VIRTUAL ECONOMICS

ISSN 2657-4047*(online)*

2022 Volume 5 Number 2

INVESTMENT IN VIRTUAL DIGITAL ASSETS VIS-A-VIS EQUITY STOCK AND COMMODITY: A POST-COVID VOLATILITY ANALYSIS

Nishi Sharma, Shailika Rawat, and Arshdeep Kaur

Abstract. Virtual digital assets including cryptocurrencies, non-fungible tokens and decentralized financial asset have been initially used as an alternative currency but are currently being purchased as an asset and hedging instruments. Exponentially growing trading volume witnesses the growing inclination of investors towards these assets, and this calls for volatility analysis of these assets. In this reference, the present study assessed and compared the volatility of returns from investment in virtual digital assets, equity and commodity market. Daily closing prices of selected cryptocurrencies, non-fungible tokens and decentralized financial assets, stock indices and commodities have been analysed for the post-covid period. Since returns were observed to be heteroscedastic, autoregressive conditional heteroscedastic models have been used to assess the volatility. The results indicate a low correlation of commodity investment with all other investment opportunities. Also, Tether and Dai have been observed to be negatively correlated with stock market. This indicates the possibility of minimizing risk through portfolio diversification. In terms of average returns, virtual digital assets are discerned to be better options than equity stock or commodity yet the variance scenario of these investment avenues is not very rosy. The volatility parameters reveal that unlike commodity market, virtual digital assets have got a significant impact of external shocks in the short-run. Further, the long run persistency of shocks is observed to be higher for the UK stock market, followed by Ethereum, Tether and Dai. The present analysis is crucial as the decision about its acceptance as legal tender money is still sub-judice in some countries. The results are expected to provide insight to regulatory bodies about these assets.
Keywords: autoregressive conditional heteroscedastic model, cryptocurrencies, decentralized financial assets, non-fungible tokens, risk-return analysis
JEL Classification: G110

ISSN 2657-4047*(online)*

Authors:

Nishi Sharma
University Institute of Applied Management Sciences, Panjab University, Chandigarh, India
E-mail: nishi.uiams@pu.ac.in; jmdnishi@yahoo.com
https://orcid.org/0000-0002-5561-331X

Shailika Rawat
University Institute of Applied Management Sciences, Panjab University, Chandigarh, India
E-mail: shailikarawat765@gmail.com
https://orcid.org/0000-0002-4772-2049

Arshdeep Kaur
Department of Commerce, Mehr Chand Mahajan DAV College for Women, Chandigarh, India
E-mail: dr.arshdeepkaur@gmail.com
https://orcid.org/0000-0002-0809-1491

Citation: Sharma, N., Rawat, S., & Kaur, A. (2022). Investment in Virtual Digital Assets Vis-A-Vis Equity Stock and Commodity: A Post-Covid Volatility Analysis. *Virtual Economics, 5*(2), 95-113. https://doi.org/10.34021/ve.2022.05.02(5)

Received: August 23, 2022. Revised: August 31, 2022. Accepted: September 27, 2022.

1. Introduction

A digital asset is an intangible asset that is created, traded and stored in a digital format. It can also be used as a currency to make transactions. David Chaum, an American cryptographer and computer scientist founded DigiCash in 1989 as 'electronic money' (Hayes 2019). DigiCash was an early electronic payment system that needed user's software to withdraw bank notes and identify certain encryption keys. Unlike other currencies, DigiCash transactions are governed by the series of cryptographic protocols (Batten and Yi 2019). The use of cryptographic protocols ensures that all information and communications are available to intended users only. Later, these protocols are being applied to some other currencies as well. Therefore, DigiCash can be assumed to be a predecessor of modern digital currencies. Here it is pertinent to mention that DigiCash remain in operation for less than a decade due to the company's failure to persuade banks to use this technology. As a result, the company declared a bankruptcy in 1998. Despite the fact that DigiCash never really took off, it proved to be a milestone to build the groundwork for today's thriving cryptocurrency industry. Apart from DigiCash, there are other significant digital currency projects such as Hashcash (1997), B-money (1998), and Bit Gold (1998). However, these projects had their own limitations and challenges. To overcome these challenges, blockchain technology was applied during 2000s. The blockchain technology was devised by Haber and Stornetta in 1991 as a decentralized database (i.e., electronic ledger) that is used to record the ownership of digital assets in a secured form. It ensures transparency, integrity and security of information (Kitsantas et al. 2019). The digital assets that transact using blockchain technology are known as 'Virtual Digital Asset' (VDA).

Virtual Digital Assets are subsets of all digital assets transacted on a blockchain technology. In simple words, VDA is a digital representation of a value that can be digitally traded or transferred or can be used for payment / investment purposes. Satoshi Nakamoto firstly utilized blockchain technology for virtual digital assets Bitcoin in 2008 (Bamakan et al. 2022). In present days, blockchain technology is frequently used in virtual digital assets including cryptocurrency, decentralized finance and non-fungible tokens (Chevet, 2018). These VDAs can be overviewed as follows:

- Cryptocurrency: Crypto-currency, also known as alternative currency and virtual currency, is a form of digital currency. The enticing characteristic of a cryptocurrency is that it allows anonymity to its users while providing safe, secure and valid transactions. Due to a distinct characteristic of not being issued by any central authority, it offers a unique advantage of the least government interference. The first cryptocurrency invented by an American cryptographer and electronic currency pioneer David Chaum (Narayanan and Clark 2017) was 'DigiCash'. The DigiCash was based on cryptography to verify and secure the transactions. During early 1990s, cryptographic protocols and software have been developed to make decentralized digital currency practicable. Satoshi Nakamotomay (2008) was given a credit for popularising the cryptocurrency at the international level through highlighting the advantages of peer-to-peer electronic cash system of Bitcoin. With the advent of Bitcoin during 2008, the market for cryptocurrencies registered a remarkable growth. Cryptocurrency is gaining popularity because it is easier to use cryptocurrency (Baur et al. 2015). During August 2022, the top five cryptocurrencies with highest market capitalization were Bitcoin, Ethereum, Tether, United States Dollar (USD) Coin, Binance Coin.

