measures of the ARMA-DCC-GARCH model (period2: during the COVID-19 pandemic)

DCC-GARCH model Period2	Estimate	Std.Error	t value	Pr(>|t|)

[BITCOIN].mu	0.005721	0.001990	2.87441	0.004048*
[BITCOIN].ar1	-0.101880	0.060418	-1.68625	0.091748
[BITCOIN].omega	0.000263	0.000138	1.90450	0.056845
[BITCOIN].alpha1	0.151050	0.125213	1.20634	0.227685
[BITCOIN].beta1	0.772243	0.079024	9.77227	0.000000*
[GOLD].mu	0.000283	0.000448	0.63189	0.527461
[GOLD].alpha1	0.125323	0.042856	2.92428	0.003453*
[GOLD].beta1	0.792047	0.069902	11.33085	0.000000*
[NASDAQ].mu	0.001132	0.000743	1.52273	0.127826
[NASDAQ].ma1	-0.098340	0.059044	-1.66555	0.095804
[NASDAQ].ma2	0.039654	0.059363	0.66799	0.504141
[NASDAQ].omega	0.000014	0.000009	1.54478	0.122401
[NASDAQ].alpha1	0.220830	0.062596	3.52785	0.000419*
[NASDAQ].beta1	0.738385	0.066583	11.08964	0.000000*
[SP500].mu	0.001110	0.000670	1.65616	0.097689
[SP500].ma1	-0.085635	0.053769	-1.59266	0.111237
[SP500].ma2	0.118537	0.066192	1.79082	0.073322
[SP500].omega	0.000009	0.000006	1.40218	0.160861
[SP500].alpha1	0.350613	0.099456	3.52533	0.000423*
[SP500].beta1	0.645053	0.086742	7.43649	0.000000*
[DJIA].mu	0.000865	0.000612	1.41303	0.157647
[DJIA].ma1	-0.043572	0.055054	-0.79144	0.428685
[DJIA].ma2	0.118489	0.065212	1.81697	0.069221*
[DJIA].omega	0.000009	0.000009	0.97172	0.331188
[DJIA].alpha1	0.313277	0.081234	3.85648	0.000115*
[DJIA].beta1	0.666503	0.125515	5.31012	0.000000*
[Joint]dcca1	0.051184	0.012520	4.08805	0.000044*
[Joint]dccb1	0.886628	0.040947	21.65289	0.000000*

*significant parameters at 5%

It can be seen from Table 4 and Table 5 that the majority of the coefficients are significant (except the constants in the mean and the variance equations). For some data series, the α coefficients from the variance equation are not significant (for the gold and the Nasdaq in period 1 and the Bitcoin in period 2). However, the results show that the β coefficients from equation 3 are significantly positive. It indicated that the lag-volatilities had a positive impact on the conditional volatility for all series.

We notice that the joint coefficients αDCC and βDCC which represent the parameters of the conditional correlations are significant. The persistence of the conditional correlation is calculated from the sum of αDCC and βDCC. For the two periods, we find a high level of persistence with values superior at 0.9.

The estimation of the ARMA-DCC-GARCH model parameters allows for determining the values of the conditional correlation for the pairs of series. The correlation values for a particular pair of series indicate the strength of the relationship between the two series. It also shows changes in the upward index and downward trends of these interrelationships over time.

Table 6 reports the means of conditional correlations. We observe that the tail behavior of Bitcoin and gold, as well as the stock market index, is very similar in terms of contemporaneous correlation. The obtained results show that the conditional correlations are the lowest for gold and Bitcoin whatever the period considered, indicating the role of Bitcoin and gold in hedging against stock indexes.

Conversely, the conditional correlation of stock market indexes is strongly positive with a value above 0.7 for both periods. Finally, the data comparison between both periods highlights the conditional correlation between Bitcoin and the stock market indexes over the second period but a decline for gold.

Table 6. Means of conditional correlations

Dataset		Gold	Bitcoin	S&P500	Dow-Jones	Nasdaq
Before COVID-19 pandemic	**Bitcoin**	0.017	1	0.089	0.108	0.093
	Gold	1	0.017	0.097	0.115	0.117
	Nasdaq	0.117	0.093	0.937	0.811	1
	S&P 500	0.115	0.089	1	0.938	0.937
	Dow Jones	0.097	0.108	0.938	1	0.811
During COVID-19 pandemic	**Bitcoin**	0.041	1	0.258	0.221	0.279
	Gold	1	0.041	0.079	0.076	0.069
	Nasdaq	0.069	0.279	0.895	0.702	1
	S&P 500	0.079	0.258	1	0.915	0.895
	Dow Jones	0.076	0.221	0.915	1	0.702

Figures 8, 9, and 10 analyze the dynamics of the relationship between the Bitcoin, gold, and stock market indexes before and during the COVID-19 pandemic.

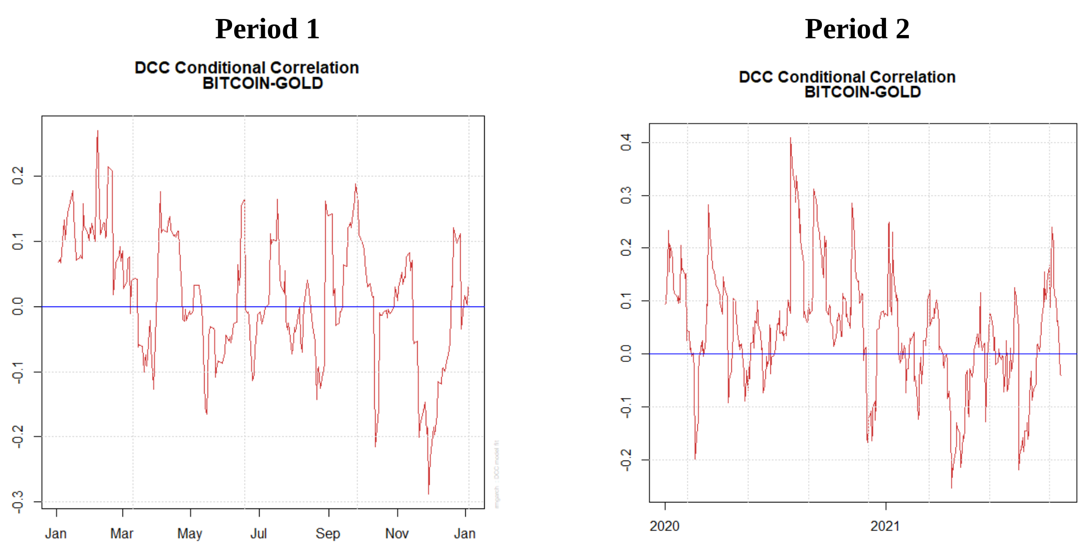

Fig 8. Conditional correlation of the Bitcoin market with the gold market before the COVID-19 pandemic and during the COVID-19 pandemic

