Impacts of the global pandemic on returns and volatilities of cryptocurrencies: An empirical analysis

Varun Kumar Rai
Research Scholar,
Department of Commerce, Delhi School of Economics, University of Delhi, Delhi, India
Email: varun.dse.du@gmail.com

Vineeta Kumari (Corresponding author)
Assistant Professor,
P. G. Department of Commerce, Magadh University, Bodhgaya, Bihar, India
Email: vidhatamu@gmail.com

Abstract

Employing the standard event study methodology and the OLS market model to examine how the global pandemic announcement impacted cryptocurrencies, we test the null hypotheses that "the global pandemic declaration did not significantly impact the abnormal returns of the cryptocurrencies", and "during the global pandemic declaration, the cryptocurrencies did not experience any significant abnormal volatilities". The average abnormal return on t-2 was nearly minus 40 percent, which is the highest negative value during the 61-day event window. The cumulative average returns are significantly negative during the event window. The global pandemic news has significantly impacted cryptocurrencies and are more volatile during the outbreak. The study's findings will empower the investors to implement proper investment strategies during emergencies.

***Keywords**: Event study; covid-19; pandemic; cryptocurrency; abnormal return; volatility*

Suggested citation:
Rai, V. K., & Kumari, V. (2021). Impacts of the global pandemic on returns and volatilities of cryptocurrencies: An empirical analysis. International Journal of Accounting, Business and Finance, 1 (1), 24-39.

1. Introduction

Cryptocurrencies have gained importance in the last few years. While most emerging nations still consider it illegal, a few developed nations have legalized its trading. During the covid-19 turmoil, researchers have debated in favor of the crypto market since they find it a safe haven at the time of crisis. While many researchers have examined the volatility in the crypto market using different econometric methods, we do not find significant contributions to the efficiency of the crypto market during the pandemic. Hence, we contribute to the event study literature examining the efficiency of the crypto market during the pandemic, primarily through the market reactions to the global pandemic declaration.

Covid-19, the improved version of "severe acute respiratory syndrome coronavirus 2" (SARS-CoV-2), is a contagious infection that firstly originated in Wuhan, China, in December 2019. It was continuously increasing worldwide, which compelled the WHO to declare it as a "public health emergency of international concern" on January 30, 2020. Later, it was declared a pandemic on March 11, 2020. Out of 274 million (approx.) confirmed cases, 5.35 million (approx.)people died worldwide with the novel coronavirus. This contagion continues with its new variant, Omicron, after the second wave variant Delta. As the stock market is efficient, it is influenced by small news. These horrible incidents affect many sectors Tourism and Hospitality, Transportation, Pharmaceuticals and Healthcare, IT, and FMCG, etc. This pandemic is also affecting the international stock market due to the negative sentiments of investors. Many studies have been conducted to test the impact of this novel coronavirus spread worldwide. While (Carter et al., 2021; Kumari et al., 2021; Maneenop & Kotcharin, 2020) examine the impacts on the global airline industry (Hu et al., 2021; Pandey & Kumar, 2021; Pandey & Kumari, 2020a; Pham et al., 2021; Yang et al., 2020) examine the impacts on the tourism industry, (Alam et al., 2020; Baker et al., 2020; Kandil Göker et al., 2020; Pandey et al., 2021; Pandey & Kumari, 2021b, 2021a, 2021c, 2021d; Polemis & Soursou, 2020) examine the impact of the pandemic on the overall stock market. The covid-19 pandemic has created great turmoil and adversely affected the global financial system. It was entirely different from other financial crises and created many problems in the market. Due to this, investors search for financial assets having safe-haven characteristics among gold, cryptocurrencies, foreign exchange, and commodities (Ji et al., 2020).

Since the emergence of cryptocurrency, it has been considered a safe haven, hedger, and risk diversifier. In support of this property (Urquhart & Zhang, 2019; Shahzad et al., 2019; Guesmi et al., 2019; Bouri et al., 2017; Bouri et al., 2017; Chan et al., 2018) stated that the inclusion of cryptocurrency in the portfolio along with the gold and stocks had reduced the risk at a considerable level. While (Pal & Mitra, 2019) argued that gold is a better player in hedging than Cryptocurrency (Bitcoin). In contrast of it (Smales, 2019) argued that the transaction of cryptocurrency is costlier than other assets and more volatile and less liquid, while (Mnif et al., 2020) enlightened its speculative nature. Further, (Corbet, Cumming et al., 2020; Corbet et al., 2018; Gandal et al., 2018; Kliber et al., 2019; Wang et al., 2019; Wang et al., 2019) mentioned its illegal transactions and financial misappropriation which creates doubt in treating cryptocurrencies as a safe-haven. Although the pre-covid-19 period was mixed, few studies support cryptocurrencies as a safe haven in the pre-Covid-19 era. In many studies, cryptocurrencies are far from safe-haven characteristics, while gold is considered a safe-haven asset during pandemics (Kristoufek, 2020).

Like the stock market, the cryptocurrency market has also been affected by the Covid-19 pandemic. Abundant literature discusses the co-movement of cryptocurrencies with other financial assets. However, there is a lack of studies examining the efficiency of the crypto market. We do not find sufficient literature addressing how cryptocurrencies react to new information. Considering the global pandemic announcement by the World Health Organization (WHO) as an event of interest, we examine the impact of this pandemic on the cryptocurrency market; we have conducted the event study in this paper, showing mixed results during the event window. We test the null hypotheses that "the global pandemic declaration did not significantly impact the abnormal returns of the cryptocurrencies", and "during the global pandemic declaration, the cryptocurrencies did not experience any significant abnormal volatilities". The study's findings will empower the investors to implement proper investment strategies during emergencies.

2. Review of literature

This section provides a brief review of cryptocurrency literature during the covid-19 pandemic. We find sufficient literature covering the cryptocurrency performance during the uncertain event. While some use the wavelet model, a few use the GARCH and ARDL models to establish a relationship with stock market returns and measure the volatility during the pandemic.

Vidal-Tomás (2021) examined the transition of 69 long-lived cryptocurrencies on the data ranges from August 01, 2019, to August 01, 2020, after the declaration of covid-19 as a pandemic. He found that cryptocurrencies were significantly affected for a short period from March 12, 2020, to April 01, 2020, due to the financial panic. It was recovered in its initial state as the pandemic disappeared in July. Ho et al. (2020) examined the position of cryptocurrencies with the help of network analysis and cross return correlation coefficient and centrality measure on the data taken from the coin market for 2013-2020. They found that the cross-return correlation among different cryptocurrencies was weakened during 2013-2016 and strengthened after this period. They also found that until mid-2016, BTC had dominated the market before developing the application to use blockchain technologies (MAID and FTC between mid-2016 and mid-2017). After that, ETH replaced the BTC and its correlated cryptocurrencies because of its smart contract capability to become the benchmark cryptocurrency. However, during the covid-19 pandemic, the ETH was replaced by BNB and QTUM due to community engagement. Umar & Gubareva (2020) examined the impact of covid-19 on the volatility of fiat currencies and cryptocurrencies from January 2020 to May 2020. He found high coherence of price movement in Euro, British pound, and Renminbi currencies and eleven major cryptocurrencies with coronavirus panic index. Rupp et al. (2021) examined the co-movement between 'Dow Jones World Stock Market' and 'Sukuk Market' along with 'Islamic Stock Market' with the help of wavelet transformation technique suggested that in comparison of short-term, long-term portfolio diversification gives benefits.