- Non-Fungible Token (NFT): Another popular VDA based upon blockchain technology is Non-Fungible Token (NFT). It has a unique feature of non-interchangeability, which distinguishes it from physical money as well as cryptocurrencies. The term 'non-fungible' implies that it is unique and cannot be traded or exchanged. Each NFT has a digital signature which makes them unique. The first-known NFT 'Quantum' was introduced by a digital artist Kevin McCoy in 2014, using Namecoin blockchain. During 2017, Ethereum block chain, which was initially used for cryptocurrencies (cryptopunks and cryptokitties), was applied for NFTs as well. During August 2022, the top five NFTs with highest market capitalization were Decentraland, Sandbox, Tezos, Theta, Chiliz.
- Decentralized Financial Assets (DeFi): DeFi, the first peer-to-peer digital currency based on blockchain technology, was launched in 2009 with Bitcoin. However, the introduction of Dai by Maker (decentralized autonomous organization) in December 2017 was a watershed moment for financial applications ranging from simple transfers and payments to lending, borrowing, trading, portfolio management and insurance. With DeFi lending, the users can lend their cryptocurrency, similar to practices of a traditional bank with fiat currency and could earn interests as a lender. As compared to traditional banks, the interest rates are more alluring in DeFi lending and also there are fewer barriers to borrow loan. Defi uses Ethereum-based protocol which is much faster and more robust than Bitcoin block-chain. Each block of information on the Ethereum blockchain is verified and created in every 10-20 seconds. During August 2022, the top five Defis with the highest market capitalization were Avalanche, Dai, Uniswap, Wrapped Bitcoin, Chainlink.

The VDA gained attention with the launch of Initial Coin Offerings (ICO) by Brock Pierce and Scott Walker in July 2013 whereby investors could buy Mastercoins (Richter 2018). ICO provided a unique way for entrepreneurs to finance startups. Hsieh and Oppermann, (2021) observed that by 2017, ICO got huge popularity because it offered a unique advantage of a stake in the project's success. But at the same time, it brings a new set of risks (like cybertheft, trading halts, market manipulation) as well. The inherent risk attracted the attention of regulatory authorities towards the usage of VDA. Since these assets are characterized by a decentralized mechanism and absence of government intervention, these are under the bracket of high risk of fraud. The feature of these currencies' anonymity enables it to be misused for funding illegal activities like terrorism. That is the reason why, different countries are comparing the pros and cons of these currencies so that a decision regarding a permission or a ban may be taken. Across the globe, different countries have different views in this context. Some countries banned the use of these VDA options, some have allowed it and other countries are still in the process of decision making. The United States, Canada, Japan, Singapore, Iran, Russia, Italy, Venezuela, Mexico, South Africa, and Australia are friendly towards its use, while Brazil and China are hostile, while South Korea, Thailand and France are neutral towards it. In India, the government has not yet legalized the status of cryptocurrencies. But it is interesting to note that income earned from these assets is subject to tax liability. Cryptocurrencies have now been included in the definition of VDA for tax purposes. Recently in the Union Budget for 2022–23, the finance minister declared that virtual digital assets such as NFTs and cryptocurrencies will be subject to a 30% tax (Economic Times, February 1, 2022). As a result of the national budget's acknowledgment of digital assets and the application of clear tax laws, investors became more confident about their investments.

But the primary concern area for investors with respect to investment in VDA is the 'price volatility'. The prices of these assets are highly sensitive to shocks infused into the economy. Amongst the recent significant shocks, the outbreak of coronavirus during late 2019 was devastating. The coronavirus has shaken the entire world including markets for equity, commodity and VDA (Estrada et al. 2020; Mnif, et al. 2020; Senol and Zeren 2020; Zhang, et al. 2020 and Salisu, et al. 2021). After the outbreak of coronavirus, the investors experienced an unprecedented volatility in returns from all investment avenue including VDA, equity and commodities. Since, volatility is the primary concern for investor, there is a huge need to analyse the volatility involved in VDAs and compare the same with other investment options. In this context, the present study aims at comparing the volatility of returns from investment in VDA, stock market and commodity market during the post-covid period. To attain this purpose this paper is structured as follows: Section 2 summarises the literature review; Section 3 provides details about the data and methods used in the study; Section 4 discusses the empirical results, and, lastly, Section 5 provides the conclusions of the study.

2. Literature Review

Since the concept of VDA is comparatively new, not much work has been done in this domain. The primary focal point of researchers has been exploring the factors affecting the price of cryptocurrency. Like, Baek and Elbeck (2015) studied the determinants of bitcoin's market returns. The results indicate that the return is primarily driven by internal factors instead of external ones. Brière et al. (2015) researched the relationship between macroeconomic indicators and the Bitcoin's value and made conclusion about the absence of cause-and-effect relationship between macroeconomic indicators and the Bitcoin's value. Ciaian et al (2017) empirically examined the short- and long-run interdependencies between Bitcoin and Altcoin markets by using time-series analysis for the period of 2013–2016. The finding highlighted the interdependencies between Bitcoin and Altcoin markets. The study reported that the long-term macro-financial indicators influence Altcoin pricing to a slightly larger extent than they do for Bitcoin. Aste (2019) studied collective movements of prices and social sentiment with regard to two thousand cryptocurrencies traded during the first six months of 2018. The results indicate that there is a significant correlation between prices and sentiments. Guizani and Nafti (2019) analysed the main factors affecting the Bitcoin prices. The daily observations from December 2011 to February 2018 were analysed through autoregressive distributed lag model. The findings revealed that demand for Bitcoins has a significant impact on the prices in the short term as well as the long term. But no significant impact of supply was observed on the prices of currency. Nasir et al. (2019) analysed the impact of Google search values to predict the volume and returns of Bitcoin. The study applied a vector autoregression model on a weekly dataset from 2013 to 2017. The results reveal that shocks to search values have a favourable impact. Caporale and Plastun (2020) looked at the aftermath momentum effect of one day abnormal returns. The study reported existence of a momentum effect as the prices tend to move in the direction of the abnormal returns. The momentum effect was also observed on the following day.

In recent years, a volatility parameters of digital assets have started to attract researchers. Such studies on digital currency are equally important as these currencies gained their position beside conventional assets and made this market very risky through severe price fluctuations (Corbet et.al 2019). In this context, few studies analysed risk volatility involved in digital assets. Like Osterrieder et al. (2017) compared the volatility of cryptocurrencies with USD through 90-day rolling annualized volatility estimates. Their results illustrated the substantially larger volatility of cryptocurrency in comparison to any other standard financial assets. Dyhrberg et al. (2018) analysed the performance of cryptocurrency-Bitcoin to examine the worthiness of investment in it. Their study noticed that, like gold and USD, Bitcoin has hedging capabilities and that trading induces additional volatility in Bitcoin.