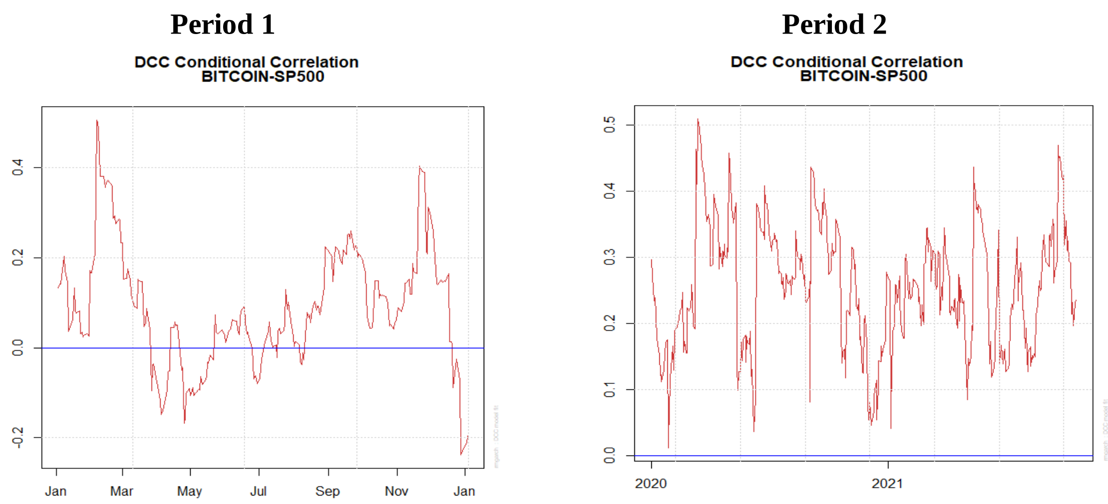

Fig 9. Conditional correlation of the Bitcoin market with the stock markets before the COVID-19 pandemic and during the COVID-19 pandemic

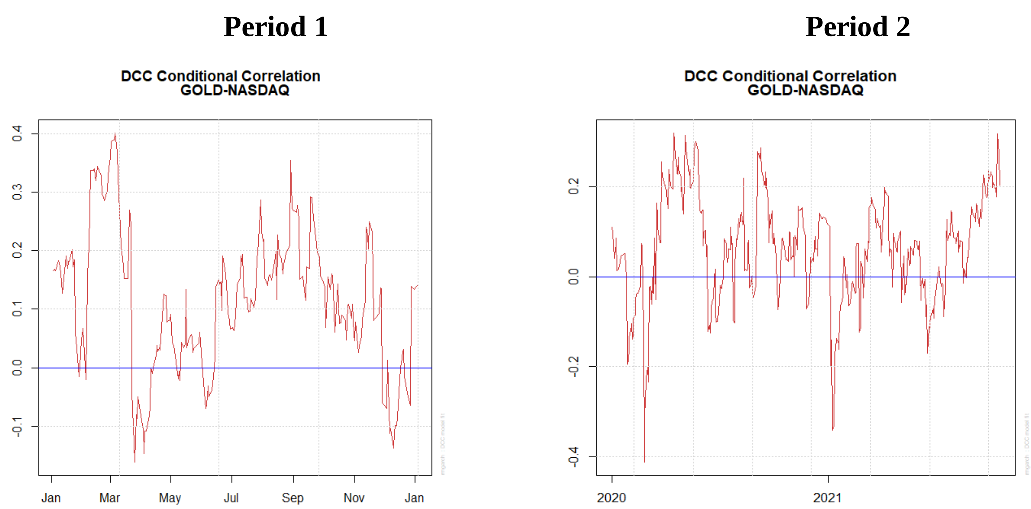

Fig 10. Conditional correlation of the gold market with the stock markets before the COVID-19 pandemic and during the COVID-19 pandemic

Except for pairwise comparison, conditional correlations are very volatile throughout the periods and markets but remain relatively low with values below 0.4.

The study finds that there is a more positive dependency between Bitcoin and the gold, stock market during the first part of each period, with the highest positive correlation reaching late 2020 (0.4). We observe that decoupling between the Bitcoin and gold markets is more pronounced just before the beginning of the COVID-19 pandemic, with the highest negative peak obtained in late 2019 (-0.3).

In addition, Bitcoin has a higher relationship with the S&P500 stock market with the most positive conditional correlation values obtained, during the COVID-19 pandemic. In particular, the strongest correlation value is observed in March 2020 with a value above 0.5. This indicates that the behavior of Bitcoin in stock markets is quite similar to traditional investments.

During the pandemic crisis period, correlations rise, reducing the effect of potential diversification of assets. Further, conditional correlations between gold-Nasdaq reached the highest positive values in the first period and the highest negative during the COVID-19 pandemic which brings into question its behavior as an asset class. This result confirms the general observation that gold returns are inversely proportionate to the situation in the stock markets. Furthermore, we observe that the conditional correlations between gold and other assets are the lowest regardless of the period.

To the forecasting performance of the ARMA-DCC-GARCH (1, 1) model, first, the predicted covariances and correlations are compared. They are both visually observed. Forecasting values calculated in a sample from the last 10 days, are represented in red. Correlations Figures give focus on the last 20 days' estimations.

