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Cryptocurrency as a safe haven for investment portfolios amid COVID-19 panic cases of Bitcoin, Ethereum and Litecoin

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Abstract

Purpose – This article examines the susceptibility of cryptocurrencies to coronavirus disease 2019 (COVID-19) induced panic in comparison with major stock indices.

Design/methodology/approach – The author employs the Bayesian structural vector autoregression to examine the phenomenon in Bitcoin, Ethereum and Litecoin from 2nd January 2020 to 30th June 2021. A similar analysis is conducted for major stock indices, namely S&P 500, FTSE 100 and SSE Composite for comparison purposes.

Findings – The results suggest that cryptocurrencies returns suffered immensely in the early days of the COVID-19 outbreak following declarations of the disease as a global health emergency and eventually a pandemic in March 2020. However, the returns for all three cryptocurrencies recovered by April 2020 and remained resistant to further COVID-19 panic shocks. The results are dissimilar to those of S&P 500, FTSE 100 and SSE Composite values which were vulnerable to COVID-19 panic throughout the timeframe to June 2021. The results further reveal strong predictive power of Bitcoin on prices of other cryptocurrencies.

Research limitations/implications – The article provides evidence to support the cryptocurrency as a safe haven during COVID-19 school of thought given their resistance to subsequent shocks during COVID-19. Thus, the author stresses the need for diversification of investment portfolios by including cryptocurrencies given their uniqueness and resistance to shocks during crises.

Originality/value – The author makes use of the novel corona virus panic index to examine the magnitude of shocks in prices of cryptocurrencies during COVID-19.

Keywords Cryptocurrency, COVID-19, Stock markets, Bitcoin

Paper type Research paper

1. Introduction

The cryptocurrency phenomenon has gained significant attention since the introduction of Bitcoin in 2008 (Nakamoto, 2008). The prominence of the phenomenon has been attributed to its uniqueness as it uses the revolutionary block chain technology which sets it apart from traditional asset classes (Liu and Tsyvinski, 2018). Unlike stocks and traditional currencies, cryptocurrencies are highly unregulated, decentralized and backed by neither real asset nor any governmental claims (Halaburda *et al.*, 2020). Over the past decade, cryptocurrencies have grown in number and market capitalization with currencies like Ethereum, Ripple and Litecoin gaining momentum alongside Bitcoin. This can be shown by the growth in price of Bitcoin which was less than US$1 in early 2013, however over four years its value had exponentially grown to US$19,000 in December 2017 (Rajput *et al.*, 2020). Although cryptocurrencies were not originally created for investment purposes, investors have been increasingly incorporating them in their portfolios (Inci and Lagasse, 2019). This is because they may offer diversification advantages for investors with short investment horizons as attributed to the fact that their returns are not correlated with those of other asset classes (Shahzad *et al.*, 2021). The growing popularity of cryptocurrencies has attracted the attention of investors, regulators and the general public. Unfortunately, some of the attention has been

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negative especially on the investment aspect as cryptocurrencies are seen as a bubble that lacks any fundamental value (Giudici *et al.*, 2019).

Traditional financial assets such as stocks have been susceptible to crises such as the current coronavirus disease 2019 (COVID-19) pandemic (Marobhe, 2021). Since the outbreak of COVID-19 in December 2019, major stock indices have exhibited bearish conditions characterized by negative returns. The S&P 500 Index in USA experienced a downward spiral in the early days of COVID-19, and the trend was exacerbated from February 2020 following the growing magnitude of the disease (Curto and Serrasqueiro, 2021). On the other hand, the value of FTSE 100 Index in the UK tumbled by 14.3% in 2020 which is the worst performance since the global financial crisis (GFC) of 2008 (Ozkan, 2021). The SSE Composite Index in China also deteriorated by 7.2% in 2020 indicating worldwide economic repercussions of the pandemic (Chen *et al.*, 2021). Unlike, stocks and bonds, cryptocurrency is a different class of assets that has been in existence for little over a decade. Other asset classes have been in existence for over a century, and they have stood the test of time especially during major crises such as the Great Depression, the Second World War, the Oil Crisis and GFC. COVID-19 is the first major crisis since the introduction of the cryptocurrency which happened soon following the GFC in 2008 (Nakamoto, 2008). Despite their apparent advantages over traditional assets, cryptocurrencies are also prone to periods of rising volatilities. A good example was the great cryptocurrency crash of 2018 which saw a 15% plunge in price of Bitcoin in a matter of hours (Burgess, 2018). So in the light of these issues, this study models the reactions of major cryptocurrencies' returns in relation to panic and hysteria incited by COVID-19.

This study adds to existing knowledge on three folds. First, it complements findings of recent studies on cryptocurrencies and COVID-19 (Demir *et al.*, 2020; Vidal-Tomás, 2021; Yousaf *et al.*, 2021; Shahzad *et al.*, 2021; Naeem *et al.*, 2021). The focus of recent studies has been directed towards the effect of the prevailing pandemic on stocks (Ozkan, 2021; Curto and Serrasqueiro, 2021; Nguyen *et al.*, 2021; Chen *et al.*, 2021; Mezhgan *et al.*, 2021). Thus, studying cryptocurrencies sheds more light on the behavior of this unique asset class during major crises as COVID-19 is the first major crisis since the introduction of these currencies (Kristoufek, 2020). The investment orientation for years has been on stocks and commodities such as gold and crude oil, however as of late, cryptocurrency has gained significant popularity among investors (Li *et al.*, 2021). The currency has grown exponentially thus raising concerns that it may disrupt the global financial system as a result of price instabilities as those experienced in 2019 (Jiang *et al.*, 2021). The study compares cryptocurrencies to stocks similar to Kristjanpoller *et al.* (2020) since stocks have traditionally been the focus of investors (Li *et al.*, 2021). However, the author applies a different approach to examine disparities between these two assets during COVID-19. By doing this, the study was able to analyze the extent at which cryptocurrency reacts to COVID-19 panic which is instrumental for traders and investment managers in planning and diversifying their portfolios.