Chowdhury (2020) analysed the volatility of 15 cryptocurrencies and volatility index (VIX) of CBOE-traded from January, 2019 to June, 2020 through GARCH model. His results indicate significant elevations in volatility for six currencies viz. Nem, Neo, Monero, Tether, Cordano and Iota. The coefficients of Generalized Auto-regressive conditional Heteroscedastic (GARCH) model demonstrate that volatility of the previous day is repeated in the returns and volatility on the following day. Cabarcos et al. (2021) compared the volatility of S&P500 Index, VIX Index and Bitcoin over a period of January 2016 to September 2019. The study applied GARCH and Exponential GARCH models, whose results conclude that cryptocurrency Bitcoin acts as a safe haven. Further, cryptocurrency becomes more attractive to speculators during the condition of stability in stock markets. Woebbeking (2021) analysed the volatility of cryptocurrency along with the two popular stock indices of United States (viz., Standard and Poor's 500and Russell 2000), Gold and EUR/USD. The study concluded that Covid shock affected Bitcoin as well, however the reaction to shock was delayed in comparison to equity and gold. The findings indicate that global shocks affect cryptocurrencies and traditional assets alike, which is a serious limit to the benefits from diversification during times when it is needed the most. Maitra et.al, (2022) examined the risk spillover and hedging effectiveness by using the five-minute interval price data of two cryptocurrencies and eight stock market indexes. The results witnessed the risk spillover from Bitcoin and Ethereum to stock market returns. The results depicted that during the COVID-19 epidemic, optimal investments in Bitcoin and Ethereum have decreased while hedging costs went up. Karim et al. (2022) analysed the risk transmission among NFTs, DeFis, and Cryptos. The study observed significant volatility connectivity among blockchain markets. Further, the study noted that from the diversification point of view, NFTs demonstrated a higher potential in comparison to DeFis and Cryptos. To assess the potential of cryptocurrencies in the portfolio diversification, Khaki et al. (2022) conducted an analysis of the major cryptocurrencies based on their market capitalization and the major markets from MENA regions. The study discerned that cryptocurrencies offer the MENA markets a significant amount of potential for diversification. However, the study also observed that the use of cryptocurrencies should be made cautiously due to their extremely volatile price movements.

 ISSN 2657-4047(online)

It is worthwhile mentioning here that many studies at the international level are making attempts to disclose various facets of cryptocurrency. Here, it is pertinent to highlight the two major limitations. The first limitation is that, in spite of growing popularity of NFT and Defi, the primary focus of most researchers has been on cryptocurrency and studies analysing the rest two VDAs i.e., NFT and Defi, are in dearth. Further researchers (like Chowdhury 2020; Cabarcos et al., 2021; Woebbeking 2021; Khaki et al, 2022; Maitra et.al, 2022) primarily made a comparison of investment in cryptocurrency with investment in stock market but studies comparing the volatility of investment in VDA vis-à-vis commodity investment are scarce. In this reference, Dyhrberg et al., (2018) made an attempt to compare the performance of Bitcoin with Gold and USD but that study too has taken only Bitcoin as a proxy of cryptocurrencies and VDAs. To bridge these research gaps, the present paper aims at comparing the volatility of returns from investments in VDA (including cryptocurrencies, NFT, Defi) with equity investment in stock market and investment in the commodity market.

3. Methods

The present study aims at comparing the volatility of returns from investment in VDA versus returns generated from equity investment in stock market and investment in the commodity market. Thus, at the outset, logarithmic daily returns were calculated by the following formula:

$$\mathrm{Return}_{\mathrm{t}} = \log\left(\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}}\right), \tag{1}$$

where $\mathrm{P_t}$ represents the closing price of investment on t day and $\mathrm{P_{t-1}}$represents the closing price of one day prior to t i.e., the day ‘t-1’.

The returns from investment in VDA, stock investment, commodity investment were compared in terms of average, minimum, maximum, standard deviation, skewness and kurtosis. To know about the statistical properties of the return, Jarque Bera test, Augmented Dickey Fuller Test (ADF) and ARCH test were conducted. Jarque Bera aims at accepting (or rejecting) the null hypothesis of normal distribution of investment returns. ADF unit root tests the null hypothesis of presence of unit root i.e., non-stationarity of the returns. ARCH test verifies the null hypothesis of homoscedasticity of the data through regressing the squared residuals on lagged squared residuals. The null hypothesis can be accepted only if the probability of calculated test statistics is more than 5%. In the present study, all three null hypotheses have been rejected i.e., returns from selected investment do not exhibit normal distribution. The returns are observed to have absence of unit root i.e., returns are stationary and have heteroscedasticity. In the light of these observations, the commonly applied analytical models like regression analysis cannot be applied because these models give unbiased estimates only under the assumption of homoscedasticity of residuals.

To capture the volatility of such data (data with non-normal distribution and heteroscedasticity of residuals), Engle (1982) proposed an Autoregressive Conditional Heteroscedastic (ARCH) model. The model conditions the volatility to some specific information like previous errors. This type of volatility is termed as a conditional volatility. The model may be represented as follows (equation 2):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2, \tag{2}$$

where a dependent variable is: σ_t^2 is the current volatility (variance)and independent variable isϵ_{t-i} which shows the past error (residual). The parameters ω and α represent the intercept and ARCH coefficient (measuring the impact of past shocks over current volatility) respectively.

Though an ARCH model is simple, it often calls for the estimation of many parameters for describing the volatility of returns. To overcome this limitation, Bollerslev (1986) proposed Generalized Auto-regressive conditional Heteroscedasticity (GARCH) that accounts for autoregressive as well as moving average to the variance (σ_t^2) through the usage of past variance (σ_{t-j}^2) and error term (ϵ_{t-i}^2). The model may be represented as follows (equation 3):

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2, \tag{3}$$

where β is a GARCH coefficient quantifying market reaction towards shock; independent variable σ_{t-j}^2 represents the past variance.

Since financial markets usually witness an asymmetric impact of shocks (a high volatility during a crisis period and relatively less volatility during the period of growth or calmness) over volatility, Nelson proposed an Exponential GARCH (EGARCH) model in 1991. The model considers a log of variance and may be represented by the following mathematical equation (4).

$$\ln \sigma_t^2 = \omega + \alpha\left(\left|\frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}}\right| - \sqrt{\frac{2}{\pi}}\right) + \gamma \frac{\epsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \beta \ln(\sigma_{t-1}^2) \tag{4}$$

where, along-with the parameters explained in GARCH model, γ represents the leverage effect and the term Ln represents the natural logarithm. If, $\gamma = 0$, the impact is assumed to be symmetric. But if, $\gamma < 0$, the asymmetric impact is considered.