Disli et al. (2021) examined the correlation among safe-haven financial assets, i.e., gold crude oil and cryptocurrencies, with the help of wavelet coherence analysis. They found that before covid-19, there was low coherence of Bitcoin, gold, and crude oil with stock index while after the onset of covid-19 connectedness were observed, which did not exhibit as Bitcoin as a safe-haven but later with time-varying co-movements, it was found that Oil, Gold, and Bitcoin created diversification opportunity to investors in long-run. Caferra & Vidal-Tomás (2021) examined the co-movement of cryptocurrencies and the stock market from November 01, 2019, to June 01, 2020, on the price data of two cryptocurrencies and two stock markets. They employ the "Wavelet coherence approach" and find that stock and cryptocurrencies fall due to financial panic, but "Markov switching Autoregressive Model" in the short term, especially in March, reveals the rapid recovery of cryptocurrency since it was in the bear market between March 09, 2020, to March 09, 2020, while stock markets were in a bear market since February 20, 2020. In simple words, cryptocurrencies and the stock market moved in the same direction for a short period, not for all frequency time, because cryptocurrencies are unrelated to the real economy and are not controlled by the government or central bank. It also does not correlate with the international exchange rate (Corbet et al. (2018); Baur et al., 2018).

Conlon et al. (2020) examined the safe-haven properties by using value at risk (VaR) and conditional value of risk (CVaR) for three cryptocurrencies, Bitcoin, Ethereum, and Tether, while adding in a portfolio of six stock indexes (S&P 500, FTSE 100, FTSE, MIB, IBEX and CSI 300) of U.S., U.K., Italy, Spain and China' respectively and MSCI was taken as world index investors repetitive. They found that only CSI 300 may reduce the downside risk due to less allocation to Bitcoin (16%), Ethereum (14%). However, Tether was a safe haven during the Covid-19 pandemic. It was the most stable cryptocurrency because it was pegged with U.S. dollar (Maiti et al., 2020). Nasreen et al. (2021) examined the interconnection and enclosed opportunities from September 30, 2015, to June 04, 2020, of the top 9 cryptocurrencies where TVP-VAR showed a high degree of interrelatedness. They find that the investor's preferences changed during the pandemic since cryptocurrency connectedness significantly reduced and the hedging efficacy varied enormously. Corbet et al. (2021) examined the volatility spillover of the stocks of the company directly involved in R&D and production of material used to contain the spread of novel coronavirus with the help of the DCC GARCH t copula model. They found directional volatility spillover on stocks and Bitcoin due to the covid-19 pandemic. Corbet, Hou, et al. (2020) examined the volatility of major cryptocurrencies during the pandemic with GARCH and found that it acted as a store of value, safe haven, and risk diversifier. However, cryptocurrencies were affected by the negative sentiments of the investors.

Kim et al. (2020) examine the time-varying relationship among Bitcoin, Gold, and S&P 500 with DCC- GARCH, NADCC-GARCH, GC-DCC-GARCH, and non-linear base GC-DCC-GARCH where GC based GARCH solved the problem which cannot be solved with DCC m based GARCH. They found in their study that the Gold and S&P 500 were significant to Bitcoin in the long run. Lahmiri & Bekiros (2021) examined returns and volatility of long memory parameters during prior and COVID 19 pandemic of digital currencies & international stock exchange using the ARFIMA and FIGARCH models. They found that the ARFIMA & FIGARCH model was notably influenced during COVID 19 pandemic and the results also suggested a hybrid long memory model that can be remarkably suitable to describe and compare cryptocurrencies and stocks. Demiralay & Golitsis (2021) examined the DECO-GARCH model, pre and during the pandemic period whereas the determinants of the market linkages found demand for Bitcoin increased notably during the pandemic, and it helps possible suggestions for investors, traders, and policymakers as well as help in the understanding cryptocurrency market at the time of extreme stress.

Hsu et al. (2021) examined a sample of three cryptocurrencies, ten traditional currencies, and two gold prices from August 07, 2015, to June 15, 2020, and found a significant co-volatility spillover effect between the three assets. Nakov et al. (2020) suggested that before the creation of Ethereun, blockchain was treated as the decentralizing technology of the financial world. All industries have created a smart contract as per their need. Bat and Theta currencies are primary proof of smart contracts which are based on Ethereum. Kumar et al. (2020) suggested the role of blockchain and cryptocurrencies in altering financial structure during the covid-19 financial panic where the government pumped money into the economy. There was the need to define the regulator's role in a decentralized economy in case accurate store value representation by Bitcoin. Further, they discussed the functioning of the Oracles technology used in blockchain.

Maiti et al. (2020) examined the behavior of five cryptocurrencies chosen based on the market influence during covid-19 with the help of threshold autoregression (TAR) and Smooth transition autoregressive (STAR) model. They found that Tether's behavior was inconsistent with the other four because the daily average time series pattern was non-linear while linear in the case of the other four. (Neslihanoglu, 2021) examined the relationship between cryptocurrency price and the CCI 30 index for the pre and during pandemic using the linear specification of the market model (LMM). The author found the time-varying linearity specification of the LMM (Tv-LMM) favorable in terms of modeling & forecasting performance of cryptocurrency price and CCI30 index. Jeribi et al. (2021) examined the price data of Bitcoin, Ethereum, Dash, Monero, Ripple, and gold from January 31, 2020, to September 17, 2020, to compare the pre-crisis period from January 01, 2016, to January 30, 2020. They conclude that the short and long-term dynamics of the stock market and cryptocurrency returns are changing during the pandemic.

González et al. (2021) used a NARDL (non-linear autoregressive distributed lag) framework to investigate asymmetric interdependencies between 12 cryptocurrencies and gold returns from January 2015 to June 2020. The findings revealed that when economies are in turmoil, such as during the COVID-19 crisis, the correlation between gold price returns and cryptocurrency returns increases. Jareo et al. (2021) looked into the relationship between oil prices and cryptocurrency prices (November 20, 2018, to June 30, 2020). Using the NARDL technique, they discovered that there was interdependence between oil and cryptocurrency during economic turmoil such as SARS-Cov-2 and Covid-19. (French, 2021) compared the effects of the Twitter-based Market Uncertainty index (TMU) and variables on Bitcoin returns before and after the pandemic and discovered that TMU has a significant effect on Bitcoin returns only and its conditions volatility is notably higher during the pandemic.

James (2021) examined a sample of 45 cryptocurrencies and 72 stocks separately. They looked at the evolution of bitcoin and the stock market dynamics at the same time. They also used freshly developed methodologies to compare the two multivariate time series trajectories, erratic behaviors, and extreme values. The findings reveal that cryptocurrencies have stronger collective dynamics than equities, and that equities perform more similarly in their trajectories and extremes, and that anomalies endure longer. Ji et al. (2020) tried to search safe have financial assets during pandemic on the data from December 2019-March 2020 with the help of Cross Quantilogram between the pair-wise return attained on the assets. They found in his study that gold and soybean commodities remain safe-haven while other financial assets are less effective during the covid-19 pandemic.