Second, the study employs the novel corona panic index (CPI) as an explanatory variable i.e. a shock transmitter on cryptocurrency prices. The index measures global panic and hysteria instigated by daily coverage of COVID-19 news in the major global media outlets (Ravenpack, 2020). This index is profound as frequent consumption of COVID-19 news coverage in the media is associated with increased anxiety and psychological distress (Bendau *et al.*, 2021). Since cryptocurrencies are different from stocks, the study compares shocks in cryptocurrencies with those from three major stock indices resulting from the COVID-19 news panic. This is motivated by the cryptocurrency as a safe haven during crisis narrative (Bouri *et al.*, 2021). Third, the study makes use of Bayesian structural vector auto regression (BSVAR) to model how cryptocurrencies react to shocks resulting from COVID-19 panic (Bruns and Piffer, 2020). This tool allows the magnitude of shocks in returns to be observed over a specified period of time by the use of impulse response functions. BSVAR is prevalent in stocks' behavior modeling. Despite being fundamentally different from stocks, similar modeling techniques can be employed to study cryptocurrencies behavior (Durcheva and Tsankov, 2019).

The remainder of this article is organized as follows. Section 2 covers literature review, section 3 discusses data and methods, Section 4 presents the results and section 5 covers the conclusions.

2. Literature review

2.1 Overview of cryptocurrencies

The concept of a digital cryptocurrency which is based on the idea of peer-to-peer (P2P) network was first proposed by Satoshi Nakamoto in 2008 (Nakamoto, 2008). This was followed by the launch of the first ever cryptocurrency famously known as Bitcoin on 3rd January 2009. The materialization of this concept provided a breakthrough towards having a decentralized cash system where individuals can conduct transactions anonymously without any intervention by monetary or central regulatory authorities (Halaburda *et al.*, 2020). In essence, a cryptocurrency is a piece of digital information than one holds onto whose value is derived from inaccessibility of that information by other individuals (Inci and Lagasse, 2019). Cryptocurrencies function through the combination of cryptology and revolutionary block chain technology which facilitates their exchange among network peers (Giudici *et al.*, 2019). Cryptology facilitates communication and secure storage of data while the use of block chain technology offers information transparency, openness, tamper-proof constructions as well as distributed ledger system (Xu *et al.*, 2019).

Despite sounding fancy and sophisticated, the cryptocurrency phenomenon is in fact complex for even major players in the market to fully comprehend (Fry and Cheach, 2016). It involves solving algorithms and puzzles using complex computers mathematical processes in linking transactions to "blocks" (Tschorsch and Scheuermann, 2016). The system has raised concerns pertaining to possibilities of attacks on the P2P network, price bubbles risk and the use of it for illegal activities such as terrorism and drug trading (Böhme *et al.*, 2015). Despite these concerns, cryptocurrency market has grown significantly since its inception in 2009. Other cryptocurrencies have also been launched and grown in market cap over the years including major names such as Ethereum, XRP, Bitcoin cash, Litecoin, Binance coin, Tether, EOS, Bitcoin SV, Monero, Stellar, Cardano, UNUS SED LEO and TRON (Coinmarketcap, 2021).

2.2 Cryptocurrencies during the COVID-19 pandemic

Similar to stocks, prices of cryptocurrencies may appreciate or depreciate due to investor's sentiments and attention to frequent news that have an effect on the currencies' market (Chakraborty and Subramaniam, 2021; Subramaniam and Chakraborty, 2020). For the case of stocks, there is a wealthy number of empirical studies that examine how the pandemic has affected stock indices across the world (Marobhe, 2021; Ozkan, 2021; Curto and Serrasqueiro, 2021, Chen *et al.*, 2021). However, for the case of cryptocurrency, there are limited studies that outright assess the impact of COVID-19 on cryptocurrencies' prices. These include the studies by Demir *et al.* (2020) that used the wavelet coherence analysis to evaluate the impact of COVID-19 deaths and cases on the prices of Bitcoin, Ethereum and Ripple. Their findings indicate a negative relationship in the early days of the crisis with the eventual positive relationship observed in the later periods. This is in alignment with Vidal-Tomás (2021) whose network analysis showed negative effects to cryptocurrencies during the period to April 2020 alone with eventual recovery afterward.

Lahmiri and Bekiros (2020) further studied 45 cryptocurrencies behavior during COVID-19 and observed that cryptocurrencies exhibit higher instability and irregularity thus riskier as opposed to stocks. Iqbal *et al.* (2021) used the quantile-on-quantile regression (QQR) and observed differences in cryptocurrencies pertaining to their responses to intensity of COVID-19 in the form of rising cases and deaths. Bitcoin, Ethereum, ADA, CRO were able to register positive gains in periods of small and large shocks unlike other cryptocurrencies. On a comparative study, Yousaf *et al.* (2021) employed dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) to examine hedging effectiveness for oil, Bitcoin and gold during COVID-19. Their findings urged investors to increase proportion of Bitcoin in portfolios that include these three assets as it is more stable.

In another study, Mnif *et al.* (2020) investigated the intensity of cryptocurrency returns during COVID-19 using the multifractal detrended fluctuation analysis (MF-DFA). The results surprisingly revealed that COVID-19 has a positive impact on the market efficiency of major cryptocurrencies namely Bitcoin, Ethereum, Litecoin, Binance and Ripple. These findings seem to be supported by those of Corbet *et al.* (2021) that showed increase in cryptocurrency market liquidity after World Health Organization's declaration of COVID-19 as a pandemic in March 2020. Their findings put arguments in favor of cryptocurrencies as investment safe havens during major crises. However, Conlon *et al.* (2020) beg to differ with this argument as their study shows that Bitcoin which is the major cryptocurrency does not act as a safe haven, and it exhibits similar behaviors to the S&P 500 Stock Index. Kristoufek (2020) further amplifies this line of though by disputing the fact that Bitcoin can be a safe haven during crises rather gold does a better job than it. Using a cross-quantilogram approach, Shahzad *et al.* (2021) further postulate that Bitcoin and gold are weaker assets in hedging COVID-19 risk as opposed to US VIX futures. This is ultimately supported by Naeem *et al.* (2021), who employed MF-DFA to show that COVID-19 has adversely affected cryptocurrencies' efficiency with Bitcoin and Ethereum being hit the most.