Period 1 **Period 2**

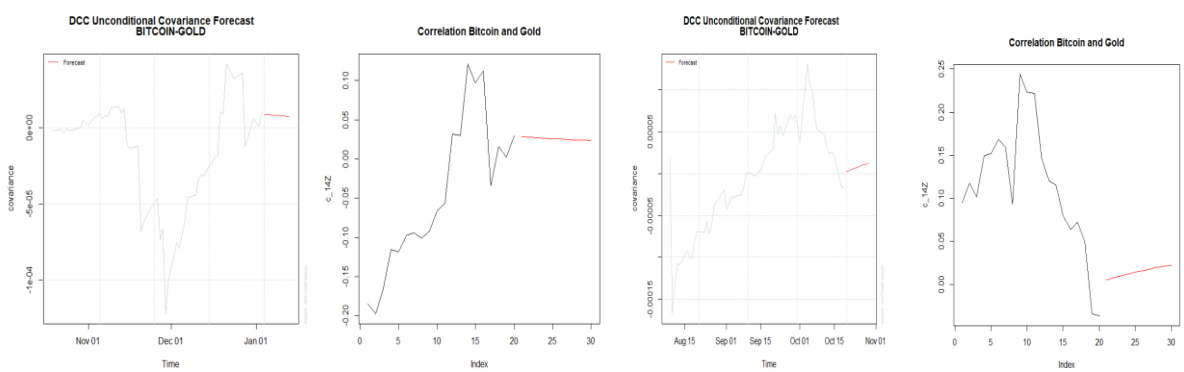

Fig 11. Forecasted conditional covariance and correlation of Bitcoin with the gold market before the COVID-19 pandemic and during the COVID-19 pandemic

Period 1 **Period 2**

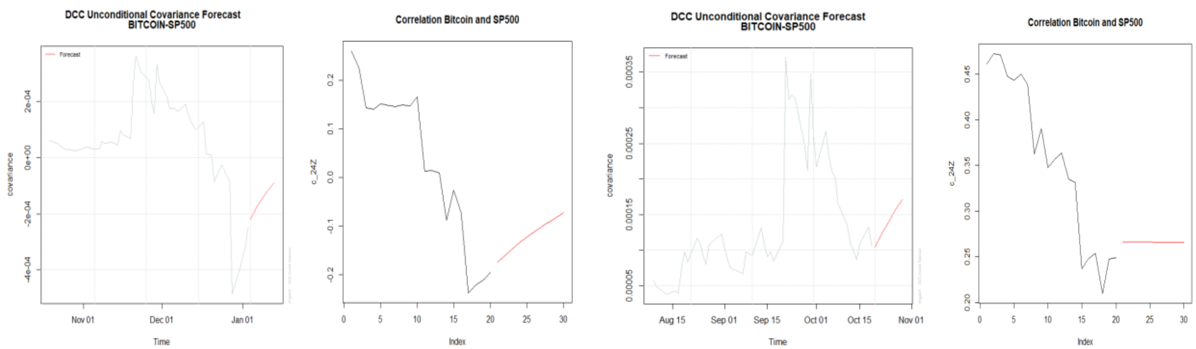

Fig 12. Forecasted conditional covariance and correlation of Bitcoin with the stocks markets before the COVID-19 pandemic and during the COVID-19 pandemic

Period 1 **Period 2**

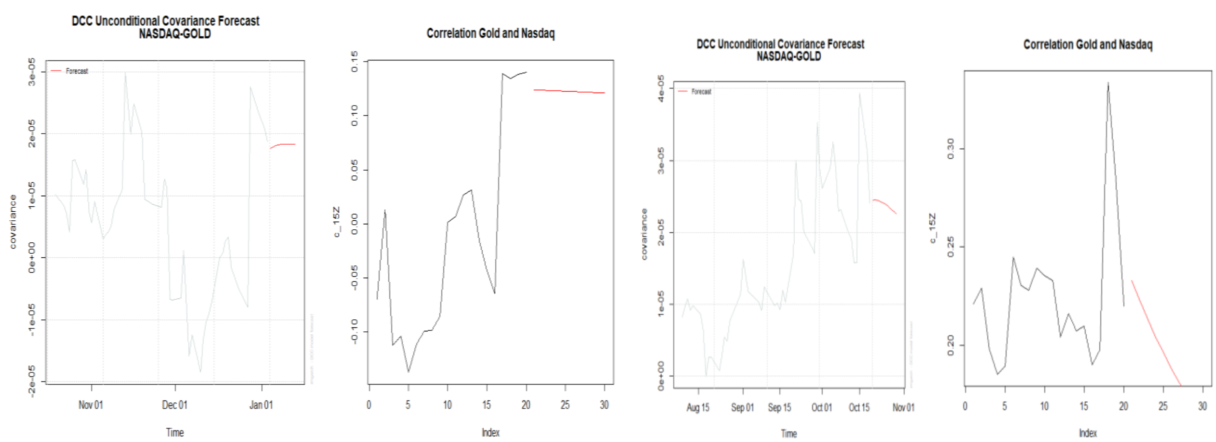

Fig 13. Forecasted conditional covariance and correlation of gold with the stocks markets before the COVID-19 pandemic and during the COVID-19 pandemic

The predicted interdependences of Bitcoin with gold observed are relatively low whatever the period (around 0.003).

The interrelations between Bitcoin and the S&P500 negatively correlated during the first period are expected to increase at the end of 2019, and during the second period, the forecasting values show a long-run tendency to behave as any asset investment with a positive correlation of around 0.2.

The same trend is observed between the gold and the S&P500 for the first period, showing that at the end of 2019, the forecasted correlation values are positive but to a lesser extent (around 0.1). However, the forecasted conditional correlations are expected to decline during the COVID-19 period.

More generally, it should be observed an increasingly noticeable value of the conditional correlations at the end of 2019 corresponds to the beginning of the pandemic period.