Lahmiri & Bekiros (2020) examined the stability and irregularity of a mix of cryptocurrency and international stock markets pre and during the pandemic. They used for estimation Largest Lyapunov Exponent (LLE) and Approximate Entropy (ApEn) after that, t-test and F-test were made. They found more instability and irregularity in cryptocurrency than in the international stock market. Mnif et al. (2020) examined the level of cryptocurrency market efficiency on the sample of five cryptocurrencies (Bitcoin, Ethreum, Ripple Litecoin, and Binance) during covid-19 through Multifractal analysis. They found that covid-19 was affected cryptocurrency positively. Kristoufek (2020) tested the quintile correlation of Bitcoin with S&P 500 and VIX. It was compared with the traditional safe-haven asset gold. He suggested that gold is safe while Bitcoin is not. Drozdz et al. (2020) examined the cross-correlation between cryptocurrency, stocks (S&P 500 and Nasdaq 100), fiat currencies, and commodities (gold and crude oil). They examined in three-phase at the first case detection in U.S. (January 2020) declaration of pandemic (March 2020) and second wave period (May-July, 2021). In the first case, they found BTC as uncorrelated with major stocks like S & P 500 and Nasdaq 100, while in the second and third case, it was found a positive correlation with stocks, fiat currencies, and commodities. Kim (2021) examined the filiation and sequel based on the theory of planned behavior of consumers' attitudes toward money. They found that power-prestige, retention-time, and distrust significantly impacted behavioral intention to use Bitcoin.

Davidovic (2021) conducted the event study to test the effect of covid-19 on the leading stock, commodity, and cryptocurrency market with the conditional value at risk (CVaR) and MCMC stochastic volatility on the data from January 2019 to June 2020. He found that the market was unstable during July-October 2019 and March-June 2020 due to the U.S.-China trade war and the covid-19 pandemic. They were more volatile during the pandemic, especially cryptocurrencies and the oil market. Due to the cross-market volatility spillover effect created global financial contagion, but later there were maintained stability because of the intensive government interventions and liquidity support.

The literature review indicates the methodological gap in accessing the impacts of the pandemic on cryptocurrencies. We find only (Davidovic, 2021) to have conducted an event study to examine how the pandemic impacted the cryptocurrencies. We use the event study method to examine the impacts on the returns and volatility of top 100 cryptocurrencies.

3. Data & Methodology

3.1. Data

Our initial sample consisted of 100 top cryptocurrencies in terms of market capitalization. The daily open-close-high-low figures were collected from www.coinmarket.com, while the CMC Crypto index data was collected from www.finance.yahoo.com. The daily open-close-high-low figures for gold and crude oil were www.nasdaq.com. However, the open-close-high-low figures for only 76 cryptocurrencies (see Table 1) were available for the sample period, i.e., from August 14, 2019, to April 10, 2020. Hence, the final sample analyzed in this study consists of 76 cryptocurrencies from among the top 100. The estimation period (August 14, 2019, to February 09, 2020) is 180 days, and the event window consists of 61 days (February 10, 2020, to April 10, 2020). We have divided the study into two parts, viz., the whole sample of 76 cryptocurrencies and the top 10 cryptocurrencies among the sample.

Table 1: List of sample cryptocurrencies

Sl. No.	Cryptocurrency	Sl. No.	Cryptocurrency
1	BITCOIN (BTC)	39	BitTorrent (BTT)
2	ETHEREUM(ETH)	40	Basic Attention Token (BAT)
3	TETHER	41	Celsius (CEL)
4	XRP	42	TrueUSD (TUSD)
5	BINANCE COIN(BNB)	43	DigiByte (DGB)
6	CHAINLINK(LINK)	44	Ren
7	LITECOIN (LTC)	45	OKB
8	CARDANO(ADA)	46	0x (ZRX)
9	BITCOIN SV(BSV)	47	Paxos Standard (PAX)
10	USD COIN(USDC)	48	HedgeTrade (HEDG)
11	EOS	49	Qtum
12	MONERO(XMR)	50	ICON (ICX)
13	CRYPTO.COM COIN(CRO)	51	Zilliqa (ZIL)
14	TRON (TRX)	52	Loopring (LRC)
15	STELLAR(XLM)	53	Quant (QNT)
16	TEZOS(XTZ)	54	Ocean Protocol (OCEAN)
17	WRAPPED BITCOIN (WBTC)	55	Kyber Network (KNC)
18	NEO	56	Decred (DCR)
19	UNUS SED LEO (LEO)	57	Augur (REP)
20	COSMOS (ATOM)	58	Reserve Rights (RSR)
21	NEM (XEM)	59	Lisk (LSK)
22	HUOBI TOKEN (HT)	60	Bitcoin Gold (BTG)
23	IOTA (MIOTA)	61	ZB Token (ZB)
24	VECHAIN(VET)	62	Siacoin (SC)
25	DASH	63	Revain (REV)
26	ZCASH(ZEC)	64	Terra (LUNA)
27	THETA	65	Enjin Coin (ENJ)
28	Ethereum Classic(ETC)	66	The Midas Touch Gold (TMTG)
29	Maker (MKR)	67	Nano (NANO)
30	Filecoin (FIL)	68	Ampleforth (AMPL)
31	OMG Network (OMG)	69	Decentraland (MANA)
32	Ontology (ONT)	70	Aragon (ANT)
33	Synthetix Network Token (SNX)	71	Bitcoin Diamond (BCD)
34	ABBC Coin (ABBC)	72	Golem (GNT)
35	FTX Token (FTT)	73	MonaCoin (MONA)
36	Waves	74	Ravencoin (RVN)
37	Dogecoin (DOGE)	75	Numeraire (NMR)
38	Algorand (ALGO)	76	Bytom (BTM)

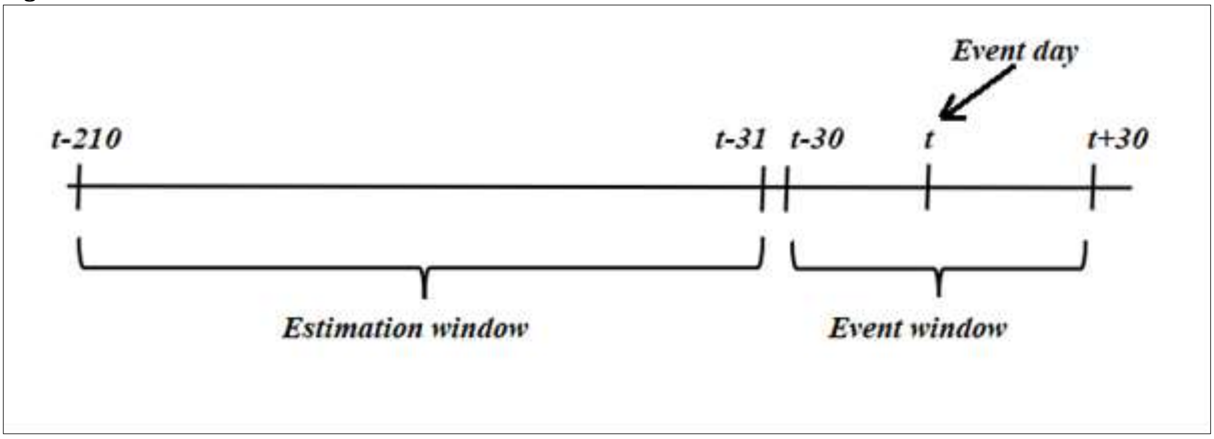
3.2. Adjustments made

The cryptocurrency prices were available seven days a week, while the CMC Crypto index prices were available five days a week. For consistency in the results, we replaced the missing figures by averaging the two figures before and after the data was missing. In the case of public holidays, where data for the index were unavailable, the same procedure has been followed to fill the gap.