2.3 Research gap

The review of recent literature on the impact of COVID-19 pandemic on the volatility of cryptocurrencies' prices reveals disparities among the findings from different studies. The first group of studies such as Mnif *et al.* (2020), Corbet *et al.* (2021), Iqbal *et al.* (2021) and Yousaf *et al.* (2021) show that cryptocurrencies have generally been stable and exhibited some positive returns during COVID-19 thus been considered a safe haven. This has also been supported by Vidal-Tomás (2021) who showed recovery and stability of cryptocurrencies since the first wave of COVID-19 which peaked in March 2020. However, the other groups, including Shahzad *et al.* (2021), Naeem *et al.* (2021), Conlon *et al.* (2020) and Kristoufek (2020), have revealed higher instability and negative returns in cryptocurrencies in comparison to major stock indices such as S&P 500. Majority of these studies have used number of deaths and cases to explain shocks in COVID-19 price volatility though they employed different estimation methods.

This study adds some invaluable insights on this matter by using the novel CPI (Ravenpack, 2020) as a shock transmitter instead of number of deaths and cases which have been predominantly used in previous studies as predictors. Panic during COVID-19 is not caused by deaths and cases alone, but overall COVID-19 news coverage including news of economic downturns, vaccine safety concerns, re-emergence of lockdowns etc. All of these are captured in the CPI which makes it a better measure of panic during the pandemic (Umar *et al.*, 2021). Furthermore, the study examines magnitude of shocks caused by COVID-19 news along the extended timeline to June 2021 as the reaction to shocks is unparallel in different time periods. BSVAR enables the use of impulse response functions that model and graphically show the magnitude of shocks in cryptocurrency prices as a result of corona panic along the pandemic's timeline (Bruns and Piffer, 2020).

3. Data and methods

3.1 Data

The study uses data from three major cryptocurrencies namely Bitcoin, Ethereum and Litecoin. These are the first three major cryptocurrencies to be launched with an aggregate market cap of 63% of the entire cryptocurrency market as of 30th June 2021 (Coinmarketcap, 2021). The study also uses data from three major stock indices, namely S&P 500 Index in USA, FTSE 100 in UK and SSE Composite in China. This is in order to compare whether impact of shocks transmitted by corona panic on major cryptocurrencies resemble those of major stock indices given different natures of these two financial assets. The stock indices were selected from the top ten largest indices in terms of market cap. To reduce sampling bias thus avoid over representation of a particular region (Johnson *et al.*, 2000), major indices were selected to represent each major economic region, namely North America, Europe and Asia. The price data for the selected cryptocurrencies and stock indices were retrieved from the website: www.investing.com, and they range from 2nd January 2020 to 30th June 2021. The choice of the time range is motivated by the fact that COVID-19 started to gain global attention and that of authorities like the World Health Organization (WHO) in early January 2020. The first wave commenced in January and peaked in March 2020 followed by slight decline in cases and deaths in June 2020 (WHO, 2020). From this month, cases kept on fluctuating until the second wave hit major economies such as India and spread to other countries in March 2021. So the selected timeline incorporates the effects of both the first and second wave of COVID-19, the latter of which was not incorporated in earlier studies (Lahmiri and Bekiros, 2020; Mnif *et al.*, 2020).

The data for CPI were obtained from the website: www.ravenpack.com, and they also range from 2nd January 2020 to 30th June 2021. The CPI measures the magnitude of COVID-19 daily news related to panic and hysteria that make global headlines. These include rising cases and deaths, imposition and re-imposition of lockdowns, social distancing and other countermeasure around the world. They also include news of problems with efficacy of vaccines such as new deaths after vaccination, boycotts around the world against vaccinations as well as economic downturns around the world such as recessions and business closures. The index ranges between 0 and 100 with 100 with a value like 10 indicating that 10% of the global news headlines on a particular day pertained to COVID-19 panic and hysteria. The index was also used by Umar *et al.* (2021) to examine the impact of COVID-19 on prices of precious metals.

3.1.1 Trends of cryptocurrencies and stock indices returns. The trends of returns for the three cryptocurrencies and three stock indices from 2nd January 2020 to 30th June 2021 are presented in Figure 1.

The trends exhibited in Figure 1 shows increasing return volatility for the cryptocurrencies and stock indices in the first three months of 2020. This was around the time the COVID-19 pandemic was spreading around the world after the discovery of the first case in the city of Wuhan in Hubei, China. The highest negative spikes were visible during this period as the most critical events pertaining to the pandemic occurred during January and March 2020. These include reports of first cases outside China, declaration of COVID-19 as a health emergency which was followed by declaration of the disease as a pandemic by WHO. The trends of Bitcoin, Ethereum and Litecoin appear to some extent resemble each other as the spikes from March 2020 to around October 2020 were not significant in all three cryptocurrencies.

However, from October 2020 onwards volatility of returns increased as spikes increased in height for all three cryptocurrencies with volatility clustering visible during this period. For the case of stocks, the trends of S&P 500 and FTSE 100 to some extent appeared to be similar with FTSE 100 having slightly higher spikes than S&P 500 from March 2020 onwards. However, the behavior displayed by the SSE Composite is quite different from the other indices as around June 2020 there were some very sharp spikes in returns. Then from June 2020 onwards, the spikes decreased in size but were relatively higher than those of S&P 500 and FTSE 100.

