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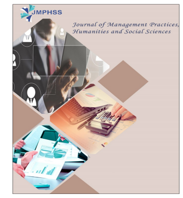

ORIGINAL CONTRIBUTION

Block Chain Markets During COVID-19. From the Perspective of Market Efficiency and Behavioral Finance

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Abstract— The Corona crisis adversely affected the financial system. Investor's behavior tends to change in periods of crisis. Therefore, current study investigated top five cryptocurrency market efficiency and its association with behavioral finance in terms of investor irrational behavior during COVID-19. Current study followed parametric or non-parametric techniques for analysis of weak form market efficiency for time period Jan 2020 till July 2020 using Statgraphics 18 and EVIEWS. Findings of study suggest that markets are inefficient during the corona crisis. This research paper provides implication both theoretically and on the regulatory authorities. Future research should consider all fifty markets in order to check validity of efficient market hypothesis. Clemente, Montañés, and Reyes (1998) tests are constructed on the basis of the advanced outlier and additive outliers. Future study should consider pre post analysis in order to draw compression for better results.Current study provides fruitful information for policy makers and regulatory authorities for decision making. Although findings of current study are introductory in nature as this study measures the presence of EMH in block chain markets. This study also provides theoretical implications.

Index Terms— COVID-19, E-Views, Inefficient market, Weak form of efficiency

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Introduction

As of March 11, 2020, COVID-19 was declared a pandemic situation by the World Health Organization (WHO). The count of confirmed cases is more than 19M as of August 11, 2020, and there is still an increase (WHO, 2020). Over 200 countries, areas, or territories are affected – the United States being one of the most affected countries. There has been a severe economic impact due to this disease outbreak. The way the financial market has evolved during this time illustrates the fact there has been an economic impact. As per certain empirical studies, financial markets have had a visible strong impact due to COVID-19. (Arias-Calluari, Alonso-Marroquin, Najafi, & Harré, 2021; Baker et al., 2020; Garcin, Klein, & Laaribi, 2023; **?**). In this global pandemic situation, the financial crisis of markets is not limited. For instance,Ammy-Driss and Garcin (2023) examined that in the 80s and 90s how the pandemic situations affected the stock market.

The current global economic crisis leads to high volatility and increased trading. This huge recession put the global financial system in chaos on the efficient market hypothesis (Castro & Murthy, 2009; Ye, 2010). Soros (2009) claims that efficient market hypotheses become

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ineffective during economic crises. According to a survey by the UK Turner Review, the efficient market hypothesis is very significant during the crisis (Andrews, 1991). Likewise, Cochrane (2011) claims that EMH supports the expansion of huge asset prices during economic crises (Sabbaghi & Sabbaghi, 2018).

The efficient market hypothesis is considered the foundation for the conventional finance theory, and it was presented by Fama (1970). However, the perspective of behavioral finance in terms of anomalies and behavioral biases contradicts the efficient market hypothesis. Additionally, academicians from the discipline of psychology and experimental economics relate an individual's decision-making with behavioral biases termed as uncertainty, overconfidence, underreaction, loss aversion, herding, and many more. Ou-Yang and Wu (2014) specifically argue that an efficient market hypothesis claims that there is no market that incorporates information in a timely and efficient manner. There are still debates about the efficient market theory and advocates of behavioral finance promotors, and unfortunately, we have not reached the same page. Surprisingly, few research claims which one is prevailing (Jiang & Li, 2020).

While making the decisions, behavioral finance, which studies the behavior of the investors and the market participants, should have studied the discipline of finance. Consideration of behavioral aspects is necessary for a better understanding of abnormal asset pricing and baffling annotations of financial markets. Explanation of a few singularities by conventional finance has unsatisfactory reasoning, which results in the emergence of behavioral finance (Jam et al., 2011; Szyszka, 2007).In comparison to traditional finance, behavioral finance claims investors behave irrationally when receiving any new information or while making decisions. Irrationality comes from multiple sources, such as psychological preconceptions and heuristics of the individual mind. It is very challenging for rational investors to restore asset prices.in these circumstances, arbitrage results in asset mispricing. This leads markets towards inefficiency, and fundamental values of assets diverge from the forecasting of conventional finance (Szyszka, 2007).

The efficient market hypothesis assumes the rationality of investors, while mainstream literature on behavioral finance claims irrationality. Undeniably, Human brains put faith in cognition. These days, contemporary research concentrates on the emotional and mental factors which ultimately affect investor's decisions (Yarovaya, Matkovskyy, & Jalan, 2021). In the case of blockchain markets, which are comparatively innovative and unfamiliar economic assets, the coronavirus is ascertained as an unparalleled shock. Hardly a year old, Bitcoin occasionally denotes increased volatility without being vulnerable to a huge economic crisis. During the economic depression and the crisis time period, cryptocurrencies were considered pecuniary assets, and they were not safe during the crisis. Recent research recommends bitcoin as a poor hedging tool and riskier investment during the COVID-19 pandemic time period (Conlon & McGee, 2020; Corbet, Larkin, & Lucey, 2020). According to these results, the current study claims coronavirus is an unpredictable event that caused behavioral anomalies like panic buying and following the flock and hugely impacted the trading of cryptocurrency (Yarovaya et al., 2021)

Through a range of econometric tests, a weak form of market efficiency is explored by the maximum number of studies. Different theories of behavioral finance have been used by past literature to explain market anomalies, but there is still a gap in relation to other areas. This can be fruitful in terms of market efficiency and market irregularities like those caused by the current pandemic. Studies on the sound effects of coronavirus are still in the embryonic stage. It is reasonable to investigate the pandemic impact specifically for the maximum time period (Akhtar, Qasim, Hussain, & Zubair, 2020; Akhtaruzzaman, Boubaker, & Sensoy, 2021).