3.3. Methodology

We employ the (Brown & Warner, 1980, 1985) standard event study methodology and the OLS market model to estimate expected returns. We first determine the event to which the reaction of the cryptocurrencies is to be analyzed. We have taken March 11, 2020, as the event day (t), i.e., the day on which the World Health Organisation declared the novel coronavirus outbreak as a 'Global Pandemic.' The event day is crucial because it was on this day when the whole world was informed that the novel coronavirus outbreak has spread to such an extent that it will impact the lives and economies worldwide. All the market players sensed that it was bad news on this day. On this day, it led to a sharp fall in the indices of financial markets worldwide. Once we have determined the event day, we need to determine the estimation and event windows. A 180-day estimation period and a 61-day event window (further divided into shorter windows) have been used. The event timeline is presented in figure 1.

Figure 1: Event timeline



3.3.1. Average Abnormal Returns

We calculate the log returns (**LR_{ct}**), as in (Elad & Bongbee, 2017), of the sample cryptocurrencies and the Crypto index on each of the 241 days. We then calculate the alpha and beta for each sample of cryptocurrencies by regressing the estimation-period log-returns of the cryptocurrency and the crypto index. Using these alpha and beta values, we estimate the normal returns on each of the 241 days. Literature suggests several estimation models for the estimation of normal returns. However, (Brown & Warner, 1980, 1985; Mackinlay, 1997) provide evidence that the results generated by different models are similar. Recent studies support the use of the market model in event studies (Anh & Gan, 2020; Pandey & Jaiswal, 2017; Pandey & Kumari, 2020b, 2020c; Phuong, 2021; Rai & Pandey, 2021; Ullah et al., 2021). So, we use the market model for estimating the normal returns, $\boldsymbol{NR_{ct}}$, of the cryptocurrency 'c', on day 't', as follows:

$$\boldsymbol{NR_{ct} = \alpha + \beta R_{mt}} \quad (1)$$

where, **α** is the intercept, and **β** is the slope coefficients of the OLS regression model; and, **R_{mt}** is the rate of return on the benchmark index (CMC Crypto Index) on day t.

Once the normal returns have been calculated, we subtract the normal return (**NR_{ct}**) from the log returns (**LR_{ct}**) to arrive at the abnormal returns (**AR_{ct}**). After that, each day's abnormal daily returns for each of the cryptocurrencies are aggregated for the 61 days event window. These aggregated abnormal returns are then divided by the total number of cryptocurrencies (**N**), to arrive at the average abnormal return (**AAR_t**) as follows:

$$\boldsymbol{AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{ct}} \quad (2)$$

The cumulative average abnormal return (CAAR) for each day is calculated by summing the AAR from the beginning of the event window to the day for which the CAAR will be calculated. Further, for the shorter event windows, we calculate the AAR as follows:

$$\boldsymbol{AAR_{p,q} = \frac{1}{n}\sum_{i=1}^{N} AAR_t} \quad (3)$$

where, **$AAR_{p,q}$** is the average abnormal return for the window period p,q; and **n** is the number of days in the window period p,q. The CAAR for the shorter event windows is calculated by summing up the AARs in that window period.

The above process is repeated, replacing the CMC Crypto Index with gold and crude oil.

3.3.2. Average Abnormal Volatility

As we did in the case of average abnormal returns, we use the CMC Crypto Index's actual volatility as our independent variable for calculating the abnormal volatilities. First of all, we calculate actual volatility (Floros, 2009) as 'the first logarithmic difference between the intraday high and low values.'

$$V_{ct} = Ln(H_{ct}) - Ln(L_{ct}) \quad (4)$$

$$V_{mt} = Ln(H_{mt}) - Ln(L_{mt}) \quad (5)$$

$$NV_{ct} = \alpha + \beta . V_{mt} \quad (6)$$

where,

V_{ct} is the simple measure of the volatility of the cryptocurrency c on day t

V_{mt} is the simple measure of the volatility of the CMC Crypto Index on day t

H_{ct} and L_{ct} are the high and low figures of the cryptocurrency c on day t

H_{mt} and L_{mt} are the high and low figures of the CMC Crypto Index on day t

NV_{ct} is the estimated volatility of cryptocurrency c on day t

α & β is the intercept and slope coefficients of the OLS regression model

Once the normal volatilities have been calculated, we subtract the normal volatility (**NV_{ct}**) from the actual volatility (**V_{ct}**) to arrive at the abnormal volatilities (**AV_{ct}**). After that, each day's abnormal daily volatilities for each of the cryptocurrencies are aggregated for the 61 days event window. These aggregated abnormal volatilities are then divided by the total number of cryptocurrencies (**N**), to arrive at the average abnormal volatility (**AAV_t**) as follows:

$$AAV_t = \frac{1}{N}\sum_{i=1}^{N} AV_{ct} \quad (7)$$

The cumulative average abnormal volatility (CAAV) for each day is calculated by summing the AAV from the beginning of the event window to the day the CAAV will be calculated. Further, for the shorter event windows, we calculate the AAV as follows:

$$AAV_{p,q} = \frac{1}{n}\sum_{i=1}^{N} AAV_t \quad (8)$$

where, **$AAV_{p,q}$** is the average abnormal volatility for the window period p,q; and **n** is the number of days in the window period p,q. The CAAR for the shorter event windows is calculated by summing up the AARs in that window period.

The above process is repeated by replacing the CMC Crypto Index with gold and crude oil.

3.3.3. Testing the significance of AARs, and CAARs

Once we have calculated the AARs, AAVs, CAARs, and CAAVs, we need to test the significance of these results to test the hypothesis that "there exists no abnormal return in the cryptocurrency market on or around the event day". We calculate the t-statistics as follows:

$$AAR_t\, t = \frac{AAR_t}{\sigma_{N,e}} \quad (9)$$

$$CAAR_t\, t = \frac{CAAR_t}{\sigma_{N,e}\sqrt{N_{t+1}}} \quad (10)$$

where, $\sigma_{N,e} = \sqrt{\frac{\sum_{i=1}^{N}\sigma_{c,e}^2}{N^2}}$, is the aggregated estimation period standard deviation, $\sigma_{c,e}^2$ is the estimation period standard deviation for each cryptocurrency; and **N_{t+1}** is the absolute value of event day t plus 1.