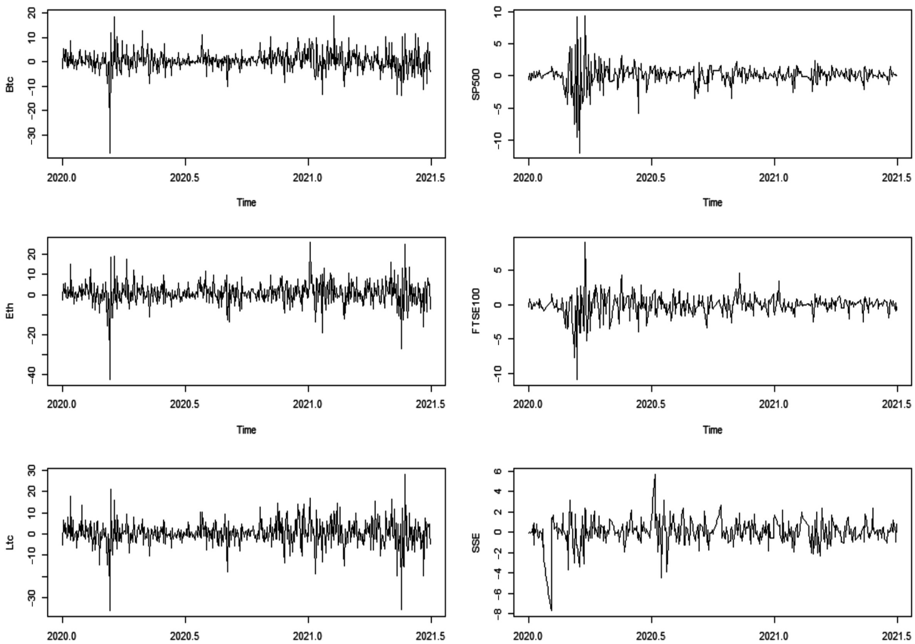


Figure 1.
Trends of returns for the selected cryptocurrencies and major stock indices

Source(s): own compilation (2021)

3.1.2 Descriptive statistics. The properties of data used for each of the variables in the period from 2nd January 2020 to 30th June 2021 are described in Tables 1 and 2.

The results of descriptive statistics indicate that all three cryptocurrencies had mean positive returns in the entire time window. For the case of stocks, S&P had positive mean returns even though the percentage is far lower than cryptocurrencies' mean returns, while on the other hand FTSE 100 and SSE Composite had negative mean returns. Despite the positive mean returns displayed by the cryptocurrencies, their returns are highly dispersed from the mean which signifies the bigger magnitude of differences between daily returns. On the other side, stocks exhibited far lower dispersion in daily returns from the mean despite having either low mean returns for the case of S&P 500 or negative returns as in the cases of FTSE 100 and SSE Composite.

When it comes to maximum and minimum returns, cryptocurrencies had largest amounts on both sides with the maximum return being 28% that was exhibited by Litecoin and the

Table 1.
Descriptive statistics for the study variables in the period from 2nd Jan 20 to 30th Jun 21

Variable	Obs	Mean	Std. dev	Min	Max
Corona panic	547	2.55256	1.26793	0	8.24
Ethereum	547	0.6726	5.59206	−42.347	25.9475
Bitcoin	547	0.37278	4.1811	−37.17	18.7465
Litecoin	547	0.39653	5.87785	−36.177	28.2016
S&P 500	547	0.08814	1.60454	−11.984	9.38277
FTSE100	547	−0.0306	1.43787	−10.874	9.05346
SSE comp	547	−0.0078	1.33384	−7.7245	5.71135

minimum of −42.347% exhibited by Ethereum. The disparities between maximum and minimum returns for the cryptocurrencies are far larger than in the stocks which explain the higher deviations of their values from the mean. In the case of CPI, the maximum measure of panic and hysteria was 8.24 as indicated by percentage of global news that covers COVID-19. The mean news coverage was 2.55% with the dispersion of 1.27% indicating relatively smaller dispersion of daily news coverage percentage from the mean.

For the case of normality, the results for non-parametric Shapiro–Wilk test for each of the study variable are presented in Table 2. The results indicate that the time series data in the entire study period for each of the seven variables are normally distributed. This is explained by the p-values of each of these variables being less than 5% critical value (Shapiro and Wilk, 1965). Then simple correlations were conducted between variables to examine how they relate to one another, and the results are presented in Table 3. The results reveal negative correlation between corona panic and returns for Bitcoin, Ethereum, Litecoin and S&P 500 however they were insignificant with the exception of Ethereum. However, the correlation is positive for both S&P 500 and SSE Composite. The results also reveal significant correlations between all three cryptocurrency returns.

For the case of stocks, all the three stock indices returns are also significantly correlated with each other. There was no significant correlation between returns for any of the cryptocurrencies and stock returns. These results coincide with Iqbal *et al.* (2021) who stressed the fact that returns of cryptocurrency are uncorrelated with those of other assets given their unique feature e.g. unregulated and decentralized.

3.2 Methods

The study employs the BSVAR to model how corona panic induces shocks in prices of cryptocurrencies. SVAR is a multivariate linear representation of a vector of endogenous variables based on its own lags and exogenous variables as a trend or a constant (Sims and Zha, 2005). The model allows setting of restrictions that allows examination of causal

Variable	Obs	W	V	z	Prob > z
Corona panic	547	0.94349	20.614	7.303	0.0000
Ethereum	547	0.91582	30.707	8.265	0.0000
Bitcoin	547	0.89222	39.316	8.862	0.0000
Litecoin	547	0.92145	28.655	8.098	0.0000
S&P 500	547	0.8027	71.972	10.321	0.0000
FTSE100	547	0.87145	46.891	9.287	0.0000
SSE comp	547	0.87217	46.63	9.273	0.0000

Table 2. Shapiro–Wilk W test for normal data

	Corona panic	Ethereum	Bitcoin	Litecoin	S&P500	FTSE 100	SSE comp
Corona panic	1						
Ethereum	−0.0873*	1					
Bitcoin	−0.0152	0.7905*	1				
Litecoin	−0.0742	0.8268*	0.7978*	1			
S&P 500	−0.0606	−0.0076	−0.003	0.0089	1		
FTSE100	0.0085	−0.0152	0.0005	−0.0156	0.6576*	1	
SSE comp	0.0836	0.0464	0.0329	0.0453	0.1930*	0.2424*	1