We carry out the analysis by forecasting conditional volatilities (Figures 14-15). Forecasting results are calculated for horizons from 1 to 10 days. To compare the conditional volatilities, we simply use the absolute values of daily returns as a proxy measure for the realized volatility.

Period 1

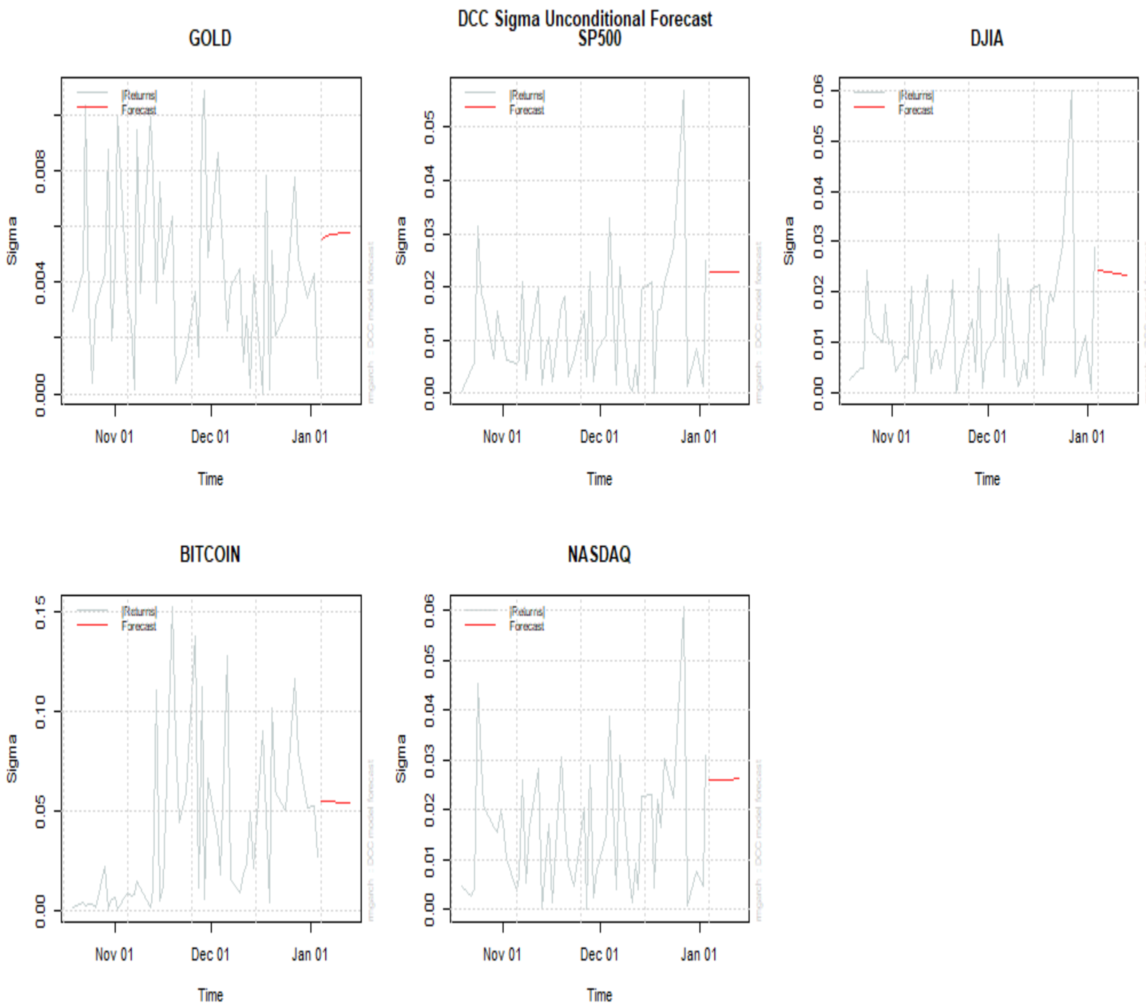

Fig 14. Conditional volatilities of all data before the COVID-19 pandemic

From the above graphs, we can observe that the volatilities have a time-varying nature. While the volatility trend is similar to the stock market indexes with a sharp increase at the end of 2019, Bitcoin has two phases with relatively low volatility until the end of November 2018 and a strong upward recovery thereafter. As for gold, it seems to have stochastic volatility. The forecasted conditional volatility among the stock market indexes follows relatively the same trend. Conversely, we observe a significant jump in volatility for Bitcoin and gold with values rising around from 0.025 to 0.05 and 0.0015 to 0.005 respectively.