4. Quantitative Analysis and Interpretation

4.1. Impact on abnormal returns and volatilities

This section deals with the quantitative analysis of abnormal returns and volatilities of the event window. Table 2 presents the t-values of the AARs and CAARs during the 61-day event window. We find a mix of significantly negative and positive AARs during the pre-and post-event period. While 11 AARs are significantly positive during the pre-event period, 14 AARs are significantly positive during the post-event period. Nine AARs are significantly negative during the pre-event period, and ten AARs are significantly negative during the post-event period. The event-day AAR is also negative. We find more positive values than negative values. The overall analysis of the AARs reveals a mixed reaction of the crypto market. Observed more closely from t-2 to t+2, we find that the two days just before the event date has insignificant positive values. The event day and t+1 have significant values, indicating that the event impacted the crypto returns. To be precise, as evident in figure 2, the AAR on t-2 was nearly 40 percent (negative). This is the highest negative AAR during the 61-day event window, which signifies the event's impact on cryptocurrencies. However, the next day AAR was nearly 13 percent (positive), indicating that the crypto market recovered the shock the very next day.

Table 2: t-values for the AARs and CAARs during the Event Window

Days	t_{AAR}	t_{CAAR}	Days	t_{AAR}	t_{CAAR}
t-30	0.92	0.17	t	-3.77*	-26.93*
t-29	5.77*	1.22	t+1	-69.22*	-67.99*
t-28	4.27*	2.04**	t+2	24.17*	-41.56*
t-27	-1.05	1.87	t+3	-6.52*	-39.25*
t-26	4.91*	2.85*	t+4	4.80*	-32.96*
t-25	-9.47*	1.05	t+5	-18.03*	-37.45*
t-24	-3.64*	0.34	t+6	5.35*	-32.65*
t-23	-2.21**	-0.10	t+7	4.46*	-28.97*
t-22	7.96*	1.56	t+8	21.99*	-19.98*
t-21	-8.38*	-0.20	t+9	-2.70*	-19.81*
t-20	2.36**	0.32	t+10	-0.21	-18.95*
t-19	2.87*	0.96	t+11	-12.48*	-21.74*
t-18	-1.37	0.67	t+12	12.51*	-17.42*
t-17	6.07*	2.13**	t+13	2.81*	-16.04*
t-16	-7.61*	0.34	t+14	-0.98	-15.75*
t-15	-9.61*	-2.05**	t+15	4.77*	-14.05*
t-14	-10.38*	-4.80*	t+16	-3.79*	-14.56*
t-13	3.45*	-4.05*	t+17	-4.16*	-15.13*
t-12	-1.10	-4.50*	t+18	-7.34*	-16.41*
t-11	-2.31**	-5.35*	t+19	11.90*	-13.33*
t-10	-0.37	-5.70*	t+20	2.42**	-12.48*
t-9	8.87*	-3.18*	t+21	2.47**	-11.67*
t-8	0.18	-3.29*	t+22	0.30	-11.35*
t-7	2.02**	-2.77*	t+23	0.67	-10.97*
t-6	3.22*	-1.75	t+24	2.46**	-10.26*
t-5	1.25	-1.37	t+25	-3.05*	-10.66*
t-4	-0.99	-1.95	t+26	11.77*	-8.19*
t-3	-20.66*	-12.51*	t+27	-0.36	-8.12*
t-2	0.24	-14.30*	t+28	4.22*	-7.19*
t-1	1.61	-16.38*	t+29	1.15	-6.86*
t	-3.77*	-26.93*	t+30	-10.41*	-8.62*

*&** indicate significant values at 1% & 5% levels, respectively

The CAARs are significantly negative through t-15 to t-7 and from t-3 to t+30, indicating the cumulative negative impacts of the event. The analysis of the CAARs reveals that although there exist both significantly negative and positive AARs, the negative AARs rule over the positive values during the event window. Figure 2 presents the AAR and CAAR-line during the event window. The CAAR-line went down to more than 50 percent on t+1, signifying the event's negative impact. The negative impacts are so intense that the CAAR-line trails below 20 percent until t+30. Figure 2 support the findings in table 2. Our findings support (Corbet et al., 2020).

We present the AAVs and CAAVs during the event window in figure 3, which depicts that the cryptocurrencies have been more volatile around the event date. It is evident that with a positive value of nearly 100 percent on the event day, the AAV-line moves below the 100 percent (negative) mark on day t+2. Although the AAV and CAAV-line move almost together, we cannot deny that the event has created abnormal volatility. We have tested the values for significance at 5% and 1% significance levels and found that the abnormal volatility has been significant during the event window. The results suggest that our findings align with (French, 2021; Davidovic, 2021).

Figure 2: AAR and CAAR-line during the event window

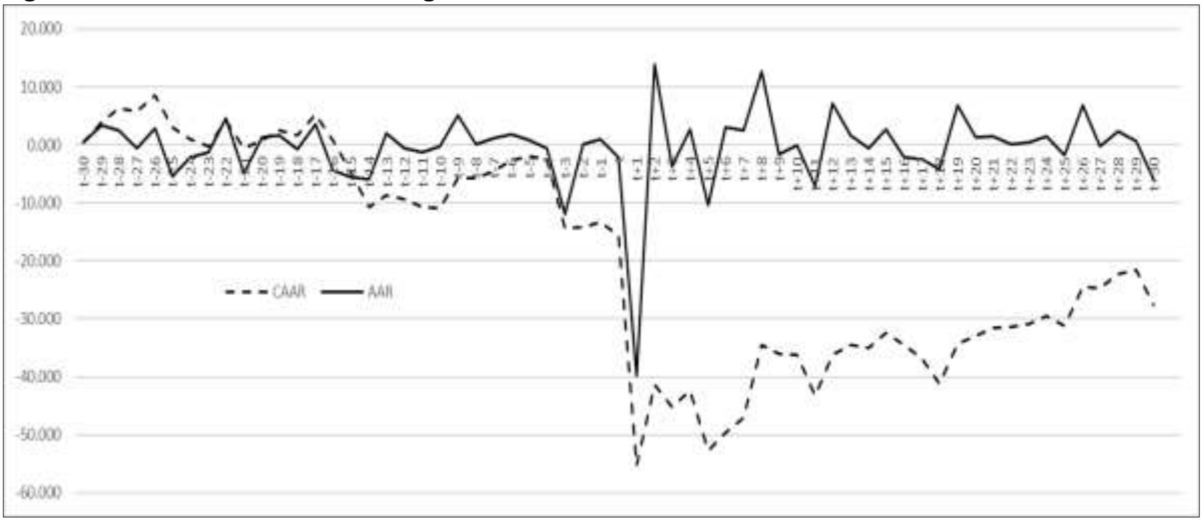
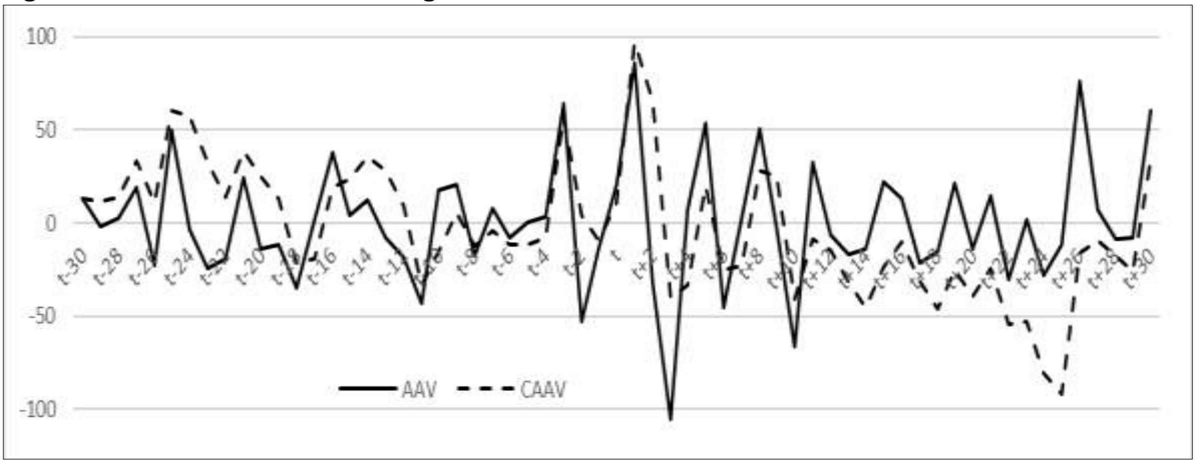


