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Article

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Examining the Volatility of Conventional Cryptocurrencies and Sustainable Cryptocurrency during Covid-19: Based on Energy Consumption

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ABSTRACT

The present study proposes to investigate the influence of the covid-19, on the adjusted closing price of the digital currency based on energy consumption during the process of mining. The study employed the secondary data analysis of top ten market capitalization of cryptocurrencies with the combination of high energy consume mechanism (proof of work) and low energy consume mechanism (proof of stake). Statistical tools like Descriptive analysis, Augmented Dickey-Fuller (ADF) test, ARCH, and GARCH models were used in the study. The present study finds that the prices of cryptocurrencies were highly volatile. This study could assist investors towards better understanding of the dynamics of the cryptocurrency market based on energy consumption which helps them to make more effective decisions, on investing cryptocurrencies with a scientific approach.

Keywords: Cryptocurrency, Volatility, Covid-19, Sustainability, GARCH
JEL Classifications: F36, G01, G15, L72, Q42

1. INTRODUCTION

Cryptocurrency is estimable as a remittance and back-and-forth currency (Livieris et al., 2021), global phenomenon has evolved around cryptocurrencies in the financial sectors (Chowdhury et al., 2020). Bitcoin was the first cryptocurrency to be decentralized (Sarkodie, 2022). Bitcoin is not universally recognized by the government and other international organizations, despite its appeal as a form of payment (de la Horra et al., 2020). There is a lot of disputes among academics over whether cryptocurrencies should be classified as money or an investment (Yuneline, 2019). Cryptocurrency price remains difficult to predict since they are highly volatile (Guo et al., 2021). But investments in cryptocurrency are considered to be one of the most popular types of investment (Livieris et al., 2021). Investors increasingly incorporate cryptocurrencies into their portfolio even though they were not originally designed for the investment purpose (Inci and Lagasse, 2019). Investors, regulators, and the general public are interested in cryptocurrencies due to their popularity and it also attracted negative attention, especially in the investment sector (Giudici et al., 2019). Investors can maximize investing selections depending on the market fear emotion in the face of extreme global uncertainty and fluctuating market sentiment (Chi-Wei SU, 2022; Valencia et al., 2019). In low-trust and high-uncertainty settings, investors switch from fiat money to Cryptocurrencies (Jin et al., 2021). The biggest challenges in adoption of cryptocurrency, it is harmful to the environment by emit carbon and it consumes more energies, the energy source is non-renewable energy (Carter, 2021).

1.1. Cryptocurrency Energy Consumption

Bitcoin alone consumes 707KwH per transaction to maintain stability of the device and it emits large amount of carbon (Yuan et al., 2022). Even the cooling system differ from device to device, hence the energy consumption level varies from one device to another as per the study of University of Cambridge (Sarkodie and Owusu, 2022). Bitcoin consumes more than 121-terawatt hour a year which is the combined total energy consumption level of Google, Apple, Facebook and Microsoft (Valeonti et al., 2021). Proof-of-work is the protocol used to generate new coin and make the transaction successfully in the network by using high amount of non-renewable energy. Even proof-of-work has security threats (Shi, 2016). USA has the world's largest crypto mining industry in the world which consume 38% of global bitcoin function (Hossain, 2021) which is equal to 0.9-1.7% of total country energy consumption that is equal to diesel fuel emission of railroad in US (House, 2022).

- The annual power consumption of bitcoin in the year 2017 is 6.6 terawatt-hours to the 138 terawatt-hours in 2022 (Ante and Fiedler, 2021)
- The maximum life span of mining computers are 1.5 years and which are not recyclable and it generates 11.5 kilotons of e-wastes every year (De Vries, 2019).

Here proof of stake is the alternative technology which consume lesser energy while compare with proof of work (Ethereum, 2023). To validate the transaction, proof of work consumes large amount of energy to maintain the operation. Even though proof of work is slowest process to complete a task while compare with other mechanism. Based on recent study, 70% of electricity consume for bitcoin is came from Chinese Hydroelectricity in 2019 (IvanOnTech, 2022). The whole mining process is depended on the computation power and 51% attack malicious block. In other hand proof of stake required low energy level and 51% attack is impossible (Saad and Radzi, 2020).