Overall, most of the studies related to coronavirus focused on volatility spillover, deviation of stock prices, stock return efficiency, and jump intensity. On the jump intensity, implied volatility, and the antecedent factor model, these studies, in general, focused it. To the best knowledge of the author, no paper measured the relationship between blockchain market efficiency and COVID-19 (Ammy-Driss & Garcin, 2023). The current study fills the gap and measures the impact of coronavirus on cryptocurrency market efficiency from the perspective of investors' irrational behavior. The objective of the current study is to investigate the efficiency of the first five leading cryptocurrency markets during COVID-19. The underlying problem of the statement of this study is whether market efficiency holds in the top five cryptocurrency markets during the COVID-19 time period.

The innovative financial tool in the stock market is cryptocurrencies, and the current study contributes to the literature on two bases. Firstly, there is limited literature available on cryptocurrency, and this study contributes to the existing literature (Husain, Shaibur, & Al Muzahid, 2021; Yarovaya et al., 2021). Secondly, it is evident from the literature that financial crises do impact market efficiency negatively. Like the Asian stock market, Hong Kong, Singapore, Thai land, and the Philippines were affected by the crisis in the past. That's why it's important to examine the relationship between the efficiency of the stock market and the Covid-19 pandemic. Our study considers this aspect and enhances the recent literature by assessing the coronavirus crisis's impact on cryptocurrency markets (Sabbaghi & Sabbaghi, 2018).

The current study analyzed the relationship between the top five cryptocurrency market efficiency and the COVID-19 pandemic situation. The current study focuses on whether the market shows true and fair information and changes the prices accordingly and whether the efficient market hypothesis of the stock market could not be exploited by the investors in the market. The current study focuses on the relationship between the time marked by global economic uncertainty and the volatility of the market. The current study mainly focuses on the efficiency of cryptocurrency in the stock market. This study contributes to the literature by focusing on the efficient market hypothesis and the application of the EMH on cryptocurrencies.

The relationship between the COVID-19 pandemic and the weak form of market efficiency is the main contribution of the current study in the prior literature. The current paper sections are as follows: the second section precisely discusses literature related to behavioral finance, market efficiency, and coronavirus. Third section is related to data and methodology. The paper concludes with a discussion of the following limitations and policy implications.

Literature Review

It is important for investors to have better information that is correct, updated, and relevant so overall market efficiency is improved and they can, in turn, perform better (Ackert, Church, & Zhang, 2002). Since information asymmetry that is present in financial markets is not completely removed by regulators, investors make decisions based on information that differs in both quality and quantity. (Aboody & Kasznik, 2000; Ivashina & Sun, 2011; Kothari, Shu, & Wysocki, 2009). There are studies that show how excessive information might not be beneficial, contradicting the positive expectations of the regulator (Huber, Kirchler, & Sutter, 2008; Joyce, 2008) Shang, Brooks, and McCloy (2014). Over the past 100 years, out of all the tested financial and economic hypotheses – EMH is of great importance. The Efficient-Market Hypothesis (EMH) finds its support in some traditional finance theories, which include as option pricing model (Black & Scholes, 1973), Arbitration pricing model (Ross, 2013), Portfolio pricing model (Markovits, Davis, & Van Dick, 2007), arbitrage principle model (Miller & Modigliani, 1961) and the Capital Assets Pricing Model (Lintner, 1965; Mossin, 1966; Sharpe, 1964; Treynor, 1961) and the arbitrage pricing theory (Black & Scholes, 1973). Moreover, researcher was of the view that economically rational man would go for personal profit at its maximum level. Such an individual, upon investing in stock markets, becomes an economically rational investor whose aim is to increase his profit in the stock market to the maximum.

Definition of market efficiency

Initial projection was done on Market efficiency by Letchworth (1889) in his book named Stocks Markets of London, Paris and New York, he described in his book "When shares are well recognized in an open market, their valuation of that shares at that time may be due to perceived findings of the concerned parties".

In 1900, a French writer, Louis Bachelier, completed his PhD thesis work on the theory of speculation. He revealed that "current, existing and previous imminent proceedings are reflected in market price, but usually they do not reflect an actual connection with deviations in the price." Hence, the market did not forecast changes in asset prices. In addition, he assumed that "The one who takes a risk, his expectation with respect to the calculation of risk is zero," and this study is connected with Samuselson, who analyzed the market in the form of the martingale. The practical consequence is that there is a haphazard change in asset prices; their ups and downs cannot be forecasted. In the work of English writers, i.e., Fama (1970), Bachelier's work has been revealed as a work of market competence.

There are three assumptions for the EMH. All of them were weaker. First of all, the ones who invest are supposed to be coherent and, hence, value assets realistically. All securities should be valued by them on their core value, i.e., the NPV of the future cash flows, using the rate for discounting of the reasonable risk level. When something new is discovered regarding future cash flows by investors or risks associated with a specific security, they should immediately take action on the novel information about the stock market when the prices are up-bidding and down when the prices are low. As a result, and as soon as possible, all information should be considered for asset prices.