Note(s): *Statistical significance @ 5% level

Table 3. Correlations between corona panic, cryptocurrencies and stock indices

relationships between contemporaneous variables (Toledo *et al.*, 2008). The use of Bayesian methods in SVAR allows estimation of models using recursive identification schemes which permit over-identification of restrictions (Kociecki *et al.*, 2012). The BSVAR model as depicted by (Kociecki *et al.*, 2012, pp. 4-5) is represented as follows;

$$Ayt = B_{(1)}y_{t-1} + B_{(2)}y_{t-2} + \ldots + B_{(p)}y_{t-p} + B_{(0)} + \varepsilon_t,\ \varepsilon_t \sim \dot{N}(0,\ \Omega) \tag{1}$$

whereby $yt = \dot{N} \times 1$ vector of observations, A and $B_{(P)}$ for $p \geq 1$ are $N \times N$ matrices of coefficients an it is estimated as follows;

$$\begin{aligned} Y_t &= \Pi_0 + \sum_{t-1}^{p} \Pi_{lyt-1} + B\varepsilon_t \\ &= \Pi\omega_t + B\varepsilon_t, \quad \varepsilon_t \sim \dot{N}(0, \Omega) \end{aligned} \tag{2}$$

whereby yt is a $k \times 1$ vector of endogenous variables, ε_t is a $k \times 1$ vector of structural shocks, and $\omega_t = (1; \acute{y}_{t-1}, \ldots, \acute{y}_{t-p})'$ is an $m \times 1$ vector of the constant and p lags of the variables, with $m = kp+1$. The matrix $\pi = [\pi_0, \pi_1, .., \pi_p]$ is of dimension $k \times m$. Hence, the covariance matrix of ε_t is normalized to identity matrix.

$B_{(0)}$ = the vector of constants. Pertaining to the covariance matrix Ω the assumption is that it is diagonal with elements ω_t.

The equation can be presented in a simplified form as follows;

$$Ayt = B_{X_t} + \varepsilon_t,\ \ \varepsilon_t \sim \dot{N}(0,\ \Omega) \tag{3}$$

whereby $x_t = [\acute{y}_{t-1}\, \acute{y}_{t-2} \ldots \acute{y}_{t-p}\ 1]'$ is a K-dimensional vector and;

$B = [B_{(1)}\, B_{(2)} \ldots B_{(P)}\, B_{(0)}]$ which is a matrix of size $N \times K$ and;

$K = PN + 1$.

The *n-th* equation of (2) can be presented as:

$$A_n yt = B_n x_t + \varepsilon_{nt} \tag{4}$$

whereby

$A_n = [a_{n1}\, a_{n2} \ldots .. a_{nN}]$ and it represents the n-th rows of matrix A

$B_n = [b_{n1}\, b_{n2} \ldots \ldots b_{nN}]$ and it represents the n-th rows of matrix B

After creating the A and B matrices, the following restrictions are imposed on matrix A;

(1) The elements on diagonal satisfy $a_{nn} = 1$ (normalization).

(2) The determinant is $|A| = 1$.

(3) There are M_n free parameters of A_n which are estimated in a row vector A_n and $N-(M_n + 1)$ parameters set to zero.

Then the restrictions are written down in accordance to Waggoner and Zha (2003) as follows;

$$A_n = [1\tilde{A}_n]S_n \tag{5}$$

$$\tilde{A}_n = A_n S_n^* \tag{6}$$

whereby S_n and S_n^* = selection matrices consisting of zeros and ones of size $(M_n + 1) \times N$ and $N \times M_n$, respectively

The assumption $|A| = 1$ means that the developed model is suitable for a lower or upper triangular A (or restricted subsets). In this case, matrix A and B can be used to capture the contemporaneous impacts of one standard deviation shock in an exogenous variable. Then the impulse response analysis is conducted recursively using model (2).

To perform BSVAR modeling the unit root diagnostics are carried out for the time series data of each variable as a crucial prerequisite for time series modeling (Baltagi, 2011). The augmented Dickey–Fuller (ADF) test was used for this purpose, and the results are presented in Table 4.

The ADF results reveal that the time series data for all the variables in question do not contain a unit root i.e. stationary. This is explained by the fact that the test statistic values of each variable were greater than the 5% critical value (Dickey and Fuller, 1979). Another important consideration for BSVAR modeling is the selection of lag order which fixes the maximum duration for the past values of endogenous variable and exogenous variables to impact the endogenous variable (Ozcicek and Mc Millin, 2001). The four criteria, namely akaike information criterion (AIC), Hannan–Quinn information criteria (HQIC), Schwartz information criteria (SBIC) and the final prediction error (FPE), were used for this purpose. The results presented in Table 5 indicate that all four criteria specify the maximum lag period of one day, and this is used to model the BSVAR.

4. Results

4.1 The Bayesian structural vector autoregression results

The BSVAR was conducted for both cryptocurrencies and stock indices. Each group of assets was subjected to the impulse from corona panic to determine how each asset in their respective

	Test statistic	1% critical value	5% critical value	10% critical value
	Dfuller	Corona panic	lags(1)	
Z(t)	−4.313	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0004				
	Dfuller	Ethereum	lags(1)	
Z(*t*)	−16.048	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0000				
	Dfuller	Bitcoin	lags(1)	
Z(*t*)	−16.299	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0000				
	Dfuller	Litecoin	lags(1)	
Z(*t*)	−16.505	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0000				
	Dfuller	S&P 500	lags(1)	
Z(*t*)	−15.319	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0000				
	Dfuller	FTSE100	lags(1)	
Augmented Dickey–Fuller test for unit root number of obs = 545				
Z(*t*)	−13.342	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0000				
	Dfuller	SSE Composite	lags(1)	
Z(*t*)	−9.355	−3.43	−2.86	−2.57
MacKinnon approximate p-value for Z(t) = 0.0000				

Table 4.
Augmented Dickey–Fuller unit root test results

groups reacts to this particular impulse. This was vital as cryptocurrencies and stocks are fundamentally different causing their returns to be uncorrelated (Shahzad *et al.*, 2021).

4.1.1 BSVAR for cryptocurrencies. The BSVAR results for the impulse–response between corona panic and each of the cryptocurrencies are presented in Figure 2.