Period 2

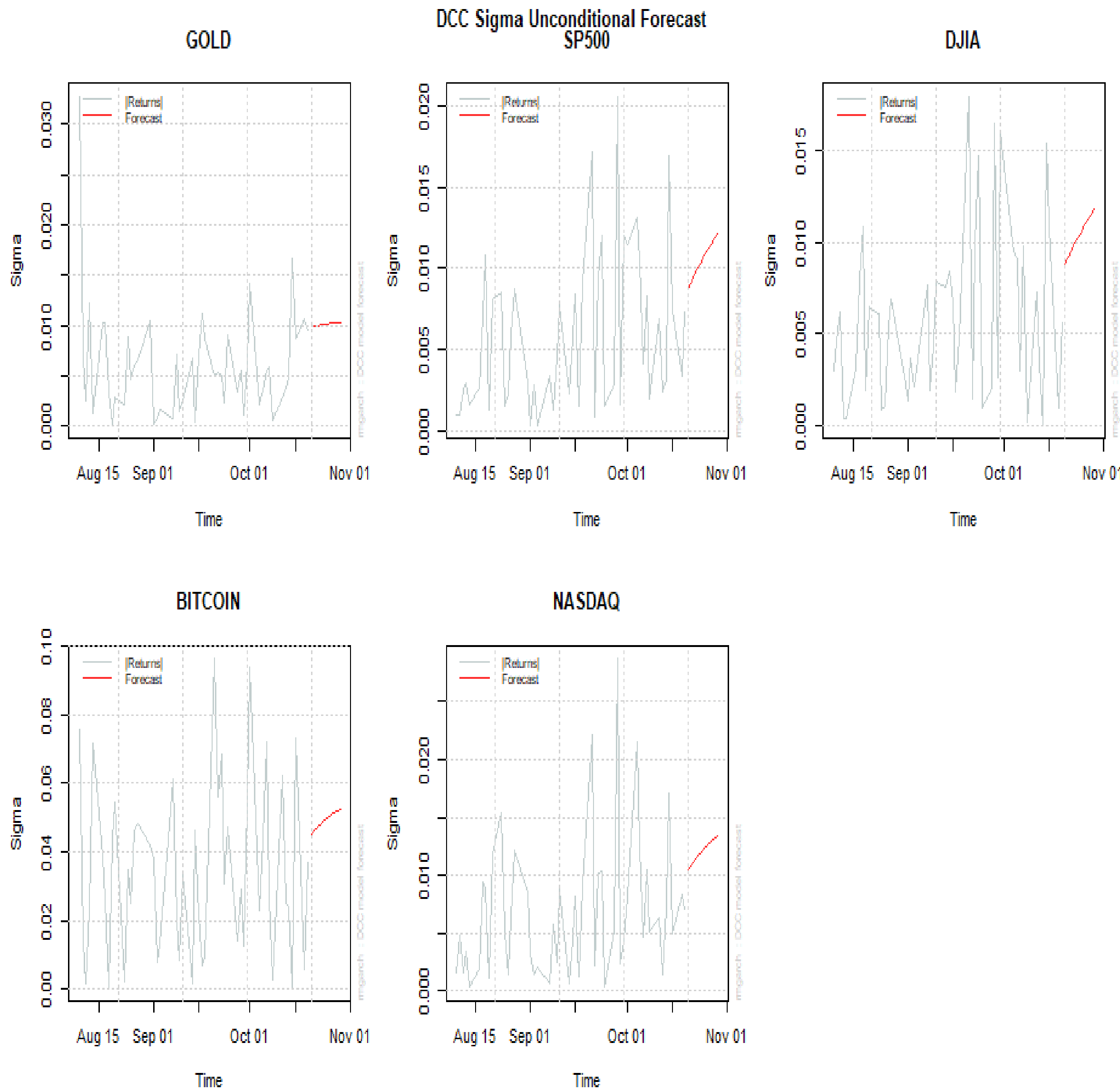

Fig 15. Conditional volatilities of all data during the COVID-19 pandemic

In the second period, all markets show close movements of volatilities to higher levels than before except the gold which acts differently from the others.

The gold market does not seem to be integrated with the other markets over the whole period. One of the major reasons for this smooth volatility in the gold market is the herding behavior of investors toward the markets where their returns were relatively much higher in particular in Bitcoin. Therefore, the forecasts of volatility are then expected to rise. To test and compare the forecast ability of our model, we use different measures of forecast error accuracies.

The measures of accuracy of the data before the COVID-19 pandemic and during the COVID-19 pandemic are given in Table 7 and Table8.

Table 7. The performance measures of the ARMA-DCC-GARCH model (before the COVID-19 pandemic)

Dataset		ME	RMSE	MAE	MSE
Before COVID-19 pandemic	Bitcoin	0.001949307	0.0315814	0.02384335	0.0009973848
	Gold	-0.001796576	0.003101673	0.002679798	9.620375e-06
	Nasdaq	0.001235751	0.01705151	0.01320691	0.000290754
	S&P 500	0.001922411	0.01637957	0.01196961	0.0002682903
	Dow Jones	0.004812155	0.01736429	0.01235008	0.0003015184

Table 8. The performance measures of the ARMA-DCC-GARCH model (during the COVID-19 pandemic)

Dataset		ME	RMSE	MAE	MSE
During COVID-19 pandemic	Bitcoin	-0.02232378	0.03465059	0.03095034	0.001200663
	Gold	0.002331242	0.004792867	0.003971269	2.297157e-05
	Nasdaq	-0.008122331	0.00902692	0.008415124	8.148528e-05
	S&P 500	-0.006509058	0.007698252	0.007249146	5.926308e-05
	Dow Jones	-0.006295033	0.007931926	0.006899123	6.291545e-05

The MSE, RMSE, and MAE indicators show that the forecasting performance of the ARMA-DCC-GARCH model is better during the COVID-19 pandemic for the stock market indexes, while for the other assets, the model better explains the realized volatility before the Covid-19 pandemic period, especially for the gold.

To obtain more results in forecasting, we apply a second approach to predict the Bitcoin, Gold, and stock markets.

5.2. Results of the NAR-NN model

The NAR-NN method is created to predict the value of Bitcoin, gold, and stock markets. Two performance measures MSE and R are used to compare the results of the NAR-NN methods (Table 9). The average squared difference between outputs and targets is known as MSE. It is better if the value is as low as possible. There is no error if the value of MSE, RMSE, and MAE is zero. For example, the value of MSE varies between 0.000505 and 0.001252. The correlation between outputs and targets is also measured by regression R values in this paper. A close relationship has an R-value of 1. In this study, the value of R varies between 0.97789 and 0.99667. The results of performance measures including MSE, RMSE, MAE, and R demonstrated that the proposed NAR-NN has remarkable performance for Bitcoin, gold, and stock markets. For modeling and prediction of nonlinear time series, NAR-NN can be used as a powerful computational method for Bitcoin, gold, and stock markets.

Table 9. The performance measures of the NAR-NN model

Dataset		MSE	RMSE	MAE	R
Before COVID-19 pandemic	Bitcoin	0.000871	0.029513	0.015446	0.987107
	Gold	0.000505	0.022472	0.017890	0.996473
	Nasdaq	0.001134	0.033675	0.021666	0.980638
	S&P 500	0.000952	0.030854	0.020254	0.984941
	Dow Jones	0.001252	0.038445	0.025593	0.977891
During COVID-19 pandemic	Bitcoin	0.000649	0.025475	0.013399	0.996665
	Gold	0.001021	0.031953	0.024353	0.984572
	Nasdaq	0.000536	0.023152	0.014896	0.995732
	S&P 500	0.000971	0.031161	0.016240	0.993483
	Dow Jones	0.000785	0.024658	0.015667	0.993182

6. Discussion and conclusion

The coronavirus had been spreading since late 2019 and has now spread around the world. This has affected almost every aspect of the world, and economics is one of the areas that had inevitably been affected.