To capture the possible leverage and asymmetric effect, Zakoian (1990) & Glosten, Jagannathan, and Runkle (1993) developed Threshold GARCH (TGARCH) which uses zero as a threshold to separate the impacts of the past shocks. The model may be represented by the following mathematical equation (5).

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \gamma \epsilon_{t-1}^2 d_{t-1} + \beta_1 \sigma_{t-1}^2, \tag{5}$$

where, along-with the parameters explained in previous models, the term $d_{t-1}$is an indicator of negative ϵ_{t-i}. If ϵ_{t-i}<0, the value of d_{t-1}will be one else it will be zero.

Ding, Granger and Engle (1993) proposed the Asymmetric Power ARCH (APARCH) model. But the asymmetry term (γ) of the model allows positive and negative shocks of equal magnitude to elicit an unequal response from the market. The value of asymmetry term (γ) lies between -1 to 1. However, the other parameters like ω α, β and δ should be non-negative. The model may be represented by the following mathematical equation (6).

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{p}(\alpha_i|\epsilon_{t-i}|-\gamma_i\epsilon_{t-i})^{\delta} + \sum_{j=1}^{q}\beta_j\,\sigma_{t-j}^{\delta}, \quad (6)$$

where, along-with the parameters explained in the previous models, the term δ is a power term parameter which is used to identify the nature of the news. In case of the bad news, the value of δ_{t-1} will be one else it will be zero.

During 1996, Baillie, Bollerslev and Mikkelsen developed a fractionally integrated GARCH model (FIGARCH), which can accommodate time dependence of the conditional variance. Replacing the first difference operator with fractional differencing operator FIGARCH can capture long run dependence properties of the variance. The model is capable of considering leptokurtic distribution of returns and long memory behaviour of conditional variances. The model may be represented by the following mathematical equation (7).

$$\sigma_t^2 = \omega + \big(1-\beta(L)-\phi(L)\pi(L)\big)\epsilon_{t-1}^2 + \beta(L)\sigma_{t-1}^2, \quad (7)$$

where $\pi(L)$ is the infinite lag operator; $\phi(L) = 1-\sum_{i=1}\alpha_i L^i$; $\beta(L) = \sum_{j=1}^{q}\beta_j L^j$; $\pi(L) = (1-L)^d\ \pi^*(L) = \sum_{i=1}^{\infty}\pi_k L^i$

Though all the above five models are frequently used to capture the volatility, it is imperative to use only that model which can provide the best possible information from the given data-set. To decide on the suitable model there are two popular criterions viz., Akaike Information Criterion (AIC) and Schwarz information criterion (SIC). According to recent studies (Gayawan and Ipinyomi 2009; Koehler and Murphree 2016), SIC is a better information criterion since AIC often overfits the data and leads to over parameterization. The present paper also applied the SIC criterion for selecting an appropriate model. This criterion was developed by Schwarz (1978) using the maximum likelihood method with a condition of a large sample. The criterion provides a measure of information that strikes a balance between the measure of goodness of fit and parsimonious specification of the model. Javed and Mantalos (2013) suggested that model with the least value of the information criterion needs to be selected. Accordingly, the values from all models have been noted and compared to identify the best suited model for further analysis.

Data: Since the present study aims at comparing the volatility of three investment options viz., VDA, stock (equity) market and commodity, the top investments of all three categories have been screened on the basis of market capitalization / popularity as on the last day of the study period. Amongst cryptocurrencies, Bitcoin, Ethereum and Tether discerned to be leaders. The preliminary data screening revealed that in contrast to all other options, Bitcoin was homoscedastic. Therefore, it was dropped and the next two cryptocurrencies i.e., Ethereum and Tether, have been selected. Amongst NFT, Decentraland, Sandbox and Tezos registered

 ISSN 2657-4047(online)

the maximum market capitalization. Since the data for Sandbox is available only from 14-08-2020, the same has been dropped and remaining two NFTs (Decentraland and Tezos) have been taken to proxy NFT investment. In case of Defi, the five best performers (in terms of market capitalization) include Avalanche, Chainlink, Dai, Uniswap and Wrapped Bitcoin. On the basis of data availability, out of these five Defis, the two Defi (Dai and Chainlink) have been used to proxy the investment in Defi.

To represent the equity market, the market capitalization suggests the stock markets of the USA, China, the UK, and Japan. Since the Chinese market experienced multiple lockdowns and massive oscillations during the study period, it was skipped. Thus, the USA and the UK stock markets were finally considered in the study. The leading two indices of these markets viz., Standard and Poor's 500 (S &P 500) and Financial Times Stock Exchange 100(FTSE-100) were taken to represent the equity investment.

The investment in commodity may be in the energy sector (like oil and natural gas), metal (like gold and silver) or agricultural product (like corn and soyabean) investment. Since the daily returns from gold and corn found to be homoscedastic, oil and silver have been taken to represent commodity investment.

Finally selected ten investment avenues can be noted as follows:
- Cryptocurrency: Ethereum and Tether
- Non-Fungible Token (NFT): Decentraland (MANA) and Tezos
- Decentralized Financial Assets (DeFi): Dai and Chainlink
- Equity: S&P 500 (USA) and FTSE-100 (UK)
- Commodity: Oil and Silver

The Study Period: The study analyses the volatility of investment returns during the post-Covid period starting from January 1, 2020 (as the first case of Covid-19 was observed at the end of December 2019). The study considers daily observations of all selected ten investment avenues till the maximum possible date allowed by the study, i.e., August 18, 2022. All data were taken from finance.yahoo.com only for post-Covid period owing to three reasons. Firstly, since the concept of VDA (particularly NFT and Defi) is comparatively new, it is deprived of the privilege of numerous observations. Secondly, the outbreak of coronavirus was a distinctive experience for the entire world resulting into an unprecedented influence over investor's sentiments and the financial system. To understand the changed scenario, it is essential to analyse the situation standalone. Lastly, many studies (like Liu et al., 2020; Estrada and Lee 2020; Shankar and Dubey, 2021; Maitra et.al, 2022) have already done the comparative analysis of the pre-Covid and post-Covid period with the respect to financial markets. Therefore, the present study analyses the daily observations for the post-Covid period i.e., from January 2020 to August 2022.