Based on the available market information to everyone, if someone regularly earns more money than the average, he should respond more sharply to the new changes than the other investors, but this is not possible all the time. Even if not all investors are realistic, markets can remain efficient, and most investors make mistakes in responding to and predicting market information (Le Tran & Leirvik, 2020). In situations like this, the illegal investors are randomly engaged in the stock market. The result will nullify each other because their trading relationship is uncorrelated. They will not, as a whole, create a market power that could affect the price of equilibrium. The only factor, i.e., the volume of the trade, is increased due to the transactions. On the behavior of irrational investors, the lack of correlation is typically based.

The prices are pushing away from the fundamental values, and a large number of the investors behave in a correlated manner; the logical arbitrators quickly note the mispricing and behave accordingly. The asset pricing is down to the equilibrium level because the selling prices of the assets are much higher, and the same assets are acquired at a cheaper rate. Without any restrictions, the fair market arbitrators act instantly in the stock market.

Cognitive publications of incoherence may be classified as follows. Firstly, when people receive information from other sources and from their beliefs, they do make mistakes. Secondly, through the contradictory expectations, the irrationality of the market comes, and it is different due to the alternative source of context. Empirically, a certain action issue can even be better handled by a certain participant whenever the circumstance is portrayed in a completely different way. The third cause of cognitive dissonance would be that of human feelings and mood swings. Generally, people who are mostly in a positive mood make optimistic choices compared to people who are in a negative mood. The optimistic investors are happy, and they make positive decisions and take riskier steps. With more analysis and condemnation, the negative mood of people is connected, and lastly, communication within the community may also result in non-realistic actions (Horcajo, Briñol, & Petty, 2014).

Although the reality is that in a market where the number of rivals is high, ongoing prices are perceived to change very quickly, in reality, disallows the investors to rely on historical information to forecast ongoing and upcoming results of the prices (Bhargava, 2014; Degutis & Novickytė, 2014; Tiwari & Kyophilavong, 2014). Accordingly, it concluded that stock values are representations of all available knowledge on the financial exchange and are exchanged at their reasonable value at all times, making it hard for market traders to reliably pick stocks that would exceed the returns of the total market. The stock market efficient hypothesis, however, was appreciated by financial and interactive economists from the 1970s to the 1990s.

Subsequent to the number of events that have materialized across the world, the judgments upon which EMH depended have also been diminished. Besides that, the level of market effectiveness relies heavily on available information circumstances in the current competitive market; so, according to Fama (1970), market information is divided into three main categories, i.e., low, semi-strong, and solid information. There must be a healthy and effective market: many experienced investors regularly research and sell the market stocks; the market information is readily accessible to all investors. Things, such as work strikes or incidents, appear to happen unexpectedly, with investors responding rapidly and reliably to new knowledge. We have weak or semi-strong market conditions when all the requirements are not present. The weak-shape EMH describes the market as being effective if current prices completely represent all the details found in the previous stock prices. This method means that historical values cannot be considered as adequate as a forecasting device for stock prices. It's difficult to only take the past historical values by using the extraordinary returns, while all the semi-strong return EMH note that current market prices would represent all the publicly available knowledge (Kelikume, Olaniyi, & Iyohab, 2020).

Normally, Cryptocurrencies, and Bitcoin, predominantly, have diverted investors towards them in a very large number of (Philippas, Philippas, Tziogkidis, & Rjiba, 2020; Urquhart, 2018) because of the advanced qualities of Blockchain technology and high chances of getting unpredictable gains and very high progress. For stock markets, attention-based trading approaches are not necessarily in a position to overtake the portfolios that are well-diversified (Barber & Odean, 2008). Prior literature on cryptocurrency shows that there are low exposures to cryptocurrency as compared to Bitcoin investments (Platanakis & Urquhart, 2020). According to Matkovskyy, Jalan, Dowling, and Bouraoui (2021), the pool of 10 cryptocurrencies can gain the stock prices in the S & P600, S & P 400, and S &P 100 indexes stock prices. The news of exchanges in the prices of cryptocurrency is never perceived correctly in the macroeconomic news or in FOMC news updates. This, in the end, creates a gap between the financial markets and the cryptocurrency (Corbet et al., 2020). Although all main finance and economics hypotheses are dependent on the assumption that investors are sensible, fully informed, and undertake their decisions about the future of an evaluation of all widely available information, certain theoretical evidence suggests that investors often behave impulsively, creating confusion in capital markets when protecting their own interests (Shleifer & Summers, 1990). In the heightened volatility of the emerging and nascent cryptocurrency, the capital market should work, and Tversky (1973) that COVID-19 is considered the emerging code. Sharif et al. (2020) examine the effects of the COVID-19 disease outbreak on the Economic Policy Instability Index (EPU), oil markets, and the U.S. stock market and consider that COVID-19 has the most significant impact on the EPU, raising the instability to unparalleled levels. Recognizing that judgment is tied to the degree of intelligence and mathematical development provided to the public (Simon, 1984), We may expect that current experience on the COVID-19 virus and poor understanding of its consequences, along with relatively low computational power to estimate this impact by the average investor using traditional forecasting models, may make the actions of Bitcoin investors unreasonable during the period from January 2020 to March 2020. This is the biggest inspiration for our article.

To observe irrationality and consequent market inefficiency in five leading cryptocurrency markets subsequently, the ambiguity made by COVID-19, the current study stipulates and tests the following hypothesis.