The BSVAR impulse–response results indicate that the biggest negative shock from corona panic occurred for all three cryptocurrencies in January 2020. In December 2019, the disease was still unknown and the city of Wuhan, China, was treating a dozen cases because the disease had not yet spread in other cities of abroad which may have not been a major concern especially among investors. However, in the month of January some major events occurred that may have caused massive panic thus resulting into significant negative shocks in cryptocurrency returns. During the month, the first death was reported in China and later cases were reported in the neighboring South Korea, Japan and Thailand (World Health Organization, 2020). Then in the next few days, cases of COVID-19 were reported in USA and

Table 5.
Lag order selection results

Lag	LL	LR	df	*p*	FPE	AIC	HQIC	SBIC
0	−7100.2				9591.22	26.1959	26.233	26.2908
1	−6876.2	448	36	0	4799.04*	25.5034*	25.6519*	25.8833*
2	−6850.7	51.029	36	0.05	4988.29	25.542	25.802	26.2068
3	−6834.2	33.029	36	0.611	5360.16	25.6138	25.9851	26.5634
4	−6808.6	51.09*	36	0.049	5571.93	25.6523	26.135	26.8868

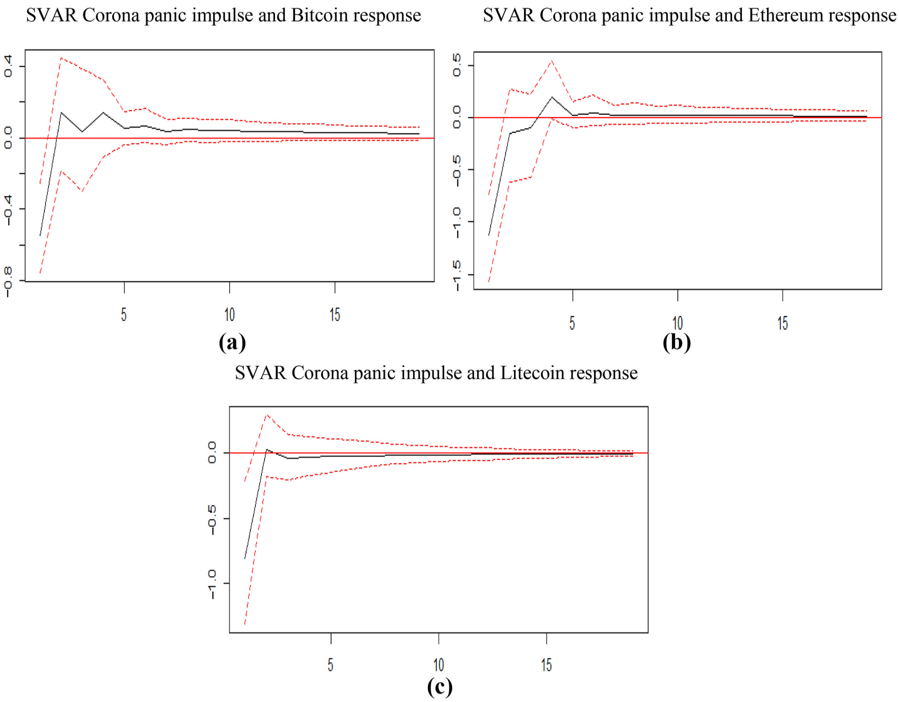


Figure 2.
Bayesian structural vector autoregression impulse responses for cryptocurrencies

Source(s): Own compilation (2021)

due to surge in cases Chinese authorities initiated a complete lockdown of the City of Wuhan cutting all access to and from other cities (Shanghai Institute for International Studies, 2020).

These developments in January were significant enough to spread panic thus leading to a sudden and significant shock in cryptocurrency prices. This is consistent with the Black Swan theory as occurrence of major events tends to cause panic among investors thus significantly affecting prices of assets (Taleb, 2007). After the initial shock all three cryptocurrencies quickly recovered with Bitcoin showing returning quickly to the positive as opposed to Ethereum and Litecoin. This seems to coincide with (Iqbal *et al.* (2021) on the aspect of the ability of Bitcoin and Ethereum to recover and post positive gains in periods of smaller and larger shocks from COVID-19.

A smaller shock in Bitcoin occurred around March 2020 when COVID-19 was declared a pandemic however this shock was small and did not send Bitcoin returns to the negative as did the first shock. Bitcoin quickly recovered and faced another smaller shock in April 2020 around when the first deaths were reported in USA however the shock was not strong enough as returns remained positive. For the case of Ethereum, the recovery from first shock was met with another smaller shock in March 2020 when the disease was declared a pandemic. Litecoin recovered from the initial shock as did the other two cryptocurrencies. However, from April 2020 to 30th June 2021, Bitcoin, Ethereum and Litecoin remained resilient to any shocks transmitted from corona panic.

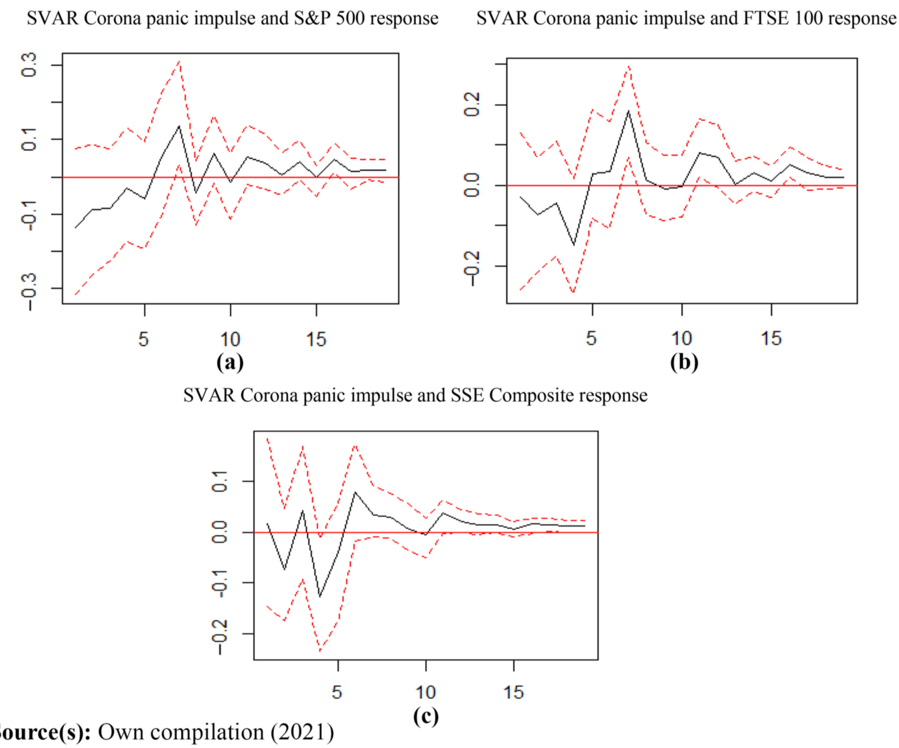
These results show that cryptocurrencies were susceptible only to initial shocks from corona panic. As the pandemic continued to unfold the investors seemed not to be distraught and remained optimistic despite the growing global panic. This appears to support the findings by Demir *et al.* (2020) which indicate that returns for cryptocurrencies suffered immensely in the early days of crisis but quickly recovered and posted positive returns in the later periods. This also explains the increase in market liquidity in March 2020 after WHO's declaration of COVID-19 as a pandemic as the cryptocurrencies already recovered from the initial shock in January (Corbet *et al.*, 2021).