4. Results and Discussion

Table 1 shows the descriptive statistics of returns from investment. The analysis reveals that Decentraland (MANA) provided the maximum return to investors during the post-Covid period. MANA is a virtual reality platform that allows users to produce and sell content. During the quarter ending in December 2021, MANA offered a return of 41.80%. The token rose steadily by 4,000 percent last year. As the concept of the metaverse grows in popularity in 2022, MANA is expected to gain much more traction, resulting in the possibly enormous price increases (Economic Times, March 12, 2022). But at the same point of time, another noticeable fact is that the return offered by another NFT i.e., Tezos is not satisfactory enough. Tezos also posted strong results last year but in comparison to other VDAs, it did not grow much. One of the reasons hindering its impressive performance is the internal dispute between its creators (Arthus and Kathleen Breitman) and the Tezos foundation. The assets experienced a bad weather during 2019-20. However, the combative nature of Tezos brought positivity around its prices in 2021. At the beginning of December 2021, Tezos extended a return of 30.59% daily. The MANA was followed by Ethereum in terms of proposing good returns to investors. Amongst Defi, investment in Dai offered better daily returns (0.025%) in comparison to commodity investment. During the study period, the average daily return from equity investment was observed to 0.022% (USA) and -0.014% (UK). The stock markets became more fragile, sensitive, and volatile due to the coronavirus outbreak. The experience of stock market investors was pretty bitter during the first half of 2022 however, recently by mid of the year, the market experienced a rebound.

Table 1. Descriptive statistics

Particulars	Daily Logarithmic Return (in percentage)				Ske	Kur	Test Statistics *	
	Ave	Max	Min	SD			JB	ADF
Ethereum	0.133	22.56	-55.07	5.70	-1.4	17.9	9.1	-33.1
Tether	0.005	5.34	-5.26	0.40	0.4	120.8	555.0	-197.3
Decentraland	0.195	41.80	-62.98	8.24	1.4	25.0	19.6	-30.0
Tezos	-0.018	30.59	-60.73	7.39	-1.0	13.1	4.3	-34.2
Dai	0.025	6.54	-5.67	0.77	-0.9	35.6	42.6	-229.9
Chainlink	-0.028	27.58	-61.46	7.35	-1.1	12.7	3.9	-33.7
S&P 500	0.022	8.97	-12.77	1.60	-0.9	15.1	4.1	-32.2
FTSE-100	-0.014	8.67	-11.51	1.38	-1.1	15.2	4.0	-26.1
Crude Oil	0.007	31.96	-33.55	4.44	-0.9	22.2	10.4	-24.2
Silver	0.003	8.88	-12.39	2.37	-0.67	7.67	654.66	-26.97

Note: Ave – average; Max – maximum; Min – minimum; SD – standard deviation; Ske – skewness; Kur kurtosis; JB – Jarque Bera (in thousand); ADF – Augmented Dickey Fuller; * – Significant at 5% level.
Source: Calculated by the authors.

Though, in terms of daily returns, MANA, Ethereum and Dai are discerned to be better options than investment in equity stock or commodity market, the variance scenario of these investment avenues is not very rosy. The market for VDA flourished during the year 2021 with a boom in some promising assets like Bitcoin, Ethereum and MANA. But since the industry is in its infancy, big highs are easily followed by big drops. The first half of 2022 has not been so good for VDA investors. The market capitalization of all cryptocurrencies has decreased by more than $2 trillion in June 2022 particularly owing to the announcement to pause all account withdrawals by the firm Celcius, a cryptocurrency lending firm that invested in Terra. Since Terra experienced an abrupt failure with a massive crash of 99.9% drop in prices, the firm banned accounts withdrawals which spooked the investors about liquidity crunch and its possible contagious effects. The investor's reaction made the market highly volatile. In terms of standard deviation, the returns of MANA followed by Tezos, Chainlink and Ethereum were found to be the most volatile. Contrary to the majority of cryptocurrencies, which are known for their volatility values, Tether found to be the least fluctuating. It was designed to be pegged and linked to tangible assets (American dollars) in order to maintain a stable value. While the value of other cryptocurrencies fluctuates frequently, Tether's price is typically equal to $1 (CNBC, 2021). Stock market investments experienced lesser variance in comparison to commodity market investments.

The return of Tether and MANA were found to be positively skewed, while the remaining returns were found to be negatively skewed. In terms of financial time-series, the skewness measures the degree of return asymmetry in terms of the probability distribution around the mean. The negative skewness represents a longer or fatter tail on the left side of the distribution, while positive skewness demonstrates the same on the right side. In general, positively skewed distribution of returns is more preferred by investors as it allows probability of gaining huge profits that can cover all the frequent small losses (CFI 2022). The returns from all investment avenues have a high level of kurtosis. The results of the Jarque-Bera test reveal that the probability is less than 5%. Thus, a null hypothesis of normal distribution cannot be accepted and it may be concluded that none of the return series is normally distributed. Similarly, the probability of ADF statistics is also less than 5%, which amounts to rejection of a null hypothesis. Therefore, it may be concluded that all return series are stationary in nature i.e., there is no unit root in any of the return series. Table 2 depicts the correlation between the returns.

Table 2. A Correlation Matrix

Investment	Ethe-reum	Tether	MANA	Tezos	Dai	Chainlink	S&P 500	FTSE-100	Oil	Silver
Ethereum	1									
Tether	**-0.23**	1								
MANA	**0.67**	**-0.19**	1							
Tezos	**0.77**	**-0.22**	**0.66**	1						
Dai	**0.15**	0.06	0.07	**0.10**	1					
Chainlink	**0.82**	**-0.18**	**0.66**	**0.80**	**0.08**	1				
S&P 500	**0.40**	**-0.22**	**0.37**	**0.39**	-0.03	**0.36**	1			
FTSE-100	**0.29**	**-0.17**	**0.27**	**0.30**	**-0.13**	**0.28**	**0.60**	1		
Oil	**0.12**	0.03	**0.10**	**0.12**	-0.01	**0.08**	**0.28**	**0.28**	1	
Silver	**0.17**	**0.08**	**0.10**	**0.15**	-0.03	**0.13**	**0.17**	**0.18**	**0.19**	1

Note: Figures in bold are statistically significant.
Source: Calculated by the authors.