1.2. Crypto Mining

Mining is the process of generating new coin and circulating it into the market, the network also confirming each transaction of cryptocurrency (Li et al., 2019; Naeem et al., 2021). It required high specification hardware, software and other sophisticated equipment to make the process smooth (Naeem et al., 2021). The life span of the hardware computers are approximately 1.5 years so it leads to E-Waste (Calvão, 2019; Livieris et al., 2020). While doing the mining process, the miner will get reward for generating new tokens and approving each transaction. Due to the verification of transaction, it controls double spending issues (Shuaib et al., 2022). First miner who resolved the complicated arithmetical problems get rewards. The whole process is called proof of work (Schinckus, 2021). The alternative source for the proof of work mechanism is proof of stake which consumes less energy. Ethereum is the best example for the proof of stake (Kiayias et al., 2017).

1.3. Technological Aspect

The cryptocurrency sector has exploded in popularity since the introduction of Bitcoin and other blockchain-based peer-to-peer payment networks (Zhang, 2021). All operations and ownerships within Bitcoin system are recorded on the distributed ledger (Thazhungal Govindan Nair, 2021). This peer-to-peer network stores a backup of the ledger entry on each node (Ethereum community). The network dismisses all hashes in a branch except for the root hash contained in the block header when the operations are merged into a block and this block is confirmed (Mikołajewicz-Woźniak et al., 2015). Bitcoin implemented Simplified Payment Verification (SPV), which requires nodes to store only a duplicate of the longest chain's transaction headers, rather than a complete record of transactions (Squarepants, 2008; Khalid Salman et al., 2020). However, these systems necessitated the involvement of a trusted third party (Susana et al., 2020). In a centralized solution, banks or even other trust-worthy governing bodies can prevent attempts to issue at the same time decentralized system, such as cryptocurrency, this issue is critical (Tschorsch et al., 2016). Here cryptocurrencies have unique blockchain technology that distinguishes them from traditional assets (Conlon et al., 2020).

1.4. Cryptocurrency Market during Covid-19

Traditional financial investments like stock, had faced the crisis during the period of Covid-19 (Marobhe, 2022). The price relationship between Bitcoin, stock, gold, and oil markets is generally minimal, but during the COVID-19 period, it became higher (Hung, 2021; Bandhu Majumder S, 2022). Following that the Federal Reserve implemented many monetary policies to mitigate the pandemic's impact on stock markets, resulting in a misconception about the cryptocurrency market's reaction (Mnif and Jarboui, 2021). The volatility series of cryptocurrencies have shown a surprising degree of endurance in comparison to global stock markets during the COVID-19 (Lahmiri and Bekiros, 2021; Corbet et al., 2022). During the massive economic crisis brought by the COVID-19 pandemic, BTC sparked significant attention (Corbet et al., 2020). The COVID-19 outbreak is a once-in-a-lifetime occurrence that has slowed the global economy in every industry (Sohrabi et al., 2020; Guzmán et al., 2021; Mnif et al., 2020). This spike in Bitcoin prices, which occurred during the COVID-19 epidemic, has been associated with a substantial body of research on whether cryptocurrency, particularly bitcoin, used as a haven during times of instability (Huynh et al., 2020; Lahmiri et al., 2020). The cryptocurrency market is an excellent opportunity to diversify and hedge your portfolio even in the face of pandemics like COVID-19 (Karim et al., 2022; Shao et al., 2021). To understand the market volatility of energy sector, ARCH and GARCH (1, 1) were examined (Babu, et al., 2022). To understand the market volatility of stock market indices GARCH (1, 1) found the volatility of Indian market (Babu et al., 2023).

1.5. Cryptocurrency Market Volatility

The extreme volatility of cryptocurrency value necessitates the development of an accurate model to forecast its value (Khedr et al., 2021; Kaya et al., 2021). Compared to the stock market; the crypto market is significantly more volatile (Bouri et al., 2020; Equity against the Odds, 2018). During times of regional price fluctuations and significant systemic events, user behavior in the bitcoin and Ethereum markets is strikingly different (Aspembitova et al., 2021). Due to the inability to place an accurate value on cryptocurrencies such as Bitcoin, their volatility is the biggest problem (Smales, 2019). Because of the large number of cryptocurrencies available, the crypto market is complex and dangerous, with frequent and significant price fluctuations (Bouri et al., 2019; Ftiti et al., 2021). Cryptocurrencies have prompted a debate about analyzing the dangers connected with their control, through technological advance (Dudukalov et al., 2021). Cryptocurrency marketplaces have been hurt by market volatility and threats (El-Berawi et al., 2021).