H1: Does weak form market efficiency hold in the cryptocurrency market during COVID-19?

Methodology

Data type and the sources of data collection

The daily price data was collected from investing.com for the top five cryptocurrency markets named Bitcoin, Ethereum, tether, and ripple and bitcoin cash for the duration January 1 2020 to July 31 2020. Selection of the top five currencies is made on the basis of investing .com reporting as of August 8 2020.

Techniques of analysis

With the help of multiple parametric and non-parametric econometric tests, the weak form of market efficiency was measured. The study considered both tests for comprehensive results. Parametric tests are named Autocorrelation, Augmented Dickey-fuller test, variance ratio, and the Jarque-Bera test. The non-parametric tests, Phillips-Perron and vLjung-Box Q tests are applied.

For conducting the parametric and non-parametric test the return of Bitcoin, Ethereum, Tether ad ripple are the prerequisites.

From the daily prices, the daily log of normal returns is calculated with the help of the following formula;

$$R_t = LNPt/Pt - 1^{*100} \tag{1}$$

Whereas Rt shows the logarithmic return in the period, Pt shows the bitcoin price at time t, and Pt-1 shows the bitcoin price at time t-1.

For conducting the test, the software used

With the help of the Statgraphics 18 software, descriptive statistics, autocorrelation test, Ljung-Box Q test, and the run test are done. The variance ratio test and the unit root test are done by using the E-Views software.

Descriptive statistics

The normality of time series data is checked through descriptive statistics.

Autocorrelation test:

Autocorrelation measures the presence of autocorrelation in a selected time period, which explains the correlation of the current as well as the lag values of time series return (Robinson, 1993), and it is calculated with the help of the following formula;

$$p_k = \frac{\sum_{t=1}^{n-k}\left(R_t - \bar{R}\right)\left(R_{t+k} - \bar{R}\right)}{\sum_{t=1}^{n}\left(R_t - \bar{R}\right)^2}$$

Here $k =$ the number of lags, and $R_t =$ Real rate of return.

Ljung-Box Q test

The Ljung-Box Q test analyzed the randomness and independence in time series data. The Ljung-Box Q test is econometrically represented as follows.

$$LB = n(n+2)\sum_{k=1}^{m}\left(\frac{p^2k}{n-k}\right)^{\sim} x^2m \tag{2}$$

Whereas n shows the size of the sample, m shows the lag length, and L.B. shows the m degree of freedom with the chi-square freedom.

Runs test

Run tests are used to analyze the randomness of data. The run tests are applied to find the positive or negative autocorrelation between the data sets. In terms of the random walk, the price behavior is explained with the help of the run test. The presence of a large number of runs denotes a negative serial correlation and vice versa in the case of a number of runs. The null hypothesis proposed outcome is unbiased, and the total number of the runs follows the normal distribution with the following mean equation;

$$\frac{n(n+1)\sum_{i=1n^2i}^{3}}{n}$$

Whereas N shows the total number of observations of returns, Ni shows the number of runs in type i.

To calculate the value of the run test, the Z-statistic is used as follows;

$$Z = \frac{R-\mu}{\zeta\mu}$$

To find out the serial dependence z statistic is used with the help of the comparison between the actual number of runs to the expected number μ in the prices series.

Unit root test

With the help of the unit root test, the stationarity of the data set is analyzed in the time series data, and mostly the Augmented Dickey-Fuller and Phillips-Perron tests are used.

Augmented Dickey-Fuller test

With the help of the ADF test hypothesis, the presence of the unit root is analyzed in the time series data. Stationary or trend stationary is the alternative proposition of the hypothesis. ADF is calculated with the help of the following econometric equation;

$$\Delta Y_t = \mathrm{a} + \beta_t + Y_{t-1} + \delta_1 \Delta Y_{t-1} + \cdots + \delta_p \Delta Y_{t-p} + \varepsilon_t \tag{3}$$

Whereas α shows the constant term; β shows the coefficient of time trend; γ and δ are the parameters; ρ shows the lag order of the autoregressive process; δ y shows the first difference of the y series, and ε shows the error term.

Phillips-Perron test

P.P. is known as the non-parametric test in the econometric equation in which the null hypothesis is 1 in time series level 1 data. By taking the non-parametric serial correlation factor, this test is used by taking the non-parametric serial correlation factor. P.P. test equation which is used is as follows;

$$\Delta Y_t = a_1 + \beta_t + \gamma_{t-1} + \varepsilon_t$$

Whereas α shows the constant term, β shows the coefficient of time trend, γ shows the parameters, and ε shows the error term.

Variance ratio test

As researcher said, the variance ratio tests are presented. Return distribution is measured by variance ratio test in multiple studies. Most theoreticians claim that this test is more consistent in comparison to other parametric tests such as ADF, Auto correlation, and P.P. If the value of The variance ratio is > 1=positive correlation. Variance ratio < than 1 = negatively correlated. The variance ratio is econometrically expressed as follows:

$$VR(q) = \frac{\delta^2(q)}{\delta^2(1)}$$

Where
$\delta^\wedge 2(q) =$ variance of the $1/q$-differences
$\delta^\wedge 2(1) =$ variance of the 1^{st} difference
Null hypotheses $= Vr(q) = 1$ weak form of efficiency is present
Alternative hypotheses $= Vr(q) \neq 1$ weak form of efficiency is not present.