On the other hand, the coronavirus pandemic in the world did not only target human health. This crisis has caused the world to experience an unprecedented recession in the economy. The value of the dollar, the euro, the pound, and other global currencies fell sharply. Industrial and economic indicators such as S&P500, Nasdaq, and Dow Jones in the United States have reached a point on the chart that may be unprecedented in the last two decades. Many investors who bought government bonds saw the real value of their savings has declined.

This paper investigates the dynamic nexus of Bitcoin, gold, and stock markets during the outbreak of the COVID-19 pandemic. We tested the model conditional volatility, and we used ARMA-DCC-GARCH and NAR-NN models.

We explored the relationship between Bitcoin and other financial assets' volatilities using data from Bitcoin, American indexes (S&P500, Nasdaq, and Dow Jones), and gold prices. Because the Bitcoin market exhibits low dynamic conditional correlations with financial assets during the stability phase, our findings support the notion that they are a new investment asset class. However, we notice that the link between Bitcoin, American indexes, and gold has strengthened since the beginning of 2020, confirming the coronavirus's contagious effect.

We tested if Bitcoin can be used as a stock market hedge in our study. We've looked into the advantages of hedging through diversification between Bitcoin and stock markets. We may compare its hedging ability to gold using this method of study. If the COVID-19 confirmed cases shocks are integrated into variance specifications, our empirical findings demonstrate a substantial dynamic conditional correlation between Bitcoin, gold, and stock markets. The existence of financialization of Bitcoin, gold, and stock markets is demonstrated by these empirical findings.

Based on our results, the estimation of the ARMA-DCC-GARCH model parameters allows for determining the values of the conditional correlation for the pairs of series, and by using the ARMA-DCC-GARCH model, we observe that the tail behavior of Bitcoin and gold, as well as the stock market index, is very similar in terms of contemporaneous correlation. Also, The MSE, RMSE, and MAE indicators reveal that the ARMA-DCC-GARCH estimations achieve better forecasting performance during the COVID-19 pandemic for the stock market indexes, while for the other assets, the model better explains the realized volatility before the COVID-19 pandemic period, especially for the gold.

Based on the results of the nonlinear autoregressive neural network model, the results of performance measures including MSE, RMSE, MAE, and R demonstrated that the proposed NAR-NN has remarkable performance for Bitcoin, gold, and stock markets.

The forecasting performance comparisons between the econometric model and the ANN type model, show that the proposed ANN type model obtains a higher accuracy for forecasting for Bitcoin, showing that the excess volatility in Bitcoin prices is better to capture for the NAR-NN model.

These results could be further confirmed in future research including a greater number of GARCH-type models and ANN types and architectures, particularly to observe if both models have been shown to outperform one another in different forecasting experiments, and to understand which specific situations each model may be better suited. This would expand the evidence obtained in this study and provide greater guidance on which models to use for different volatility profiles for the best forecasting results.

Our findings contribute to the study of the pandemic's financial and economic effects by demonstrating that COVID-19 surprises have bidirectional spillover impacts on the Bitcoin, gold, and stock markets. Considering these results, the observed behavior in all markets indicated verification of the COVID-19 surprises, but the degree of influence of the pandemic on the data was different. The most market efficiency declines in American indexes, while the least in the Bitcoin market.

7. Managerial and theoretical implications

This paper provides evidence on which analyzed assets are the best safe haven for the investors acting in the time of the crisis. Also, our findings have important implications for investors who seek protection from downward movements in financial markets. Furthermore, our findings could be of interest to regulators and governments to engage in more discussion of the role of Bitcoin in financial markets.

From a theoretical perspective, the results of our study give theoretical proof that COVID-19 has effects on the Bitcoin, gold, and stock markets.

From a policy-making perspective, getting accurate practical justifications of the volatility of the Bitcoin, gold, and stock markets during the COVID-19 pandemic is an essential stage in establishing advantageous monetary policy strategies and correct tactics.

From the perspective of portfolio risk managers, we discovered that the diversification benefits of Bitcoin are generally consistent and increase dramatically during periods of market volatility. As a result, using Bitcoin in a stock market portfolio lowers the portfolio's risk. These findings have important implications for investors and portfolio managers. Also, our findings have substantial implications for regulators' oversight of financial markets during a global crisis, as well as investors' cross-market hedging of systemic shock spillover risks.

8. Limitations of the study and scope for further research

The key limitation of the study is the small study duration covering the pandemic period. Extension in time gives more choices to select other proxies as a market return to evaluate financial markets. Also, it is still unclear whether the economic or political conditions of each country under study may affect the empirical results.

These limitations open the door for future research to investigate the nexus of the volatility of the Bitcoin, gold, and stock markets over a longer period and the different models that it is helpful for policymakers, investors, and portfolio risk managers while investing in these markets. Additionally, concerning reported volatility interaction, it is interesting to expand the analysis for the observation of structural breaks in the level of correlation with the separation of high and low volatility periods of the Bitcoin, gold, and stock markets and asymmetric leverage effect by using different volatility models.

Appendix: Further analysis

Appendix A

The BDS test results

Appendix A shows the full estimation result of the BDS test. These results are given in tables A1-A10.