According to Gallersdörfer et al. (2020), bitcoin consume more energy which affect the environment drastically but the study does not focus on sustainable cryptocurrencies. Hence this study analyzes the combination of conventional cryptocurrency as well as sustainable cryptocurrency by examine the market volatility of the sampled cryptocurrency. Hence, the study was attempted to analyze the market volatility for top ten cryptocurrencies based on energy consumption level. To understand the volatility of the market during Covid-19, Descriptive Statistics, ADF Test and GARCH (1,1) Model were used for the study (Babu et al., 2022). Finally, Babu and Srinivasan (2014) selected ten commodities to analyze the volatility of commodity market.

2. THEORETICAL DEVELOPMENT

The motivational, attitudinal, and self-efficacy elements of numerous theories are included in the health belief model. The theories of planned behavior (TPB) and theories reasoned action (TRA), proposed by Ajzen in 1985 and 1991, respectively. As precise indicators of behavioural intentions toward investment, Fishbein and Ajzen 1975 consider the individual's attitude and social norms as well as the individual's perception of control. TRA and TPB are the main metrics to measure investor behavior towards developing investment instruments like bitcoin. TRA is most effective when used to activities that are under an individual's voluntary control. As a result, present study uses the TRA and TPB theories to assess how the cryptocurrency markets' pricing behavior would affect COVID-19. The present study examines the effects of the covid-19 pandemic on cryptocurrency markets.

3. METHODOLOGY

3.1. Null Hypotheses of the Study

- NH01: The conventional cryptocurrency and sustainable cryptocurrency returns are not normally distributed
- NH02: The conventional cryptocurrency and sustainable cryptocurrencyreturns are not stationary
- NH03: There is no correlation among the conventional cryptocurrency and sustainable cryptocurrency returns
- NH04: There is no volatility among the conventional cryptocurrency and sustainable cryptocurrency returns.

3.2. Data Variables and Data Sources

COVID-19 received its first formal confirmation on December 31, 2019 in Wuhan (AlTakarli, 2022). In this study, cryptocurrencies were selected based on the highest market capitalization of the cryptocurrencies during the covid-19 pandemic period from November 01, 2019 to March 01, 2022. Thedetails of the Market Capitalization of cryptocurrencies are presented in Table 1. Here Solana, Avalanche and Polkadot were not selected for the analysis because complete daily adjusted closing price data were not available for the specified period. In this study, Binance coin, Binance USD, Bitcoin, Ethereum, Cardano, Dogecoin, and Terra, Tether, USD Coin, and XRP were used as the sample.

The aim of the study is to analyses the market volatility of conventional cryptocurrency (consume more energy) and sustainable cryptocurrencies (eco-friendly) based on energy consumption. Under proof of work Bitcoin, Tether, Usd coin (stable coin) and Dogecoin which consumes more energy especially nonrenewable energy. Proof of stake is the concept of eco-friendly cryptocurrencies which generate by using low energy as well as renewable energy for mining process which are Ethereum, Binance coin, Cardano, Terra and Binance Usd (stable coin). Xrp coin is based on RPCA concept which generate coin without mining activities. Figure 1 shows that division of Conventional Cryptocurrency and Sustainable Cryptocurrency based on Energy Consumption.

- Low Energy consumption while during mining process-Ethereum, Binance coin, Cardano, Terra and Binance Usd (stable coin)
- High Energy consumption while during mining process-Bitcoin, Tether, Usd coin (stable coin) and Dogecoin
- No mining process-Xrp coin.

4. EMPIRICAL RESULTS

This section discusses the price fluctuation of the highest market capitalization of cryptocurrencies, by using Descriptive analysis, Augmented Dickey-Fuller Test, Correlation analysis, and GARCH (1,1) Model.

4.1. Descriptive analysis for the Sample Cryptocurrencies Return

The data for the daily adjusted closing price of the cryptocurrencies were collected from Yahoo Finance and Coin Market Capital. The overall sample period began in November 2019 and ended in March 2022, which recorded 852 daily observations for the cryptocurrencies. This study mainly focused on the daily price fluctuation of cryptocurrencies during the study period. It is clear from the Table 2 that the descriptive analysis of the topmost market capitalization of cryptocurrencies, Tether and Binance USD, had reported the highest average returns of −0.0000231 and −0.0000278 respectively. Dogecoin and Terra USD had recorded the lowest average returns, at −0.010054 and −0.009408, respectively. The maximum returns were reported by Bitcoin and Ethereum, with 1 and 0.423 respectively and the minimum returns were reported by Dogecoin and Terra USD, with −3.55 and −0.887 respectively. Only Bitcoin and Ethereum's return distributions were positively skewness, with 8.68 and 0.532 respectively. Binance coin, Binance USD, Cardano, Dogecoin, Terra, Tether, USD coin, and XRP coin, were the eight cryptocurrencies, which were negatively skewed. The normal distribution of 10 cryptocurrencies was examined by using (Jarque-Bera [J-B]), and the results indicated that they were all normally distributed