Jarque-Bera-test

Jarque Bera test also measures the random walk of time series. With the two degrees of freedom, the Jarque-Bera tests used the two sum of the squares, which are asymptotically independent. It is statistically defined as

$$\mathrm{JB} = \frac{n}{6} \cdot \left(S^2 + \frac{(K-3)^2}{4} \right)$$

$$\hat{\mu}_j = \frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^j, j = 2, 3, 4.$$

Results

Table I
Descriptive statistics

	BTC	ETH	TET	XRP	BCH
Mean	0.21401	0.459729	-0.00506	0.139428	0.182076
Maximum	14.59411	21.65603	1.01021	15.48225	26.89267
Minimum	-49.7278	-58.9639	-0.674138	-42.5166	-59.7721
Std. Dev.	4.912442	6.211392	0.144688	4.911187	6.632206
Skewness	-4.64304	-3.85949	0.313954	-2.93405	-3.03631
Kurtosis	52.4535	42.01403	18.45029	29.3436	34.75762

Table 1 shows the result of the descriptive statistics. According to the result of the above table, the mean value of the tether is negative, while in the rest of the market, it is positive. Bitcoin cash reports a higher value of standard deviation among all markets, which shows more deviations in data. Values of skewness and kurtosis are greater than zero in all markets, except the value of skewness tether is less than zero. This shows that data is not normally distributed and that there is an absence of a weak form of efficiency during the current pandemic.

Table II
Unit root Test

	ADF		PP	
Series	Prob. 1%	Prob. 5%	Prob. 1%	Prob. 5%
BCH	0.000	0.000	0.000	0.000
BIT	0.000	0.000	0.000	0.000
ETC	0.000	0.000	0.000	0.000
TEX	0.000	0.000	0.000	0.000
XRP	0.000	0.000	0.000	0.000

From the results of table 2 value of ADF and P.P. are significant at 1% and 5% which shows null hypotheses of stationarity is rejected and cryptocurrencies markets shows inefficiency during COVID-19.

Table III
Jarque-Bera test

	BTC	ETH	TET	XRP	BCH
Jarque-Bera	22364.94	13971.48	2112.1	6434.374	9234.572
Probability	0.000	0.000	0.000	0.000	0.000

According to Table 3, the P values of the Jarque-Bera test indicate significance at 5%; hence, null hypotheses of normality of the residuals are rejected and exhibit inefficiency in all cryptocurrency markets.

Table IV
Variance ratio test

Period	BTC		ETH		XRP		TET		BCH	
	Var. ratio	z-Statistic	Var. ratio	z-Statistic	Var. ratio	z-Statistic	Var. ratio	z-Statistic	Var. ratio	z-Statistic
2	0.35913	-2.10519	0.36735	-2.38924	0.372802	-2.71581	0.388477	-3.14667	0.386163	-2.663357
4	0.17349	-1.82804	0.15315	-2.049886	0.152706	-2.30379	0.182988	-2.48111	0.165443	-2.32572
8	0.11158	-1.58876	0.10952	-1.702801	0.099765	-1.87144	0.116481	-1.94455	0.105946	-1.966214
16	0.05869	-1.4455	0.05569	-1.521367	0.056634	-1.60426	0.056139	-1.69937	0.053319	-1.724606
20	0.05081	-1.39539	0.05187	-1.456443	0.049435	-1.52513	0.043254	-1.62441	0.04968	-1.638387

Table 4 shows the results of the variance ratio test for all five leading cryptocurrency markets. All markets shows values of Variance ratio is less than 1 which states weak form of market efficiency does not hold during coronavirus time period.