These results are in alignment with those of Vidal-Tomás (2021) that reveal the fact that cryptocurrencies suffered during the first wave of COVID-19 that peaked in March 2020. However, they recovered from this adversity and remained stable from April 2020 onwards. The stability of Bitcoin and Ethereum shown by these results reflect the evidence put forward by Iqbal *et al.* (2021) that suggest the resilience of these two major cryptocurrencies amid small and large shocks. The findings further support the assertion by Yousaf *et al.* (2021) that investors should increase proportion of Bitcoin in their portfolios during COVID-19 as it is more stable than gold and crude oil. However, Naeem *et al.* (2021) do not support the findings of this study as they postulate that COVID-19 has severely affected cryptocurrencies with Bitcoin and Ethereum taking the major hit.

4.1.2 BSVAR for major stock indices. After thorough analysis of impulse–response for corona panic and cryptocurrency returns, the same analysis is done for stock indices returns. In this case, BSVAR is carried out to model by subjecting each of the three stock indices' returns to the CPI to study how the returns' responses to the impulse from corona panic. The results are presented in Figure 3.

The BSVAR results for responses of the three stock indices from the corona panic impulse paint a different picture compared with the previous results for cryptocurrencies. First, the initial shocks from COVID-19 in January 2020 were not as significant as those shown by cryptocurrencies. S&P 500, FTSE 100 and SSE Composite reacted to the initial corona panic in January 2021 however the magnitudes of the shocks were smaller than those exhibited by cryptocurrencies.

For the case of S&P 500 in USA, the returns recovered slowly from the initial negative shock however the rate of recovery slowed down in March 2020 which may be a result of the shock from declaration of COVID-19 as a pandemic. Another smaller shock occurred in April



Source(s): Own compilation (2021)

Figure 3.
Bayesian structural vector autoregression impulse responses for stock indices

2020 before the returns fully recovered to the positive. This may be due to growing panic as the first deaths were reported in USA and the global cases kept on surging worldwide surpassing 200,000 (The American Journal of Managed Care, 2020). The largest positive shock in the entire time frame occurred in May 2020 which saw a recovery to the highest positive point however this was followed by a sharp shock in returns to the negative side during June 2020. The plausible explanation can be sudden surge in cases of COVID-19 in the Southern states of USA. The returns recovered, however in the remaining timeframe the returns continued to respond to shocks transmitted by Corona panic in a positive and negative fashion.

For the case of FTSE in UK, the returns from the initial shock continued to deteriorate with the eventual recovery observed in February 2020. The recovery was hit by another shock which caused a sharp plunge in the returns to the lowest point of the entire timeframe in March 2020. This can be explained by deepening panic after declaration of the disease as a pandemic during the month of March 2020. The returns recovered from the biggest shock and in May 2020 the returns returned to positive and kept on climbing to the highest point in July 2020. Then there was a sudden and significant negative shock in July 2020 causing deterioration in returns to August 2020 as the pandemic kept on infecting people around the globe resulting into recessions in developed economies. For the rest of the period, the returns continued to respond to shocks from corona panic with positive and negative responses though not significant as those in the preceding months.

In the case of SSE Composite, the initial small initial shock was followed by a deterioration of returns to the negative until February when they started to recover to the positive by March 2020. However, the biggest shock of the entire time frame occurred in the same month of March 2020, this was the time when the corona panic was significant given the fact that the disease was declared a pandemic (World Health Organization, 2020). The returns from this shock kept on plunging to the lowest point in April 2020 and eventually started to recover and kept on climbing until the month of June 2020. Then another shock occurred but it was not significant enough to cause the returns to cross to the negative side. This shock was followed by a steady decline in returns that persisted to October 2020. A slight recovery occurred in October 2020 which was followed by steady decline in returns to March 2021.

The comparative assessment of the results from impulse–response of corona panic with both cryptocurrencies and stock indices returns reveal unparallel behavior between these two asset groups. For the case of cryptocurrencies, the biggest negative shocks occurred early in January 2020, these were severe as opposed to the initial shocks exhibited by stock returns. However, the initial shocks in cryptocurrencies quickly recovered and from April 2020 to 30th June 2021 the returns were resistant of any shocks from corona panic. However, the initial responses in stock indices returns early in January were not significant and some of them as in the case of SSE Composite remained in the positive side. However, significant negative shocks occurred later on in the months of either April or June 2020 and smaller shocks kept on occurring for the rest of the timeframes to 30th June 2021. This shows that stocks were not able to resist shocks transmitted by corona panic throughout the study period as opposed to the resistance exhibited by cryptocurrencies after recovery from the initial negative shocks. These results are in contrast to those of Conlon *et al.* (2020) that contest the cryptocurrency as a safe haven during COVID-19. They argue in favor of stocks as safer investments during the pandemic similar to Shahzad *et al.* (2021) who also undermine the role of cryptocurrency in favor of equity futures.

4.2 The forecast error variance decomposition (FEVD) results

To further estimate the extent of the variability in cryptocurrency returns in relation to corona panic and their lagged returns, the forecast error variance decomposition (FEVD) was conducted, and the results are presented in Figure 4.