Table 1: Market capitalization of cryptocurrencies

S. No.	Cryptocurrencies	Ticker	Initial issue November 2019	Market capitalization (US$)
1	Bitcoin (high energy consumption)	BTC	May 2010	US$813,929,628,581
2	Ethereum (low energy consumption)	ETH	July 2015	US$363,960,604,012
3	Tether (high energy consumption)	USDT	October 2014	US$80,714,727,098
4	Binance coin (low energy consumption)	BNB	July 2017	US$68,873,171,909
5	USD coin (high energy consumption)	USDC	September 2018	US$52,335,073,752
6	Solana	SOL	April 2020	US$39,808,659,990
7	XRP (no mining process)	XRP	June 2012	US$40,050,396,160
8	Cardano (low energy consumption)	ADA	September 2017	US$36,920,648,824
9	Terra (low energy consumption)	LUNA	January 2018	US$33,477,626,915
10	Avalanche	AVAX	September 2020	US$23,860,330,505
11	Polkadot	DOT	May 2020	US$20,267,358,578
12	Dogecoin (high energy consumption)	DOGE	December 2013	US$18,099,678,873
13	Binance USD (low energy consumption)	BUSD	July 2017	US$17,619,649,515

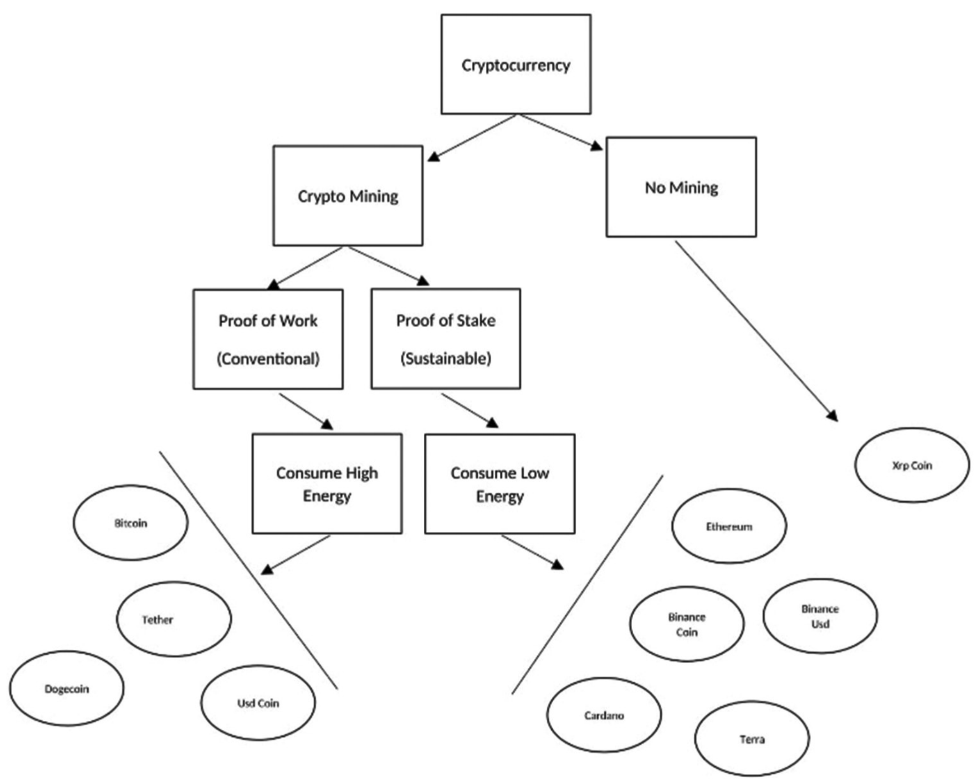
Source: YahooFinance and CoinMarketCapital

Table 2: Result of normality distribution for cryptocurrencies based on energy consumption