Table A1. Results of the BDS test for the Bitcoin (period1)

Standard Normal	[0.0255]	[0.051]	[0.0766]	[0.1021]
[2]	3.5935	1.4685	0.621	0.4114
[3]	5.3615	2.2931	1.338	1.4777

p-value	[0.0255]	[0.051]	[0.0766]	[0.1021]
[2]	3e-04	0.1420	0.5346	0.6808
[3]	0e+00	0.0218	0.1809	0.1395

Table A2. Results of the BDS test for Bitcoin (period 2)

Standard Normal	[0.0257]	[0.0514]	[0.0771]	[0.1028]
[2]	1.5313	1.6129	1.6859	1.1467
[3]	1.9129	1.7570	1.9782	1.5056

p-value	[0.0257]	[0.0514]	[0.0771]	[0.1028]
[2]	0.1257	0.1068	0.0918	0.2515
[3]	0.0558	0.0789	0.0479	0.1322

Table A3. Results of the BDS test for the gold (period1)

dimension	[0.0029]	[0.0058]	[0.0087]	[0.0116]
[2]	0.6175	0.5726	0.7929	1.1822
[3]	1.7178	1.3244	1.1294	1.8261

p-value	[0.0029]	[0.0058]	[0.0087]	[0.0116]
[2]	0.5369	0.5669	0.4278	0.2371
[3]	0.0858	0.1854	0.2587	0.0678

Table A4. Results of the BDS test for the gold (period2)

dimension	[0.0054]	[0.0107]	[0.0161]	[0.0215]
[2]	2.0750	2.3132	2.2700	1.9440
[3]	2.6231	3.0084	3.1218	2.8998

p-value	[0.0054]	[0.0107]	[0.0161]	[0.0215]
[2]	0.0380	0.0207	0.0232	0.0519
[3]	0.0087	0.0026	0.0018	0.0037

Table A5. Results of the BDS test for the Nasdaq (period 1)

Standard Normal	[0.0067]	[0.0134]	[0.0201]	[0.0268]
[2]	3.3238	3.9718	4.0741	2.8009
[3]	4.9243	5.5791	5.3840	3.4733

p-value	[0.0067]	[0.0134]	[0.0201]	[0.0268]
[2]	9e-04	1e-04	0	0.0051
[3]	0e+00	0e+00	0	0.0005

Table A6. Results of the BDS test for the Nasdaq (period 2)

Standard Normal	[0.0093]	[0.0186]	[0.0279]	[0.0372]
[2]	6.2939	6.4428	7.2422	8.4309
[3]	9.5319	9.4761	9.9760	10.6629

p-value	[0.0093]	[0.0186]	[0.0279]	[0.0372]
[2]	0	0	0	0
[3]	0	0	0	0

Table A7. Results of the BDS test for the S&P 500 (period1)

Standard Normal	[0.0055]	[0.011]	[0.0165]	[0.022]
[2]	3.1116	4.4262	5.4745	4.7751
[3]	5.1545	6.1545	6.1165	4.7849

p-value	[0.0055]	[0.011]	[0.0165]	[0.022]
[2]	0.0019	0	0	0
[3]	0.0000	0	0	0

Table A8. Results of the BDS test for the S&P 500 (period 2)

Standard Normal	[0.0086]	[0.0173]	[0.0259]	[0.0345]
[2]	9.9265	9.5387	10.0702	10.3698
[3]	13.5177	12.7361	12.9357	12.9930

p-value	[0.0086]	[0.0173]	[0.0259]	[0.0345]
[2]	0	0	0	0
[3]	0	0	0	0

Table A9. Results of the BDS test for the Dow Jones (period1)

Standard Normal	[0.0058]	[0.0116]	[0.0174]	[0.0232]
[2]	2.6649	3.4484	4.5587	4.0871
[3]	4.3535	4.6992	5.0688	4.2625

p-value	[0.0058]	[0.0116]	[0.0174]	[0.0232]
[2]	0.0077	6e-04	0	0
[3]	0.0000	0e+00	0	0

Table A10. Results for the Dow Jones (period 2)

Standard Normal	[0.0091]	[0.0182]	[0.0273]	[0.0364]
[2]	9.4903	10.4222	11.1876	10.8716
[3]	12.4147	13.0544	13.6174	13.3733

p-value	[0.0091]	[0.0182]	[0.0273]	[0.0364]
[2]	0	0	0	0
[3]	0	0	0	0

Appendix B

The Ljung box test Results

Appendix B shows tests for autocorrelation in the returns using the Ljung Box test.

Tables B1-B2 report the Q-Statistic and P-value for Bitcoin, gold, and the stock market indexes.

Table B1. Q-Statistic and P-value for return series (period 1)

Return Series	Q-Statistic	P-value
Bitcoin	26.321	0.155
Gold	28.856	0.090
Nasdaq	25.763	0.173
SP500	22.787	0.299
Dow Jones	21.088	0.391

Table B2. Q-Statistic and P-value for return series (period 2)

Return Series	Q-Statistic	P-value
Bitcoin	26.724	0.1432
Gold	44.644	0.0012
Nasdaq	201.24	<2.2e-16
SP500	275.06	<2.2e-16
Dow Jones	276.69	<2.2e-16

Tables B3-B12 report the estimation of ARMA processes in the returns of the series for 2 periods.

Table B3. Estimation of ARMA processes in the returns for Bitcoin (period 1)

Bitcoin	Estimate	Std.Error	Z.value	Pr(>|z|)
ar1	-0.8038801	0.1414516	-5.6831	1.323e-08***
ma1	0.6952982	0.1673226	4.1554	3.247e-05***
intercept	-0.0054691	0.0029931	-1.8273	0.06766.