Table V
Autocorrelation

Lag	BTC			ETH			XRP			TET			BCH		
	AC	Q-Stat	Prob	AC	Q-Stat	Prob	AC	Q-Stat	Prob	AC	Q-Stat	Prob	AC	Q-Stat	Prob
I	-0.21	9.4451	0.002	-0.21	9.8163	0.002	-0.307	20.309	0.000	-0.21	9.6407	0.002	-0.2	8.561	0.003
2	0.137	13.473	0.001	0.114	12.602	0.002	0.02	20.397	0.000	0.103	11.941	0.003	0.073	9.725	0.008
3	0.128	17.045	0.001	-0.11	15.321	0.002	-0.141	24.692	0.000	-0.16	17.138	0.001	-0.063	10.59	0.014
4	0.181	24.202	0.000	0.274	31.701	0.000	0.049	25.217	0.000	0.275	33.627	0.000	0.217	20.83	0.000
5	-0.043	24.609	0.000	-0.05	32.272	0.000	0.077	26.521	0.000	-0.05	34.203	0.000	-0.055	21.49	0.001
6	0.039	24.945	0.000	0.014	32.317	0.000	0.074	27.711	0.000	0.018	34.279	0.000	-0.013	21.53	0.001
7	-0.115	27.886	0.000	-0.08	33.78	0.000	0.002	27.713	0.000	-0.09	36.082	0.000	-0.1	23.77	0.001
8	-0.028	28.064	0.000	-0.01	33.785	0.000	-0.156	33.099	0.000	0.066	37.061	0.000	0.028	23.94	0.002
9	0.017	28.13	0.001	·0.02	33.842	0.000	0.114	35.987	0.000	0.022	37.168	0.000	·0.015	23.99	0.004
10	0.014	28.176	0.002	0.045	34.292	0.000	-0.053	36.614	0.000	0.026	37.317	0.000	0.008	24.01	0.008
11	-0.079	29.588	0.002	-0.04	34.57	0.000	0.015	36.665	0.000	0.007	37.327	0.000	-0.02	24.I	0.012
12	-0.03	29.792	0.003	0.01	34.595	0.001	0.087	38.385	0.000	0.07	38.306	0.000	·0.037	24.42	0.018
13	0.095	31.871	0.003	0.05	35.161	0.001	-0.026	38.539	0.000	0.026	38.466	0.000	0.079	25.84	0.018
14	0.006	31.881	0.004	-0.02	35.294	0.001	-0.004	38.543	0.000	-0.12	41.658	0.000	-0.02	25.93	0.026
IS	0.118	35.092	0.002	0.087	37.052	0.001	0.025	38.687	0.001	0.094	43.704	0.000	0.077	27.29	0.026
16·	0.007	35.103	0.004	0.038	37.387	0.002	·0.061	39.SS4	0.001	0.012	43.737	0.000	0.041	27.67	0.035
17	0.068	36.165	0.004	0.064	38.344	0.002	-0.072	40.759	0.001	0.093	45.768	0.000	0.073	28.9	0.035
18	-0.096	38.312	0.004	-0.06	39.261	0.003	0.073	42.012	0.001	-0.09	47.516	0.000	-0.092	30.88	0.03
19	0.02	38.403	0.005	0.045	39.732	0.004	o.oi5	42.065	0.002	0.004	47.519	0.000	0.044	31.35	0.037
20	0.044	38.853	0.007	-0.07	40.955	0.004	0.035	42.361	0.002	-0.03	47.727	0.000	-0.065	32.36	0.04
21	0.037	39.186	0.009	0.027	41.126	0.005	0.047	42.882	0.003	0.096	49.93	0.000	0.033	32.62	0.051
22	0.004	39.19	0.013	0.016	41.191	0.008	-0.186	51.128	0.000	0.038	50.282	0.001	0.062	33.54	0.055
23	0.083	40.836	0.012	-0.09	43.139	0.007	0.108	53.932	0.000	-0.07	51.472	0.001	·0.033	33.8	0.068
24	0.064	41.825	0.013	0.043	43.581	0.009	0.006	53.94	0.000	0.023	51.596	0.001	0.023	33.93	0.086

This table shows the estimated autocorrelations between values of BTC, ETH, TET, XRP, and BCH at various lags. The correlation between values of lag k autocorrelation measures the correlation between values of BTC, ETH, TET, and XRP & BCH at time t and time t-k. around 0 the probability limit is 5%. At the 95% confidence level, the probability limit exists if the particular lag is not contained in the estimated coefficient. In this case, 2 of the 24 lag autocorrelation coefficients are statistically significant for TET and XRP. BTC & ETH are significant from lag 2 to the 19th, implying that the time series is not random (white noise), hence predicting the presence of market inefficiency in these markets. While bitcoin cash reveals opposite results, the p-value is significant for only lag 1 and 4 till 9th and insignificant values for the rest of the lags, which shows weak form market efficiency is absent on few lags. Figure 1-5 plots estimated autocorrelation for all five markets. Data points are within range, which shows the significant level during the Coronavirus Crisis.

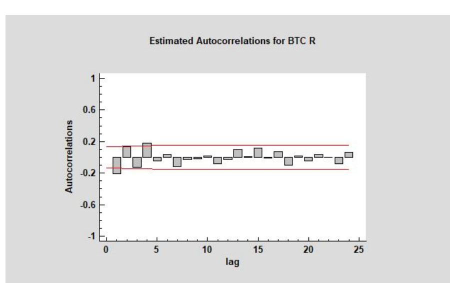

Fig. 1 *Estimated autocorrelation BTC*

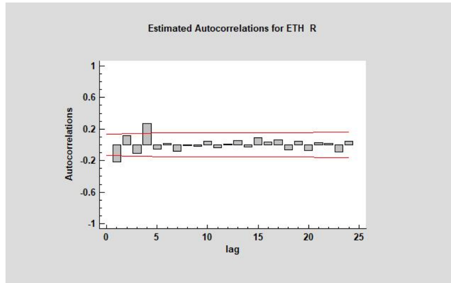

Fig. 2 *Estimated autocorrelation ETH*

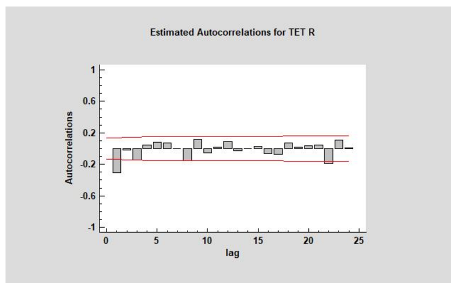

Fig. 3 *Estimated autocorrelation TET*

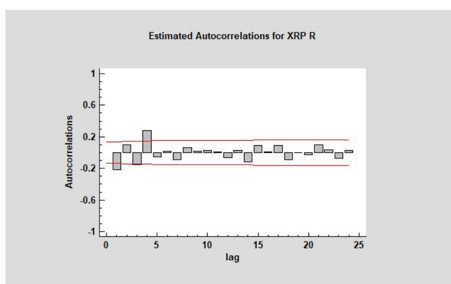

Fig. 4 *Estimated autocorrelation XRP*

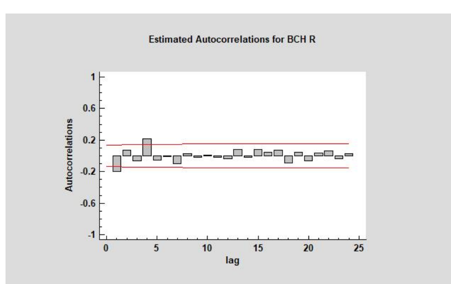

Fig. 5 *Estimated autocorrelation BCH*

Table VI
Ljung-Box Q test

	BTC	ETH	TET	XRP	BCH
Test statistic	41.8248	43.5814	53.9396	51.5964	33.9246
p-value	0.0135	0.008531	0.000434	0.000883	0.086019