Figure 3: AAV and CAAV-line during the event window



4.2. Impact on abnormal returns and volatilities of top 10 cryptocurrencies

After analyzing the impact of the global pandemic announcement on the top 100 cryptocurrencies, we examine the abnormal returns of the top ten cryptocurrencies. Table 3 presents the t-values for the AARs and CAARs of the top ten cryptocurrencies during the 61-day event window. We find four significant positive and six significant negative AARs during the pre-event period. During the post-event period, seven AARs are significantly positive, and six AARs are significantly negative. Although this indicates a mixed reaction, the significant negative CAARs through t-3 to t+30 indicate that the overall cumulative impact was significantly negative. The top ten cryptocurrencies reacted similarly to the whole sample.

The event day AAR was not significant but followed with a negative AAR on t+1 and a positive AAR on t+2. The cumulative impacts are also negative. Although our analysis reveals negative impacts on cryptocurrencies, researchers (Conlon et al., 2020; Corbet et al., 2020) who compared cryptocurrencies with other financial assets found the former to be a safe haven.

4.3. Shorter Window Analysis

To conclude, we also examine the abnormal returns around shorter event windows for the eight shorter event windows. Table 4 presents the t-values for the AARs and CAARs, indicating that the abnormal returns, both average, and cumulative average, are significantly negative during all the shorter event windows.

Table 3: t-values for the AARs and CAARs of the top ten cryptocurrencies

Days	t_{AAR}	t_{CAAR}	Days	t_{AAR}	t_{CAAR}
t-30	-1.09	-0.20	t	-1.48	-12.74*
t-29	2.17	0.20	t+1	-23.51*	-25.64*
t-28	2.42**	0.65	t+2	10.13*	-15.08*
t-27	0.01	0.66	t+3	-3.66*	-14.89*
t-26	1.99	1.06	t+4	3.09*	-11.94*
t-25	-4.88*	0.12	t+5	-6.71*	-13.64*
t-24	-0.94	-0.06	t+6	0.98	-12.25*
t-23	-0.33	-0.13	t+7	0.62	-11.24*
t-22	2.88**	0.47	t+8	7.18*	-8.21*
t-21	-3.00**	-0.16	t+9	-0.81	-8.04*
t-20	-0.41	-0.26	t+10	0.40	-7.55*
t-19	0.86	-0.07	t+11	-5.35*	-8.77*
t-18	-0.60	-0.21	t+12	5.30*	-6.96*
t-17	2.80**	0.44	t+13	1.17	-6.39*
t-16	-3.02**	-0.28	t+14	-0.62	-6.34*
t-15	-3.36*	-1.13	t+15	1.53	-5.75*
t-14	-3.54*	-2.08	t+16	-2.21	-6.12*
t-13	1.09	-1.86	t+17	-0.84	-6.14*
t-12	-0.26	-2.00	t+18	-3.48*	-6.78*
t-11	-1.13	-2.41**	t+19	5.19*	-5.44*
t-10	-0.98	-2.81**	t+20	0.78	-5.14*
t-9	3.63*	-1.81	t+21	1.28	-4.75*
t-8	0.72	-1.66	t+22	0.06	-4.63*
t-7	-0.21	-1.84	t+23	0.58	-4.42*
t-6	0.71	-1.70	t+24	-0.27	-4.38*
t-5	1.02	-1.42	t+25	-1.47	-4.59*
t-4	-0.29	-1.68	t+26	6.01*	-3.34*
t-3	-7.58*	-5.68*	t+27	-0.15	-3.31*
t-2	0.38	-6.33*	t+28	3.38*	-2.63*
t-1	-0.29	-7.96*	t+29	0.40	-2.51**
t	-1.48	-12.74*	t+30	-4.24*	-3.23**

*&** indicate significant values at 1% & 5% levels, respectively

The significant negative impacts in the shorter windows reveal that the global pandemic announcement has significantly impacted the cryptocurrency returns. The shorter window analysis supports the findings of the analysis of the CAARs in table 2. The cumulative impacts of the global pandemic declaration have been more damaging.

Table 4: t-values for AARs and CAARs for the shorter period

Window Period	t_{AAR}	t_{CAAR}
-7 to +7	-4.80*	-18.61*
-3 to +3	-10.59*	-28.03*
-1 to +1	-23.79*	-41.21*
0 to +3	-13.84*	-27.67*
0 to +5	-11.43*	-28.00*
0 to +7	-7.35*	-20.78*
0 to +10	-3.61*	-11.97*
0 to +15	-2.07**	-8.27*

*&** indicate significant values at 1% & 5% levels, respectively

4.4. Summary of findings

The research question that drove us to conduct this study was the lack of sufficient literature examining the crypto market's efficiency. Although the efficiency of various cryptocurrencies has been conducted in the past (for example see, Tran & Leirvik, 2019), we did not find such studies during the pandemic period. The efficient market hypothesis indicates that market prices reflect all available information and can react only to new information. We selected the widely used event study methodology with the OLS market model to measure efficiency. We use the global pandemic declaration by the WHO as the information event around which the abnormalities in the market are to be examined. Our results suggest that the crypto market has been efficient during the pandemic. An average abnormal return of nearly minus 40 percent on the next day to the announcement signifies the strength of the news content and the deep impact it had on the crypto returns. According to the test of significance, both the null hypotheses, "the global pandemic declaration did not significantly impact the abnormal returns of the cryptocurrencies", and "during the global pandemic declaration, the cryptocurrencies did not experience any significant abnormal volatilities", are rejected.

5. Conclusions, implications, and limitations

We employed the (Brown & Warner, 1980, 1985) standard event study methodology and the OLS market model to examine how the global pandemic announcement impacted cryptocurrencies. We examine the abnormal returns and volatilities during the event window. We replicated the analysis replacing the CMC Crypto index with the Gold and Crude Oil prices and found similar results, both for abnormal returns and abnormal volatility. The findings are robust because they are similar for varying estimation windows. We find a significant negative impact on cryptocurrencies. The cryptocurrencies are more volatile during the outbreak. Our results align with (Corbet et al., 2020; French, 2021; Davidovic, 2021).