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B4. Estimation of ARMA processes in the returns for Gold (period 1)

Gold	Estimate	Std.Error	Z.value	Pr(>|z|)
ma1	1.6755e-01	6.5118e-02	2.5730	0.01008*
ma2	-1.6851e-01	7.1446e-02	-2.3586	0.01835*
intercept	-7.9725e-05	3.6214e-04	-0.2201	0.82575

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B5. Estimation of ARMA processes in the returns for Nasdaq (period 1)

Nasdaq	Estimate	Std.Error	Z.value	Pr(>|z|)
Intercept	-0.00032550	0.00085021	-0.3828	0.7018

Table B6. Estimation of ARMA processes in the returns for S&P500 (period 1)

SP500	Estimate	Std.Error	Z.value	Pr(>|z|)
Intercept	-0.00038900	0.00069905	-0.5565	0.5779

Table B7. Estimation of ARMA processes in the returns for Dow Jones (period 1)

Dow Jones	Estimate	Std.Error	Z.value	Pr(>|z|)
ar1	-0.84525625	0.09072018	-9.3172	<2.2e-16***
ma1	0.87313807	0.10948323	7.9751	1.523e-15***
ma2	-0.08122078	0.07436275	-1.0922	0.2747
intercept	-0.00034696	0.00070417	-0.4927	0.6222

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B8. Estimation of ARMA processes in the returns for Bitcoin (period 2)

Bitcoin	Estimate	Std.Error	Z.value	Pr(>|z|)
ar1	-0.584364	0.038407	-15.215	<2.2e-16***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B9. Estimation of ARMA processes in the returns for Gold (period 2)

Gold	Estimate	Std.Error	Z.value	Pr(>|z|)

ma1	0.08010648	0.04397207	1.8218	0.06849.
intercept	0.00034865	0.00054814	0.6361	0.52474

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B10. Estimation of ARMA processes in the returns for Nasdaq (period 2)

Nasdaq	Estimate	Std.Error	Z.value	Pr(>|z|)
ma1	-0.2673590	0.0459941	-5.8129	6.140e-09***
ma2	0.2269849	0.0454838	4.9905	6.024e-07***
intercept	0.0011666	0.0007935	1.4701	0.1415

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B11. Estimation of ARMA processes in the returns for S&P500 (period 2)

SP500	Estimate	Std.Error	Z.value	Pr(>|z|)
ma1	-0.24952508	0.04497351	-5.5483	2.885e-08***
ma2	0.27280904	0.04618864	5.9064	3.496e-09***
intercept	0.00074805	0.00077772	0.9619	0.3361

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Table B12. Estimation of ARMA processes in the returns for Dow Jones (period 2)

Dow Jones	Estimate	Std. Error	Z.value	Pr(>|z|)
ma1	-0.23666319	0.04722927	-5.0109	5.416e-07***
ma2	0.28672704	0.04561841	6.2853	3.271e-10***
ma3	-0.07561065	0.04787882	-1.5792	0.1143
intercept	0.00047930	0.00078347	0.6118	0.5407

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Appendix C

The Lagrange Multiplier Test

Appendix C shows autocorrelation in the squared of the returns using the Lagrange Multiplier Test for 2 periods (See Table C1-C10).

Table C1. Estimation of autocorrelation in the squared of the returns for Bitcoin (period 1)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	173.4	0.00e+00
[2,]	8	77.6	4.23e-14
[3,]	12	46.7	2.39e-06
[4,]	16	27.8	2.27e-02
[5,]	20	20.9	3.41e-01
[6,]	24	11.3	9.80e-01

Table C2. Estimation of autocorrelation in the squared of the returns for gold (period 1)

Lagrange-Multiplier test	order	LM	p.value
[1,]	4	65.17	4.63e-14
[2,]	8	29.24	1.31e-04
[3,]	12	18.33	7.42e-02
[4,]	16	12.77	6.20e-01
[5,]	20	9.56	9.63e-01
[6,]	24	7.34	9.99e-01

Table C3. Estimation of autocorrelation in the squared of the returns for Nasdaq (period 1)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	156.03	0.00e+00
[2,]	8	55.70	1.09e-09
[3,]	12	31.95	7.78e-04
[4,]	16	19.90	1.76e-01
[5,]	20	12.75	8.51e-01
[6,]	24	9.22	9.95e-01

Table C4. Estimation of autocorrelation in the squared of the returns for S&P500 (period 1)

Lagrange-Multiplier test	order	LM	p.value
[1,]	4	224.6	0.00e+00
[2,]	8	86.4	6.66e-16
[3,]	12	54.1	1.11e-07
[4,]	16	28.4	1.90e-02
[5,]	20	19.9	3.99e-01
[6,]	24	13.1	9.49e-01

Table C5. Estimation of autocorrelation in the squared of the returns for Dow Jones (period 1)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	171.9	0.00e+00
[2,]	8	76.5	7.11e-14
[3,]	12	47.7	1.62e-06
[4,]	16	30.1	1.16e-02
[5,]	20	20.7	3.53e-01
[6,]	24	12.5	9.62e-01

Table C6. Estimation of autocorrelation in the squared of the returns for Bitcoin (period 2)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	1711	0
[2,]	8	770	0
[3,]	12	495	0
[4,]	16	358	0
[5,]	20	279	0
[6,]	24	225	0

Table C7. Estimation of autocorrelation in the squared of the returns for gold (period 2)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	647.2	0.00e+00
[2,]	8	165.7	0.00e+00
[3,]	12	106.2	0.00e+00
[4,]	16	71.7	2.23e-09
[5,]	20	56.1	1.57e-05
[6,]	24	44.7	4.35e-03

Table C8. Estimation of autocorrelation in the squared of the returns for Nasdaq (period 2)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	277.2	0.00e+00
[2,]	8	125.4	0.00e+00
[3,]	12	71.4	6.57e-11
[4,]	16	52.0	5.62e-06
[5,]	20	36.6	8.87e-03
[6,]	24	27.6	2.29e-01

Table C9. Estimation of autocorrelation in the squared of the returns for S&P500 (period 2)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	289.8	0.00e+00
[2,]	8	121.8	0.00e+00
[3,]	12	60.6	7.31e-09
[4,]	16	43.8	1.18e-04
[5,]	20	30.5	4.54e-02
[6,]	24	24.3	3.87e-01

Table C10. Estimation of autocorrelation in the squared of the returns for Dow Jones (period 2)

Lagrange-Multipliertest	order	LM	p.value
[1,]	4	317.7	0.00e+00
[2,]	8	121.7	0.00e+00
[3,]	12	54.6	9.04e-08
[4,]	16	38.6	7.46e-04
[5,]	20	27.7	9.00e-02
[6,]	24	22.0	5.18e-01

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