On the basis of the first 24 sum of squares of autocorrelation of the Ljung-Box Q tests. We cannot reject the null hypothesis because the series is random at the 95% confidence interval, and the p-value is greater or equal to 0.05. Table 6 shows that BTC, ETH, TET, and XRP have significant values of less than 0.05, which shows that null hypotheses are rejected and that a weak form of market efficiency did not hold during COVID-19.

Table VII
Runs Test

	BTC	ETH	TET	XRP	BCH
Expected Number of Runs	128	118	121	124	128
Actual Number of Runs	107	107	103	107	107
z Statistic	2.82259	1.44572	2.45655	2.27184	2.82259
p-Value	0.004764	0.148256	0.014028	0.023096	0.004764

During COVID-19, the analysis of whether the series is random or not is calculated with the help of run tests. These time series observations are commonly known as white noise because it contains the equal contributions at many frequencies. The run test counts the number of times the sequence was above or below the median. The number of such runs in BTC, ETH, TET, XRP and BCH are equals to 128, 118,121,124,128 as compared to an expected value of 107 & 103. The result shows that the *p*-value is less than 0.05, so we reject the hypothesis that the series is random at a 95% confidence interval and that the weak form of market efficiency is absent. In the case of ETH, the *p*-value is greater than 0.05, and the series is random. Figure 6-10 plots the randomness of time series returns of all five cryptocurrency markets according to the run test.

For different types of random behaviors the of the tests are sensitive in nature and failure to pass this test known as that time series may not be completely random in nature.

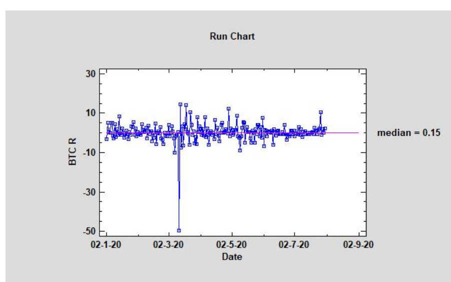

Fig. 6 *Runs test chart BTC*

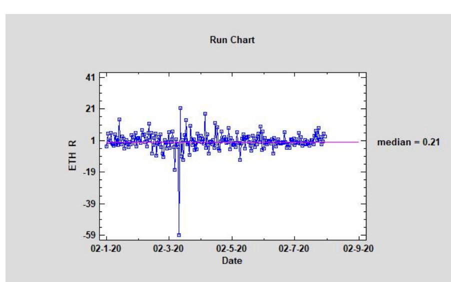

Fig. 7 *Runs test chart ETH*

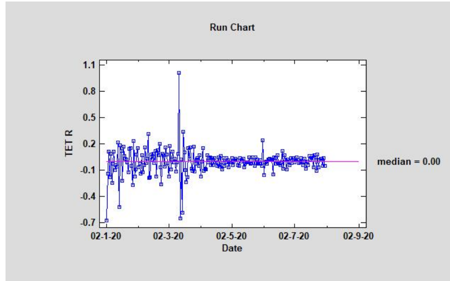

Fig. 8 *Runs test chart TET*

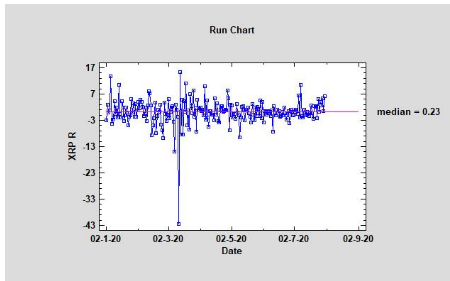

Fig. 9 *Runs test chart XRP*

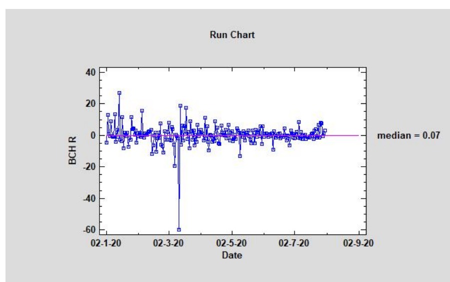

Fig. 10 *Runs test chart BCH*

Discussion

Multiple research studies aim to investigate market efficiency during crisis periods. Findings of one study revealed that during crisis periods how, investors' behavior and first perception is investors move towards cryptocurrency over traditional markets (Jabotinsky & Sarel, 2022).on; the other hand, several studies predict the opposite results and states Cryptocurrencies/Blockchains have become popular in the 20th century in the context of time and nature, but investors are still confused on the idea of portfolio diversification through blockchains. Further studies show that during financial crises, these blockchains do not hedge risk or are not termed safe havens (Conlon & McGee, 2020). Tables 1–7 show the results of the various tests for the efficient market hypothesis on Bitcoin, Ethereum, Tether Ripple, and Bitcoin Cash, respectively. A COVID-19 duration analysis was performed, and overall results indicate the majority of p values with few exceptions like (Runs test) ETH shows significant values and shows the presence of market inefficacy. The results of the current study are in line with prior studies, which also predict market inefficiency in the cryptocurrency market (Le Tran & Leirvik, 2020). The prior literature shows the relationship between cryptocurrency and the inefficiency of the market (Zhang, Hu, & Ji, 2020).