As it is evident from table 2, Ethereum has a significant high degree correlation with Chainlink, Tezos and MANA. Ethereum shows higher significantly positive correlations with the US stock market, this result being in line with the findings by Maitra et al. (2022). The commodity investment has a low to moderate degree of correlation with all other investment opportunities. The returns from Tether are found to be negatively correlated with NFTs as well as stock indices. Dai also has a low degree of negative correlation with equity stock and commodity investments. Such negative correlation indicates the possibility to reap the benefits from the portfolio diversification. Umar et al. (2020) pointed out that a correlation matrix enables investors to create an effective and risk-hedging investment portfolio. Accordingly, Tether and Dai can can be used to reduce the potential risk from portfolio investment.

The probability of test statistics as demonstrated by the ARCH test is found to be 0.00 for all investment avenues, which is less than 5% for all investment avenues. Therefore, the null hypothesis of homoscedasticity of data series cannot be accepted and it can be concluded that all return series are heteroscedastic in nature. Considering the heteroscedastic nature of return series, ARCH based models have been applied to capture volatility. As discussed in the research methodology, the study applied five prominent models (viz., GARCH, EGARCH, TARCH, APARCH and FIGARCH) and to select the best one, SIC criteria were adopted. Table 4 represents the results of the model recommended by information criteria. The ARCH (α) term represents the impact of the past shocks over the current volatility. The beta(β) coefficient depicts the presence of volatility clustering i.e., the reaction of market towards any shock. The asymmetric effect of shocks i.e., the leverage effect, is represented by gamma variable (γ). The parameters not applicable to the specific models were represented as NA. The significance of the variable was tested by comparing the p-value of all coefficients with 1% level as well as 5% level of significance and was highlighted by ** and * mark respectively.

Table 3. Volatility parameters from the selected models

Investment	Model	ARCH term (α)	GARCH term (β)	Leverage (γ)	Power term (δ)	Fraction (D)
Ethereum	GARCH	0.050*	0.839**	NA	NA	NA
Tether	APARCH	0.215**	0.805**	0.572**	0.076	NA
MANA	APARCH	0.224**	0.606 **	0.193*	0.334**	NA
Tezos	FIGARCH	0.938**	0.485**	NA	NA	-0.378**
Dai	FIGARCH	0.326**	0.801**	NA	NA	0.973**
Link	TARCH	0.102	0.441**	0.376**	NA	NA
S&P 500	GARCH	0.217**	0.741**	NA	NA	NA
FTSE-100	APARCH	0.102**	0.896**	0.999**	0.749**	NA
Oil	TARCH	0.096**	0.762**	0.219**	NA	NA
Silver	FIGARCH	0.317	0.270	NA	NA	0.162**

Note: * statistically significant at 5% and ** statistically significant at 1%.
Source: Calculated by the authors.

Whenever there is an infusion of any shock into the financial market, it affects the stocks' demand and supply dynamics. However, due to a short memory, the memory of such a shock quickly disappears. The α coefficient attempts to capture the impact of the past shocks over the present volatility of the returns. It represents a short-term impact of shocks infused into the market. As evident from Table 3, during the short period, the commodity market was not much affected by shocks. The volatility parameters for Silver were found to be insignificant to influence the variance. The alpha coefficient for oil was also observed to be less than 10%, which shows the efficacy of the market under a short period of turmoil. Tezos has the highest influence by the previous shocks. It was quite evident in the return analysis also whereby; Tezos registered a negative daily return of 0.018% on the average basis during 2020-22. Further, the standard deviation of returns was also high in the case of Tezos, which homologates the results of FIGARCH model. The variances of returns from other VDAs were also discerned to get significant impact from the external shocks in the short period. In the case of equity investment, the impact was higher in the USA stock market (21.7%) as compared to the UK market (10.2%). The persistence of the market reaction as captured by β coefficient reveals that there is a larger impact of the long-run shocks on the UK stock market volatility. Ethereum was observed to be the least influenced from shocks in the short-run but the shocks were found to be persistent in the long run. The long-run persistency of shocks was observed to be higher for FTSE, followed by Ethereum, Tether and Dai. The volatility parameters of APARCH and TARCH model expose that γ estimates for Tether, MANA, Chainlink, FTSE-100 and Oil are significant at 1% level of significance. Thus, it may be concluded that there is a leverage effect and the null hypothesis of symmetric impact for these currencies can be rejected. In other words, positive and negative shocks do not influence the market with same magnitude. In case of FIGARCH model, the fraction term D assists in testing the null hypothesis of no long memory. If the fraction term is positive, the underlying series has long memory else it has a short memory. The estimated parameters depict the short memory for Tezos and long memory for Dai and Silver. Therefore, investors and portfolio managers, in particular, should pay close attention to the conditions in the stock and cryptocurrency markets.

5. Conclusions

VDAs are gaining huge popularity around the world due to their distinct features. The feature of anonymity of these currencies put them under the bracket of high risk of fraud and also to be misused for funding illegal activities. That is the reason why different countries are comparing the pros and cons of these currencies. At present, it has been legally acceptable while in some countries it remains not to be recognized as a legal tender. However, it is worthwhile noting that cryptocurrencies, NFTs and Defis have been initially used as an alternative currency but are currently being purchased as an asset and hedging instruments, leading to a huge surge in the demand of these assets across the globe. The growing popularity of these assets is evident from the exponential growth in its trading volume. These assets offer lucrative returns to investors but at the same time are observed to be highly volatile. Many researchers perceived the same but unfortunately most of the studies limited their scope to cryptocurrencies only (like Chowdhury 2020; Cabarcos et al., 2021; Woebbeking 2021; Khaki et al, 2022; Maitra et.al, 2022). Since volatility is an important tool to measure the risk, the present paper analysed the volatility of returns accrued from investing in VDA (including cryptocurrencies, NFT and Defi). This volatility is used to compare the investment in VDA vis-a-vis equity stock investment and investment in commodity market. Daily closing prices over a period of around 2.5 years from January 2020 to August 2022 were used to compute logarithmic returns from investments.