Measures	Bitcoin	Ethereum	Tether	Binance coin	USD coin	XRP	Cardano	Terra	Dogecoin	Binance USD
Mean	−0.001420	−0.004505	0.0000231	−0.005232	0.0000368	−0.003276	−0.005549	−0.009408	−0.010054	0.0000278
Median	−0.001425	−0.003902	0.000010	−0.002164	0.0000240	−0.001597	−0.002090	−0.000179	0.000376	0.000000
Maximum	1.0	0.423089	0.038453	0.419098	0.030503	0.422720	0.395337	0.385117	0.397987	0.053576
Minimum	−0.187677	−0.259513	−0.054657	−0.697126	−0.042863	−0.560308	−0.322323	−0.887508	−3.556075	−0.054925
SD	0.051899	0.051057	0.003731	0.061531	0.003854	0.067450	0.060903	0.087279	0.148765	0.003988
Skewness	8.680641	0.532927	−2.757743	−1.678037	−1.993288	−1.355380	−0.393528	−2.241093	−16.64952	−0.617489
Kurtosis	167.5281	11.42553	78.25791	27.67572	40.18514	17.57087	7.633684	20.78609	384.3612	89.38323
Jarque-Bera	971,666.7	2560.457	202,143.2	22,015.48	49,651.28	7797.876	784.2121	11,943.44	5202356.	264,957.4
Probability	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000	0.00000
Sum	−1.210127	−3.838120	−0.019658	−4.457278	−0.031334	−2.791209	−4.727739	−8.015645	−8.566350	−0.023663
Sum square deviation	2.292136	2.218433	−0.019658	3.221938	0.012640	3.871620	3.156537	6.482637	18.83347	0.013537
Observations	852	852	852	852	852	852	852	852	852	852

SD: Standard deviation

Figure 1: Division of Conventional Cryptocurrency and Sustainable Cryptocurrency based on Energy Consumption



Source: Design by author

during the study period. Hence, (NH01), the conventional cryptocurrency and sustainable cryptocurrencyreturns are not normally distributed was rejected. The graphical representation of the daily time-series data of the selected cryptocurrencies is presented in Figure 2.

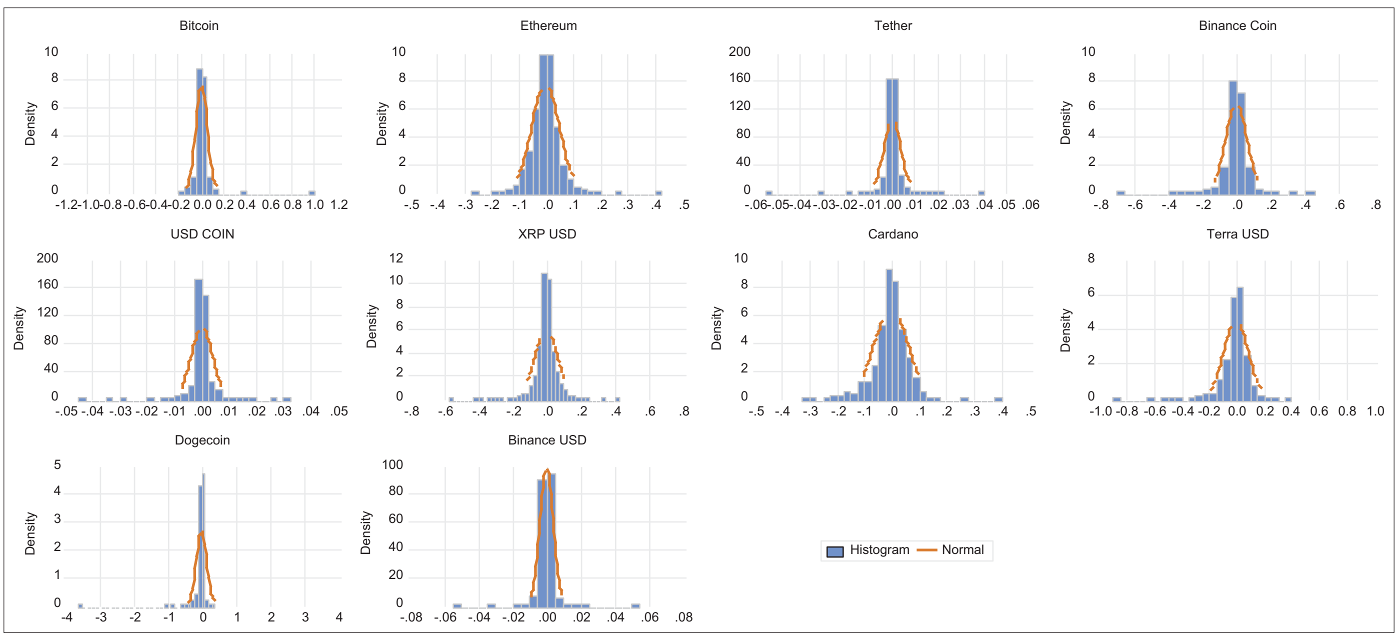
4.2. Stationarity Test for the Sample Cryptocurrencies Return