The results reveal that at least 95% of the variability in Bitcoin returns was lagged by their own variances while the remaining percentage is explained by the corona panic. For the case of Ethereum, only 4% of the variations in its returns were explained by corona panic. About 56% of the variations are explained by changes in Bitcoin value, while the remaining 40% are influenced by Ethereum's lagged variance. Lastly, 58% of variability in Litecoin's returns is explained by variations in Bitcoin while only 2% are explained by corona panic. The remaining 40% of variations is explained by the lagged variances of Litecoin itself. These results indicate that though corona panic can influence variations in cryptocurrency returns, its influence is very minimal. Most of the variations in Bitcoin are influenced by its own past values and at the same time this currency significantly influences variations in Litecoin and Ethereum. This is explained by the dominant role of Bitcoin in the cryptocurrency market as prices of other cryptocurrencies tend to co-move with that of Bitcoin (Kumar and Ajaz, 2019).

5. Conclusions

Using daily data from three cryptocurrencies namely Bitcoin, Ethereum and Litecoin ranging from 2nd January 2020 to 30th June 2021, this article examines susceptibility of cryptocurrencies to COVID-19 panic. The author compares these currencies reaction to those from three major stock indices namely S&P 500, FTSE 100 and SSE Composite. The results suggest that all three cryptocurrencies experienced major negative return shocks during the first wave of COVID-19. However, they eventually recovered in April 2020 and

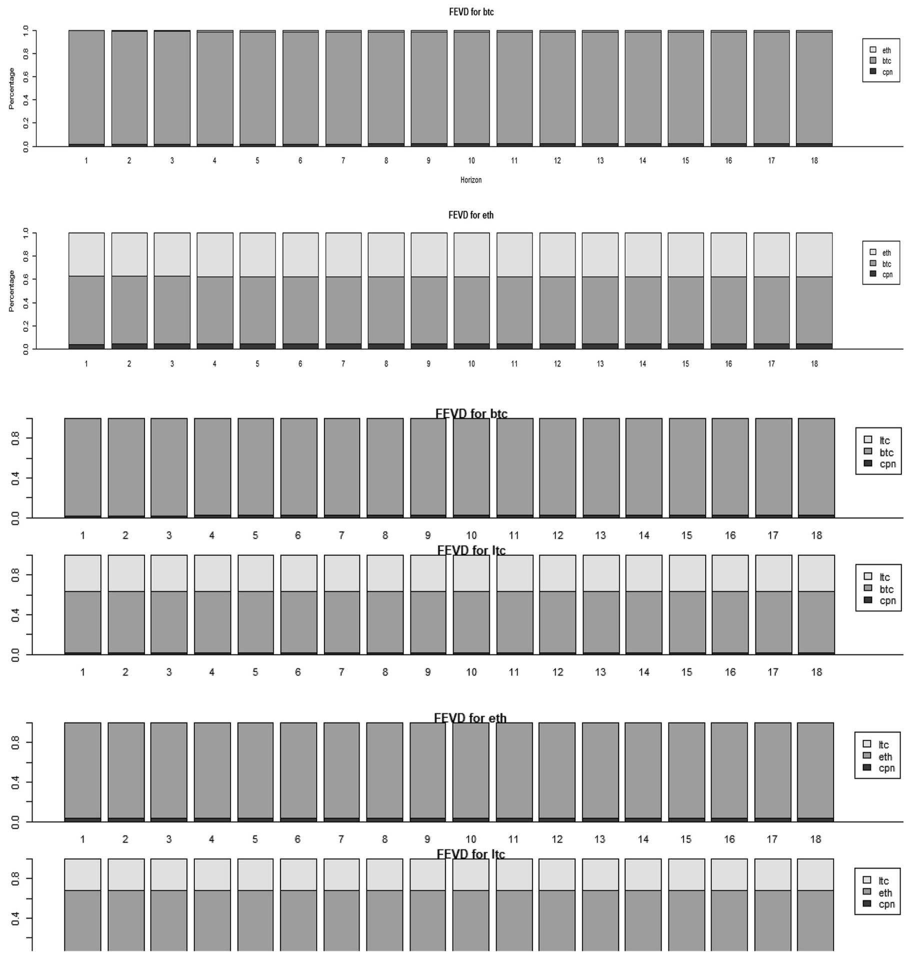


Figure 4.
FEVD results for the variability of cryptocurrencies returns and corona panic

Source(s): Own compilation (2021)

remained resistant to further COVID-19 panic shocks. A different story can be said about S&P 500, FTSE 100 and SSE Composite as they were susceptible to shocks throughout all two waves of COVID-19. The results of this study have tremendous theoretical and policy implications. First, they provide evidence to support the cryptocurrency as a safe haven during COVID-19 hypothesis which is also advocated by Corbet *et al.* (2021); Iqbal *et al.* (2021) and Yousaf *et al.* (2021). This is paramount for cryptocurrency theories development as empirical literature has been divided on the subject due to application of different approaches to examine the phenomenon.

Secondly, the results present evidence to support incorporation of cryptocurrencies as part of the investment portfolios. This is because cryptocurrencies have displayed long-term resilience to COVID-19 thus making them stable. Furthermore, cryptocurrencies offer tremendous diversification benefits not offered by stocks and commodities. The reason is prices of major commodities such as gold, silver, crude oil and grain as well as those of stocks are driven by similar factors. This makes their returns highly correlated thus offering less diversification benefits (Li *et al.*, 2021). However, cryptocurrencies have the potential to offer significant diversification benefits for investment managers because their prices are not correlated with those of major commodities and stocks (Shahzad *et al.*, 2021). Thus incorporating them in the portfolio will help to hedge against risks of unexpected deterioration in value of investments from exogenous shocks such as COVID-19. This is vital for traders, investment managers and policymakers as each of these are highly interested in the risk aspect of investments. Policymakers have been questioning the safety of cryptocurrencies since the inception of the concept. However, these results provide evidence to enlighten them on the benefits of cryptocurrencies amid COVID-19 pandemic. By having a strong predictive power over other cryptocurrencies, Bitcoin should be given priority over other cryptocurrencies whose prices co-move with that of Bitcoin.

Future researchers should apply more advanced techniques apart from SVAR to analyze the impact of corona virus panic on cryptocurrencies. They can benefit from the use of CPI to predict cryptocurrency volatility using different families of symmetrical and asymmetrical GARCH models. Instead of examining the impact of corona panic on cryptocurrencies using inter day returns, future studies should focus on assessing the intra-day volatilities. This can be attributed to the fact that intraday volatility examination is crucial for market participants engaged in frequent trading (So and Xu, 2013).

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