The only known limitation of our study is that to examine the impact of this pandemic on the cryptocurrency market, we have used the event study method, showing mixed results during the event window. Further research may be conducted using a few more statistical methods to test the significance of the results. However, in spite of this limitation, the study's findings will empower the investors to implement proper investment strategies during emergencies. This study addresses the methodological gap and provides evidence for the significance of information content in the crypto market. The crypto market adjusts the new information soon, which is visible through the abnormal returns after the release of significant news content. We conclude this using the event study methodology on the crypto market reactions to the global pandemic declaration news event. We find that the crypto returns were significantly abnormal the very next day. The findings will help the regulators, traders, and potential stakeholders understand the market dynamics and behavior, especially during a crisis. However, we suggest that future research compare our findings using the (Tran & Leirvik, 2019) "Adjusted Market Inefficiency Magnitude (AMIM)" method.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding information

The authors declared no financial support for the research, authorship, and/or publication of this article.

Acknowledgements: None

References

Alam, M. M., Wei, H., & Wahid, A. N. M. (2020). COVID-19 outbreak and sectoral performance of the Australian stock market: An event study analysis. *Australian Economic Papers*. https://doi.org/10.1111/1467-8454.12215

Anh, D. L. T., & Gan, C. (2020). The impact of the COVID-19 lockdown on stock market performance: evidence from Vietnam. *Journal of Economic Studies*. https://doi.org/10.1108/JES-06-2020-0312

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The Unprecedented Stock Market Reaction to COVID-19. *The Review of Asset Pricing Studies*. https://doi.org/10.1093/rapstu/raaa008

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87–95. https://doi.org/10.1016/j.frl.2017.02.009

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198. https://doi.org/10.1016/j.frl.2016.09.025

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205–258. https://doi.org/https://doi.org/10.1016/0304-405X(80)90002-1

Brown, S. J., & Warner, J. B. (1985). Using Daily stock returns: The Case of Event Studies. *Journal of Financial Economics*, *14*, 3–31. https://doi.org/10.1016/0304-405X(85)90042-X

Caferra, R., & Vidal-Tomás, D. (2021). Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. *Finance Research Letters*, *43*(February), 101954. https://doi.org/10.1016/j.frl.2021.101954

Carter, D., Mazumder, S., Simkins, B., & Sisneros, E. (2021). The stock price reaction of the COVID-19 pandemic on the airline, hotel, and tourism industries. *Finance Research Letters*, 102047. https://doi.org/10.1016/J.FRL.2021.102047

Chan, W. H., Le, M., & Wu, Y. W. (2018). Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *The Quarterly Review of Economics and Finance*, 1–26. https://doi.org/10.1016/j.qref.2018.07.004

Conlon, T., Corbet, S., & McGee, R. J. (2020). Are cryptocurrencies a safe haven for equity markets? An international perspective from the COVID-19 pandemic. *Research in International Business and Finance*, *54*, 101248. https://doi.org/10.1016/j.ribaf.2020.101248

Corbet, S., Cumming, D. J., Lucey, B. M., Peat, M., & Vigne, S. A. (2020). The destabilising effects of cryptocurrency cybercriminality. *Economics Letters*, *191*(xxxx), 108741. https://doi.org/10.1016/j.econlet.2019.108741

Corbet, S., Hou, Y. (Greg), Hu, Y., Larkin, C., & Oxley, L. (2020). Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. *Economics Letters*, *194*, 109377. https://doi.org/10.1016/j.econlet.2020.109377

Corbet, S., Hou, Y. (Greg), Hu, Y., Oxley, L., & Xu, D. (2021). Pandemic-related financial market volatility spillovers: Evidence from the Chinese COVID-19 epicentre. *International Review of Economics and Finance*, *71*(September 2020), 55–81. https://doi.org/10.1016/j.iref.2020.06.022

Corbet, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters*, *26*, 81–88. https://doi.org/10.1016/j.frl.2017.12.006

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

Davidovic, M. (2021). From pandemic to financial contagion: High-frequency risk metrics and Bayesian volatility analysis. *Finance Research Letters*, *42*(August 2020), 101913. https://doi.org/10.1016/j.frl.2020.101913

Demiralay, S., & Golitsis, P. (2021). On the dynamic equicorrelations in cryptocurrency market. *Quarterly Review of Economics and Finance*, *80*, 524–533. https://doi.org/10.1016/j.qref.2021.04.002

Disli, M., Nagayev, R., Salim, K., Rizkiah, S. K., & Aysan, A. F. (2021). In search of safe haven assets during COVID-19 pandemic: An empirical analysis of different investor types. *Research in International Business and Finance*, *58*. https://doi.org/10.1016/j.ribaf.2021.101461

Drozdz, S., Kwapień, J., Oświecimka, P., Stanisz, T., & Watorek, M. (2020). Complexity in economic and social systems: Cryptocurrency market at around COVID-19. *Entropy*, *22*(9), 1–25. https://doi.org/10.3390/E22091043

Elad, F. L., & Bongbee, N. S. (2017). Event Study on the Reaction of Stock Returns to Acquisition News. *International Finance and Banking*, *4*(1). https://doi.org/10.5296/ifb.v4i1.10409

Floros, C. (2009). Modelling Volatility Using High, Low, Open and Closing Prices: Evidence from Four S&P Indices. In *International Research Journal of Finance and Economics*. http://www.eurojournals.com/finance.htm

French, J. J. (2021). #Bitcoin, #COVID-19: Twitter-based uncertainty and bitcoin before and during the pandemic. *International Journal of Financial Studies*, *9*(2). https://doi.org/10.3390/ijfs9020028

Gandal, N., Hamrick, J. T., Moore, T., & Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. *Journal of Monetary Economics*, *95*, 86–96. https://doi.org/10.1016/j.jmoneco.2017.12.004

González, M. de la O., Jareño, F., & Skinner, F. S. (2021). Asymmetric interdependencies between large capital cryptocurrency and Gold returns during the COVID-19 pandemic crisis. *International Review of Financial Analysis*, *76*(July 2020). https://doi.org/10.1016/j.irfa.2021.101773

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, *63*(2017), 431–437. https://doi.org/10.1016/j.irfa.2018.03.004

Ho, K. H., Chiu, W. H., & Li, C. (2020). A Network Analysis of the Cryptocurrency Market. *2020 IEEE Symposium Series on Computational Intelligence, SSCI 2020*, 2178–2185. https://doi.org/10.1109/SSCI47803.2020.9308282

Hsu, S. H., Sheu, C., & Yoon, J. (2021). Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. *North American Journal of Economics and Finance*, *57*(April), 101443. https://doi.org/10.1016/j.najef.2021.101443

Hu, H., Yang, Y., & Zhang, J. (2021). Avoiding panic during pandemics: COVID-19 and tourism-related businesses. *Tourism Management*, *86*, 104316. https://doi.org/10.1016/j.tourman.2021.104316

James, N. (2021). Dynamics, behaviours, and anomaly persistence in cryptocurrencies and equities surrounding COVID-19. *Physica A: Statistical Mechanics and Its Applications*, *570*, 125831. https://doi.org/10.1016/j.physa.2021.125831