The analysis of returns shows that all returns are stationary, heteroscedastic and not normally distributed. In terms of average returns, the virtual digital assets (MANA followed by Ethereum and Dai) are discerned to be better options than investment in equity stock or commodity market yet the variance scenario of these investment avenues is not very rosy. Particularly, the abrupt failure of Terra spooked the investors and turned the market highly volatile (Nahar 2022). The outbreak of coronavirus compelled the stock markets to be very fragile and sensitive (Estrada and Lee 2020; Awan, et al. 2021). Even the market could not meet investor’s expectations during the first half of 2022. However, recently by the mid of the year, the market has experienced a rebound. The commodity investment has low to moderate degree of correlation with all other investment opportunities. The results witness that Tether (cryptocurrency) and Dai (Defi) have a negative correlation with investments in the stock market. The negative correlation indicates the possibility to reap the benefits from portfolio diversification to reduce the potential risk. Jareño et al. (2021) also considered Tether to be a more stable currency with a unit value of one US dollar and found it to be a good option for diversification. Karim et.al, (2022) found that NFTs manifested a higher diversification potential against DeFis and Cryptocurrencies.

The best-fit ARCH-based model was applied, as recommended by the information criterion, to capture the volatility. The results witnessed volatility clustering i.e., large changes are followed by large changes and small changes tend to be followed by small changes. During a short period, the commodity market was not much affected by shocks. Tezos has the highest influence of previous shocks. The variances of returns from other VDAs were also discerned to get a significant impact of external shocks in the short period. In case of equity investment, the impact was higher in the US stock market (21.7%) as compared to the UK market (10.2%). The persistence of a market reaction as captured by β coefficient reveals that there is a more significant impact of the long-run shocks on the UK stock market volatility. The long-run persistency of the shocks was observed to be higher for FTSE-100, followed by Ethereum, Tether, and Dimitra et al. (2022) also witnessed an increased persistency for FTSE-100 during the Covid period. A leverage effect has been observed for Tether, MANA, Chainlink and FTSE, which implies that positive and negative shocks will not influence the market with same magnitude. Therefore, investors and portfolio managers, in particular, should pay close attention to the conditions in the stock and cryptocurrency markets because the best methods for capital allocation, diversification, and risk hedging may drastically vary based on the particular events in each market (Ji. et al. 2020).

Undoubtedly, VDA offers good returns but at the same time have significant impact of external shocks in the short run. In its comparison, the commodity market is not much affected by

 ISSN 2657-4047*(online)*

shocks. Since VDA may have negative correlation with the stock market (Tether and Dai), it may be included in the portfolio for diversification. The results of the present study are expected to be fruitful for investors intending to make investment in VDAs to diversify their portfolio. Further, since the decision about the VDAs is still sub judice in India as well as in some other countries, the results are expected to provide an insight to regulatory bodies and government through providing empirical evidences about the volatility of these assets. However, the study has three limitations that may be overcome in the further research. The first limitation is that it did not consider macroeconomic variables (such as political uncertainties, weather and climatic conditions, inflation, unemployment, etc.), which have a major impact on the returns. Secondly, the volatility was analysed through ARCH-based models, yet it will be interesting to analyse the results of applying the models based on machine learning. Thirdly, nowadays, there is a strong inclination towards VDA. It will be interesting to conduct an empirical study regarding behavioural aspects motivating (restraining) the adoption of VDA.

6. Acknowledgements

The authors are thankful to anonymous reviewers for their valuable comments and suggestions to improve the quality of the manuscript.

7. Presenting the sources of funding

This research received no specific grant from any funding agency.

References

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B. N. Petrov and F. Csaki (Eds.), *Proc. 2nd International Symposium on Information Theory* (267-281). Budapest: AkademiaiKiado.

Aste, T., (2019). Cryptocurrency market structure: connecting emotions and economics. *Digital Finance*, *1*(1–4), 5–21. https://doi.org/10.1007/s42521-019-00008-9

Awan, T. M., Khan, M. S., Haq, I. U., & Kazmi, S. (2021). Oil and stock markets volatility during pandemic times: a review of G7 countries. *Green Finance,* 3(1), 15-27.

Baek, C. and M. Elbeck, (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters*, *22*(1), 30–34.

Baillie, R. T., Bollerslev, T., & Mikkelsen, H. O. (1996). Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *74*(1), 3–30. https://doi.org/10.1016/S0304-4076(95)01749-6

Bamakan, S. M. H., Nezhadsistani, N., Bodaghi, O., & Qu, Q. (2022). Patents and intellectual property assets as non-fungible tokens; key technologies and challenges. *Scientific Reports*, *12*(1), 1-13.

Batten, L., and Yi, X. (2019). Off-line digital cash schemes providing untraceability, anonymity and change. *Electronic Commerce Research,* 19, 81–110. https://doi.org/10.1007/s10660-018-9289-8

Baur, A. W., Bühler, J., Bick, M., & Bonorden, C. S. (2015). *Cryptocurrencies as a disruption? Empirical findings on user adoption and future potential of bitcoin and Co.* Retrieved from https://hal.inria.fr/hal-01448070/document

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, *31*, 307-327.

Brière, M., Oosterlinck, K. and A. Szafarz, (2015). Virtual currency, tangible return: portfolio diversification with bitcoin. *Journal of Asset Management*, 16, 365–373.

Cabarcos, M., Perew-Pico, Q., Pineiro, J., and Sevic, A. (2021), Bitcoin volatility, stock market and investor sentiment. Are they connected? *Finance Research Letters* 38(1), https://doi.org/10.1016/j.frl.2019.101399

Caporale, G. M., and A. Plastun, (2020). Momentum effects in the cryptocurrency market after one-day abnormal returns. *Financial Markets and Portfolio Management*. Retrieved from https://doi.org/10.1007/s11408-020-00357-1

CNBC, (2021). *Why tether, the world's third-biggest cryptocurrency, has got economists worried.* Retrieved from https://www.cnbc.com/2021/07/07/tether-cryptocurrency-usdt-what-you-need-to-know.html

Chevet, S. (2018). *Blockchain Technology and Non-Fungible Tokens: Reshaping Value Chains in Creative Industries.* Retrieved from https://ssrn.com/abstract=3212662

Chowdhury, E., K. (2020). Volatility in Cryptocurrency Market – Before and During Covid-19 Pandemic. *CIU Journal, 3*(1) 69–86.

CFI. (2022). *Positively Skewed Distribution.* Retrieved from https://corporatefinanceinstitute.com/resources/knowledge/other/positively-skewed-distribution/

Ciaian, P., Rajcaniova, M., & ArtisKancs, D. (2019). Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions & Money, 52*, 173–195.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis,* 62, 182-199. https://doi.org/10.1016/j.irfa.2018.09.003

Ding, Z., Granger, C.W.J., & Engle, R.F. (1993). A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, *1*(1), 83-106. https://doi.org/10.1016/0927-5398(93)90006-D

Dyhrberg, A.H., Foley, S., Svec, J. (2018). How investible is bitcoin? Analysing the liquidity and transaction costs of Bitcoin market. *Economic Letters,* 171, 140–143.