According to the literature, the efficiency of cryptocurrency during a crisis period was also affected by investors' behavior, including other markets. According to behavioral finance literature, during crisis periods, investors move toward safe heavens, and irrationality becomes dominant over rationality (Yarovaya et al., 2021). The crisis pushed volatility in markets. similarly, during the Corona crisis, volatility increased in stock and cryptocurrency markets. According to past literature, blockchain markets are significantly associated with volatility spillover, co-movement, and lead-lag effect. (Corbet, Lucey, Urquhart, & Yarovaya, 2019; Omane-Adjepong, Ababio, & Alagidede, 2019; Omane-Adjepong & Alagidede, 2019).

A study conducted by Mnif, Jarboui, and Mouakhar (2020) also predicts the same results and reports during COVID-19 markets become inefficient. In almost all of the markets the volatility is negatively affects the market efficiency, contingent on the quantiles, which denotes that the greater the volatility, the lesser the efficiency of cryptocurrency markets (Al-Yahyaee, Mensi, Ko, Yoon, & Kang, 2020). It is evident from previous literature that the market efficiency of blockchains was negatively affected during COVID-19 for multiple reasons, as explained by prior studies. Current research provides fruitful research and policy implications.

Limitations and future directions

The current study has a few limitations. First, it only considered the top five cryptocurrency markets. Future research should consider all fifty markets in order to check the validity of the efficient market hypothesis. The availability of data is not an issue, considering all markets will provide more accurate and robust results about the presence of an efficient market hypothesis. Secondly, this study used first-generation techniques. Future research must use advanced techniques, which include structural breaks in series and also check endogeneity, such as Lumsdaine and Papell (1997)) and Clemente et al. (1998). Clemente et al. (1998) tests are constructed on the basis of the advanced outlier and additive outliers. Thirdly, the current study only considers the time period from January 1. It ignores the time period before the coronavirus. Future studies should consider pre-post analysis in order to draw compression for better results. Future research should also consider other factors that are linked with the coronavirus crisis and behavioral finance, like behavioral biases (Kelikume et al., 2020).

Policy discussions

Researcher forecast that 7 billion individuals will get infected by coronavirus globally, which causes a number of deaths of around 40 million. Due to the Covid-19 pandemic, almost 7 billion people worldwide were affected, and 40 million deaths. It is fabricated to claim that no policies are imposed. While governments already closed their border, strict lockdowns and health-related policies are implemented globally in around 136 economies. citepWHO2020, which is working hard to stop the spread of the virus. At the same time, other aspects of these policies are economic downturn (Barro, Ursúa, & Weng, 2020) and crash of financial markets (Ramelli & Wagner, 2020).

In the meantime, financial establishments have executed rigorous policy checks to protect these financially distressed markets. These policies may be effective for a short run like somehow panic of investors in the U.S. is controlled. However there is still a threat that these policies will generate a gap among investors' short term and long term goals (Gormsen & Koijen, 2020).

Policies implemented by the USA may generate ambiguity in global financial markets and adversely affect emerging countries (Chen, Filardo, He, & Zhu, 2016; Tillmann, 2016). Yang and Zhou (2017), for instance, discovered that after the financial crisis of 2008, the USA QE resulted in increased systematic risk.

It is important to design such policies that are related to viruses and financial markets, as non-traditional policies result in high levels of uncertainty and financial trouble. Further, economies are not on the same page; hence, they are not working together to reduce the adverse impact. Every country is dealing with the current pandemic differently, which negatively affects the integration of financial markets globally and is a bigger threat than the coronavirus. The current study provides fruitful information for policymakers and regulatory authorities for decision-making. However, the findings of the current study are introductory in nature, as this study measures the presence of EMH in blockchain markets. This study also provides theoretical implications. From the perspective of behavioral finance investors, rationality or irrationality is linked with the coronavirus crisis and market efficiency, which has been supported by past literature.

Conclusion

As a new financial instrument, cryptocurrencies emerged in the stock market. This financial instrument is new in terms of both nature and terms. Due to the COVID-19 pandemic situation, a serious decline has occurred in the production, employment rates, and sales of the companies. This may cause the market to be highly volatile in nature and unpredictable. The current paper analyzed the simple research framework, but it is important in terms of literature that it examines the impact of COVID-19 on the stock market. A range of tests are applied to check the robust statistical tests pre- and post-COVID-19 pandemic on the stock markets. The current study analyzed how both the regularity and the stability of the stock market changed during the pandemic. During the pandemic, cryptocurrency has been more affected than the international stock market. Compared to the equities, the cryptocurrency markets show great instability and higher irregularity as compared to the equity market. So, it is concluded that cryptocurrency markets are riskier and unpredictable. In order to make the appropriate decisions, this research could be helpful for policymakers and decision-makers. For optimal comparative purposes, future research could take a longer time period to measure the pandemic situation more clearly.

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