Table 3 shows the results of summary result of the ADF test for the daily adjusted closing price of the cryptocurrencies, during the study period from November 2019 to March 2022. According to Table that, the P-values, for all the sample variables, were zero. The statistical values, for all ten cryptocurrencies values, were −26.3 (BITCOIN), −31.7 (Ethereum), −19.3 (Tether), −18.8 (Binance Coin), −11.3 (USD Coin), −29.4 (XRP), −31.2 (Cardano), −30.0 (Terra), −28.9 (Dogecoin), −13.1 (Binance USD), at 1%, 5%, and 10%. Throughout the study period, the actual values of the t statistic test for cryptocurrencies were lower than the actual values of the critical test value. The overall analysis of ADF test clearly exhibit that, there was stationarity in the cryptocurrency returns during the study period. Hence, the Null Hypothesis (NH02), the conventional cryptocurrency and sustainable cryptocurrency returns are not stationarity, was not accepted.

4.3. Correlation Analysis for the Sample Cryptocurrencies Return

The degree of correlation between the base mean returns was determined by using linear regressions, to obtain the Pearson correlation. Table 4 clearly shows the results of this correlation for the COVID-19 timeframe. The study demonstrated that bitcoin and other cryptocurrencies did have positive relationship except for Tether and the USD coin which reported negative relationship, with a value of −0.12 and −0.056, respectively. It means that when the value of bitcoin would increase by 100%, the value of the USD coin would go down by 5.6% and the value of Tether would go down by 12.4%. Ethereum and bitcoin had demonstrated positive relationship with bitcoin, with value of 59.5% and 48.2% respectively. This indicated that when bitcoin price went up by 100%, Ethereum and Binance coins would go up by 59.5% and 48.2% respectively. The graphical representations of the daily adjusted closing price of cryptocurrency daily price fluctuations of the cryptocurrencies are shown in Figure 3. The Table shows that, with the exception of Tether and USD Coin, there was a statistically significant positive association between the sample cryptocurrencies during the study period. Hence the null hypothesis (NH03): There is no Correlation among the conventional cryptocurrency and sustainable cryptocurrency return, was partially accepted.

Figure 2: Graphical representation of normality distribution from November 2019 to March 2022