Economic Times. (2022). *Cryptocurrency and Budget 2022 – Everything you need to know.* Retrieved from https://economictimes.indiatimes.com/markets/cryptocurrency/cryptocurrency-and-budget-2022-everything-you-need-to-know/articleshow/89278494.cms

Economic Times. (2022). *10 Best Altcoins to Invest in 2022.* Retrieved from https://economictimes.indiatimes.com/industry/banking/finance/10-best-altcoins-to-invest-in-2022/articleshow/89349596.cms?from=mdr

Estrada, M. A., & Lee, M. (2020). *How COVID-19 can affect the worldwide stock markets? The Social Environment Terrorism*. Retrieved from https://doi.org/10.13140/RG.2.2.14705.43363/1

Guizani, S., & Nafti, I.K. (2019). The Determinants of Bitcoin Price Volatility: An Investigation with ARDL Model. *Procedia Computer Science, 164*, 233-238.

Gayawan, E., & Ipinyomi, R. (2009). A Comparison of Akaike, Schwarz and R Square Criteria for Model Selection Using Some Fertility Models. *Australian Journal of Basic and Applied Sciences*, 3(4), 3524-3530.

Hayes, A. (2019). The socio-technological lives of bitcoin. *Theory, culture & society, 36*(4), 49-72.

Hsieh, H., & Oppermann, J. (2021). Initial coin offerings and their initial returns. *Asia Pacific Management Review,* 26(1), 1-10, https://doi.org/10.1016/j.apmrv.2020.05.003

Jareño, F., González, M. de la O., López, R., & Ramos, A. R. (2021). Cryptocurrencies and oil price shocks: A NARDL analysis in the COVID-19 pandemic. *Resources Policy*, *74*. https://doi.org/10.1016/j.resourpol.2021.102281

Javed, F., & Mantalos, P. (2013). GARCH-type models and performance of information criteria. *Communications in Statistics-Simulation and Computation*, *42(*8), 1917-1933.

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, 71, 101526.

Karim, S., Lucey, B. M., Naeem, M. A., & Uddin, G. S. (2022). Examining the interrelatedness of NFTs, DeFi tokens and cryptocurrencies. *Finance Research Letters*, 47, 102696. https://doi.org/10.1016/j.frl.2022.102696

Kitsantas, T., Vazakidis, A., & Chytis, E. (2019, July). A review of blockchain technology and its applications in the business environment. Retrieved from https://www.researchgate.net/publication/334615432_A_Review_of_Blockchain_Technology_and_Its_Applications_in_the_Business_Environment

Khaki, A. R., Al-Mohamad, S., Jreisat, A., Al-hajj, F., & Rabbani, M. R. (2022). Portfolio diversification of MENA markets with cryptocurrencies: Mean-variance vs higher-order moments. *Scientific African*, 17, e01303. https://doi.org/10.1016/j.sciaf.2022.e01303

Koehler AB, Murphree ES (2016). A Comparison of the Akaike and Schwarz Criteria for Selecting Model Order. *Journal of the Royal Statistical Society*, *34*(2), 187-195.

Liu, H., Manzoor, A., Wang, C., Zhang, L., Manzoor, Z. (2020). The COVID-19 Outbreak and Affected Countries Stock Markets Response. *International Journal of Environmental Research and Public Health*, *17*(8), 2800. https://doi.org/10.3390/ijerph17082800

Maitra, D., Ur, M., & Ranjan, S. (2022). North American Journal of Economics and Finance Do cryptocurrencies provide better hedging? Evidence from major equity markets during COVID-19 pandemic. *North American Journal of Economics and Finance*, 62, 101776. https://doi.org/10.1016/j.najef.2022.101776

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance research letters*, *36*, 101647.

Nahar, P. (2022, May 11). 'Depegged' TerraUSD butchered LUNA; Terra plunged 97% in a month. Retrieved from https://economictimes.indiatimes.com/markets/cryptocurrency/depegged-terrausd-butchered-luna-terra-plunged-97-in-a-month/articleshow/91492360.cms?utm_source=contentofinterest&utm_medium=text&utm_campaign=cppst

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, 21260.

Narayanan, A., & Clark, J. (2017). Bitcoin's academic pedigree. *Communications of the ACM*, *60*(12), 36-45.

Nasir, M. A., Huynh, T. L. D., Nguyen, S. P., & Duong, D. (2019). Forecasting cryptocurrency returns and volume using search engines. *Financial Innovation*, *5*(2), https://doi.org/10.1186/s40854-018-0119-8

Nelson, D. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, *59*(2), 347-370.

Osterrieder, J., Lorenz, J., & Strika, M. (2017). Bitcoin and cryptocurrencies - not for the faint-hearted. *International Finance and Banking, 4*(1), 56–94.

Richter, S. (2018, February 21). Initial Coin Offerings and the New Age of Startup Fundraising**,** *Entrepreneur.* Retrieved from https://www.entrepreneur.com/article/309556

Salisu, A. A., & Ogbonna, A. E. (2021). The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect. *Global Finance Journal*, 100641.

Şenol, Z., & Zeren, F. (2020). Coronavirus (COVID-19) and stock markets: The effects of the pandemic on the global economy. *Eurasian Journal of Researches in Social and Economics (EJRSE)*, *7* (4), 1-16.

Shankar, R., & Dubey, P. (2021). Indian Stock Market during the COVID-19 Pandemic: Vulnerable or Resilient? Sectoral analysisю *Organizations and Markets in Emerging Economies*, *12*(1), 131-159, https://doi.org/10.15388/omee.2021.12.51

Schwarz, G. (1978). Estimating the dimension of a model. *Annals of Statistics*, 6, 461-4.

Umar, M., Hung, N. T., Chen, S., Iqbal, A. & Jebran, K. (2020). Are stock markets and cryptocurrencies connected? *The Singapore Economic Review.* Retrieved from ttps://doi.org/10.1142/S0217590820470050

Woebbeking, F. (2021). Cryptocurrency volatility markets. *Digital Finance, 3*(3-4), 273-298. https://doi.org/10.1007/s42521-021-00037-3

Zakoian, J.-M. (1991). Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control*, *18*(5), 93.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, 101528.