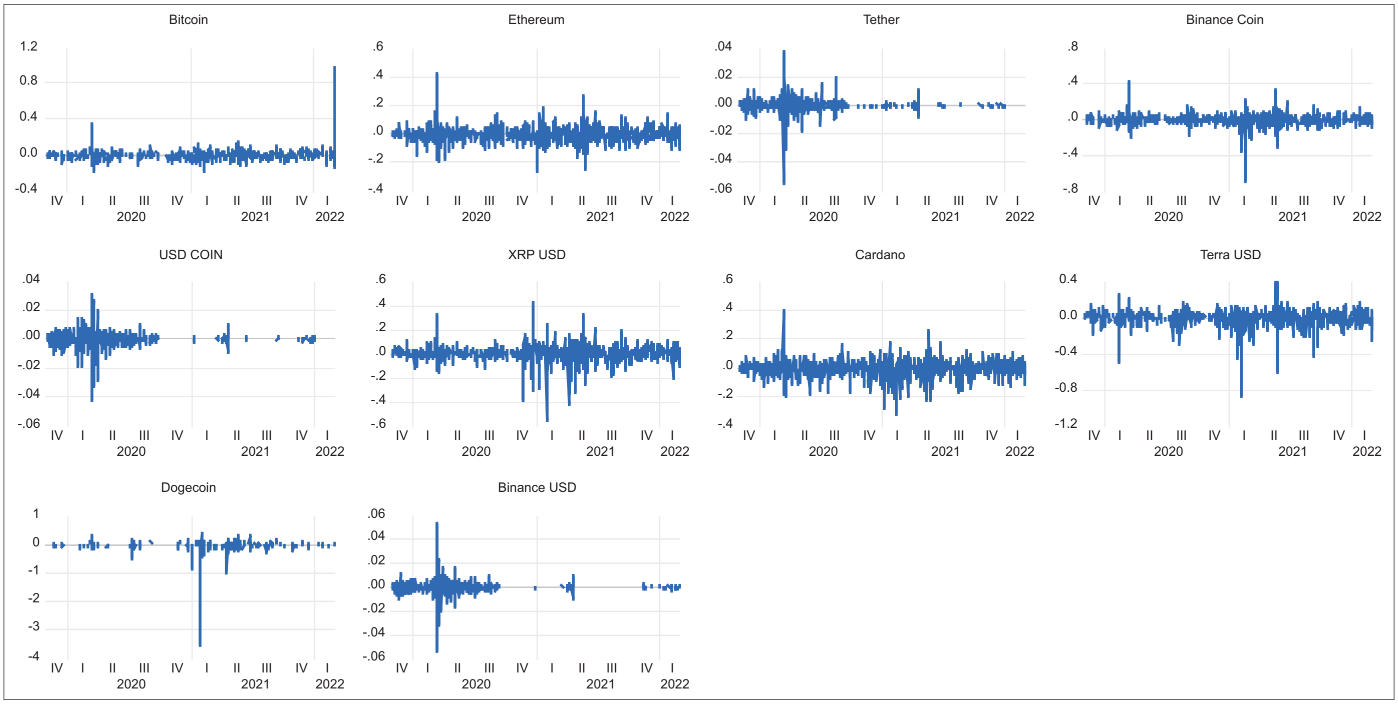


Source: computed by using E-views

Table 3: The result shows that the Augmented Dickey-fuller test for cryptocurrencies from November 2019 to March 2022

Cryptocurrency	Statistical value	1%	5%	10%	Probability
Bitcoin	−26.26368	−3.437810	−2.864722	−2.568518	0.0000
Ethereum	−31.75215	−3.437810	−2.864722	−2.568518	0.0000
Tether	−19.37778	−3.437865	−2.864746	−2.568531	0.0000
Binance coin	−18.84313	−3.437819	−2.864726	−2.568521	0.0000
USD coin	−11.33946	−3.437892	−2.864759	−2.564759	0.0000
XRP	−29.47320	−3.437810	−2.864722	−2.568518	0.0000
Cardano	−31.22339	−3.437810	−2.864722	−2.568518	0.0000
Terra	−30.05179	−3.437810	−2.864722	−2.568518	0.0000
Dogecoin	−28.98646	−3.437810	−2.864722	−2.568518	0.0000
Binance USD	−13.14579	−3.437929	−2.864775	−2.568547	0.0000

Figure 3: Graphical representation of price fluctuation of ten cryptocurrencies during a pandemic outbreak



Source: Computed by using E-views

Table 4: Result of correlation analysis of cryptocurrencies during pandemic period

Variables	Bitcoin	Ethereum	Tether	Binance coin	USD coin	XRP	Cardano	Terra	Doge coin	Binance USD
Bitcoin	1									
Ethereum	0.59560525	1								
Tether	−0.1247986	−0.1794165	1							
Binance coin	0.48290686	0.67866509	−0.1301379	1						
USD coin	−0.0569599	−0.0909717	0.76320813	−0.0595483	1					
XRP	0.41599187	0.59454357	−0.1024021	0.51551381	−0.0554725	1				
Cardano	0.48189085	0.70673441	−0.1369162	0.58752297	−0.0606518	0.54251569	1			
Terra	0.34699948	0.44844138	−0.0137030	0.40245781	−0.0169865	0.33122583	0.37148753	1		
Dogecoin	0.24042391	0.26143189	−0.0429964	0.17772815	−0.0232528	0.19901772	0.25796386	0.21118962	1	
Binance USD	−0.1662094	−0.2284240	0.91240250	−0.1602449	0.76866129	−0.1336926	−0.1844017	−0.0252709	−0.0525775	1

Table 5: The result of the GARCH model for highest market capitalization of cryptocurrencies

Cryptocurrency	C	α	β	α+β
Bitcoin	0.0002	0.4209	0.6744	1.0952
Ethereum	0.0001	0.0757	0.8961	0.9718
Tether	0.0000	0.5036	0.6752	1.1788
Binance coin	0.0001	0.1614	0.8307	0.9921
USD coin	0.0000	0.3788	0.7207	1.0996
XRP	0.0004	0.7179	0.4916	1.2095
Cardano	0.0002	0.1243	0.8207	0.9450
Terra	0.0004	0.1785	0.7910	0.9695
Dogecoin	0.0012	5.2207	0.0072	5.2278
Binance USD	0.0000	0.4992	0.6678	1.1670

4.4. GARCH (1, 1) Model for the Selected Cryptocurrencies

Table 5 displays the results of the GARCH (1,1) model for the daily returns of sample cryptocurrency returns from November 2019 to March 2022. It is to be noted that the values ($\alpha + \beta$) of cryptocurrencies were 1.0952 (Bitcoin), 0.9718 (Ethereum), 1.1788 (Tether), 0.9921 (Binance Coin), 1.0996 (USD Coin), 1.2095 (XRP), 0.9450 (Cardano), 0.9695 (Terra), 5.2278 (Dogecoin), 1.1670 (BinanceUsd). The results of GARCH (1, 1) Model revealed that, the Dogecoin (5.2278) was highly volatile, followed by XRP (1.2095), Tether (1.1788), Binance Usd (1.167), USD Coin (1.0996), Bitcoin (1.0952), Binance Coin (0.9921), Ethereum (0.9718), Terra (0.9695), and Cardano (0.945), during the study period. The GARCH Model research revealed that the $\alpha + \beta$ values of all ten cryptocurrencies were close to one. This demonstrated that the returns data for all ten cryptocurrencies' prices were extremely volatile over the study period. Thus the null hypothesis (NH04), there is no volatility among the conventional cryptocurrency and sustainable cryptocurrency return, was rejected.

During COVID-19, the theories of reasoned action (TRA) and theory of planned behaviour (TPB) were employed for study in prediction to measure the impact of price behaviour of cryptocurrency marketplaces. Empirical research (e.g., Armitage and Talibudeen, 2010; Doll and Ajzen, 1992) and a meta-analysis have all validated the efficacy of the TPB and TRA (Armitage and Conner, 2001). Doll and Ajzen (1992) discovered that direct experience with a behaviour leads to an increase in investment preference. The current study is one of the first to examine the market movement of popular cryptocurrencies such as Bitcoin, Ethereum, Tether, Binance Coin, USD Coin, XRP, Cardano, Terra, Dogecoin, and BinanceUSD during COVID-19. As a result, the aforesaid theoretical advances are achieved by this research work.

5. CONCLUSION

This paper examined the market movement of the top cryptocurrencies like Binance coin, Binance USD, Bitcoin, Ethereum, Cardano, Dogecoin, and Terra, Tether, USD Coin, and XRP based on energy conventional cryptocurrency and energy sustainable cryptocurrency. The top ten market capitalized cryptocurrencies are combination of high energy consume mechanism (proof of work) and low energy consume mechanism (proof of stake). Even there are zero energy consume mechanism cryptocurrencies are available in the crypto market but the market capitalization and the return value is low. Hence this study does not consider the zero energy consume cryptocurrency, also known as green cryptocurrency. The Descriptive Statistics, Unit root test, Correlation, and GARCH were used to test the price movements of the top ten Cryptocurrencies. The normality test revealed that all the sample cryptocurrencies were normally distributed. Furthermore, the results of the Unit root tests demonstrated that the sample variables had attained stationarity.

During the COVID-19 period, the present study proved that there was positive relationship between the cryptocurrency returns series except for Tether and USD Coin. The results of the GARCH (1,1) Model revealed that the Dogecoin (5.2278) was highly volatile, followed by XRP (1.2095), Tether (1.1788), BinanceUSD (1.167), USD Coin (1.0996), Bitcoin (1.0952), Binance Coin (0.9921), Ethereum (0.9718), Terra (0.9695) and Cardano (0.945). As per the result of GARCH (1, 1) model, the low energy consuming cryptocurrency Cardona is not highly fluctuated cryptocurrency while compare with the high energy consuming cryptocurrencies in market. High energy consuming cryptocurrencies like Dogecoin and XRP are highly fluctuating cryptocurrency.

Based on the result, the study suggests the investor to consider Cardano in the investment portfolio. During the study period with asymmetric relationship among the sample cryptocurrencies, investors are advertising to craft better investment strategies while making investment decisions in the cryptocurrency investments. The present study would also help the investors to make better investment strategies. For further study, researcher can do market research on green cryptocurrency.

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