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

Jeribi, A., Jena, S. K., & Lahiani, A. (2021). Are cryptocurrencies a backstop for the stock market in a covid-19-led financial crisis? Evidence from the nardl approach. *International Journal of Financial Studies*, *9*(3). https://doi.org/10.3390/ijfs9030033

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, *71*, 101526. https://doi.org/10.1016/j.irfa.2020.101526

Ji, Q., Zhang, D., & Zhao, Y. (2020). Searching for safe-haven assets during the COVID-19 pandemic. *International Review of Financial Analysis*, *71*. https://doi.org/10.1016/j.irfa.2020.101526

KANDİL GÖKER, İ. E., EREN, B. S., & KARACA, S. S. (2020). COVID-19 (Koronavirüs)'un Borsa İstanbul Sektör Endeks Getirileri Üzerindeki Etkisi: Bir Olay Çalışması. *Gaziantep University Journal of Social Sciences*. https://doi.org/10.21547/jss.731980

Kim, J. M., Kim, S. T., & Kim, S. (2020). On the relationship of cryptocurrency price with us stock and gold price using copula models. *Mathematics*, *8*(11), 1–15. https://doi.org/10.3390/math8111859

Kim, M. (2021). A psychological approach to Bitcoin usage behavior in the era of COVID-19: Focusing on the role of attitudes toward money. *Journal of Retailing and Consumer Services*, *62*(January), 102606. https://doi.org/10.1016/j.jretconser.2021.102606

Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). Bitcoin: Safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation — A stochastic volatility approach. *Physica A: Statistical Mechanics and Its Applications*, *524*, 246–257. https://doi.org/10.1016/j.physa.2019.04.145

Kristoufek, L. (2020). Grandpa, Grandpa, Tell Me the One About Bitcoin Being a Safe Haven: New Evidence From the COVID-19 Pandemic. *Frontiers in Physics*, *8*(July), 1–6. https://doi.org/10.3389/fphy.2020.00296

Kumari, V., Tiwari, B. K., & Pandey, D. K. (2021). *How the global airline industry behaved to restrictions on air travel to India? An event study analysis*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3925992

Lahmiri, S., & Bekiros, S. (2020). The impact of COVID-19 pandemic upon stability and sequential irregularity of equity and cryptocurrency markets. *Chaos, Solitons and Fractals*, *138*, 109936. https://doi.org/10.1016/j.chaos.2020.109936

Lahmiri, S., & Bekiros, S. (2021). The effect of COVID-19 on long memory in returns and volatility of cryptocurrency and stock markets. *Chaos, Solitons and Fractals*, *151*, 1–8. https://doi.org/10.1016/j.chaos.2021.111221

Mackinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, *35*(1), 13–39. http://www.jstor.org/stable/2729691

Maiti, M., Grubisic, Z., & Vukovic, D. B. (2020). Dissecting Tether's non-linear dynamics during covid-19. *Journal of Open Innovation: Technology, Market, and Complexity*, *6*(4), 1–12. https://doi.org/10.3390/joitmc6040161

Maneenop, S., & Kotcharin, S. (2020). The impacts of COVID-19 on the global airline industry: An event study approach. *Journal of Air Transport Management*, *89*. https://doi.org/10.1016/j.jairtraman.2020.101920

Manoj Kumar, N. and Ri. S. (2020). Decentralising finance using decentralised blockchain oracles. *International Conference for Emerging Technology*, 1–4. https://doi.org/10.1109/INCET49848.2020.9154123

Mnif, E., Jarboui, A., & Mouakhar, K. (2020). How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Finance Research Letters*, *36*. https://doi.org/10.1016/j.frl.2020.101647

Nakov, O., Gotseva, D., & Tomov, Y. (2020). Comparative study of selected cryptocurrency. *IOP Conference Series: Materials Science and Engineering*, *1002*(1). https://doi.org/10.1088/1757-899X/1002/1/012020

Nasreen, S., Tiwari, A. K., & Yoon, S. M. (2021). Dynamic connectedness and portfolio diversification during the coronavirus disease 2019 pandemic: Evidence from the cryptocurrency market. *Sustainability (Switzerland)*, *13*(14), 23–30. https://doi.org/10.3390/su13147672

Neslihanoglu, S. (2021). Linearity extensions of the market model: a case of the top 10 cryptocurrency prices during the pre-COVID-19 and COVID-19 periods. *Financial Innovation*, *7*(1). https://doi.org/10.1186/s40854-021-00247-z

Pal, D., & Mitra, S. K. (2019). Hedging bitcoin with other financial assets. *Finance Research Letters*, *30*, 30–36. https://doi.org/10.1016/j.frl.2019.03.034

Pandey, D. K., & Jaiswal, A. K. (2017). Impact of Demonetization on Indian Stock Market-An Empirical Study. *Al-Barkaat Journal of Finance & Management*, *9*(2), 46. https://doi.org/10.5958/2229-4503.2017.00015.7

Pandey, D. K., & Kumar, R. (2021). *Lockdown, unlock, stock returns, and firm-specific characteristics: the Indian tourism sector during the Covid-19 outbreak*. https://doi.org/10.1080/13683500.2021.2005549

Pandey, D. K., & Kumari, V. (2020a). Performance of the Indian Tourism and Hospitality Stocks during the 2019-nCoV Outbreak-An Event Study using Stocks Listed on the NSE. *Orissa Journal of Commerce*, *XXXXI*(2), 19–30. https://doi.org/10.5281/zenodo.4698464

Pandey, D. K., & Kumari, V. (2020b). Impacts of Demonetization on Indian Banking Sector Stocks. *The Indian Journal of Commerce*, *73*(1 & 2), 178–193. https://doi.org/10.5281/zenodo.4698468

Pandey, D. K., & Kumari, V. (2020c). Effects of merger and acquisition announcements on stock returns: An empirical study of banks listed on NSE and NYSE. *The Review of Finance and Banking*, *12*(1), 49–62. https://doi.org/10.24818/rfb.20.12.01.04

Pandey, D. K., & Kumari, V. (2021a). An event study on the impacts of Covid-19 on the global stock markets. *International Journal of Financial Markets and Derivatives*, *8*(2), 148–168. https://doi.org/10.1504/IJFMD.2021.10038839

Pandey, D. K., & Kumari, V. (2021b). Impacts of Corporate Announcements on Stock Returns during the Global Pandemic: Evidence from the Indian Stock Market. *SSRN*. https://doi.org/10.2139/ssrn.3851438

Pandey, D. K., & Kumari, V. (2021c). Event study on the reaction of the developed and emerging stock markets to the 2019-nCoV outbreak. *International Review of Economics & Finance*, *71*. https://doi.org/10.1016/j.iref.2020.09.014

Pandey, D. K., & Kumari, V. (2021d). Do dividend announcements override the pandemic impacts? Evidence from the BSE 500 constituent firms. *Asia Pacific Management Review*. https://doi.org/10.1016/J.APMRV.2021.09.002

Pandey, D. K., Kumari, V., & Rai, V. K. (2021). Pandemic effects on the Asian Emerging Markets and the Korean Stock Market. *The Indian Journal of Commerce*, *74*(1 & 2), 1–23. https://doi.org/10.5281/zenodo.5211097

Pham, T. D., Dwyer, L., Su, J. J., & Ngo, T. (2021). COVID-19 impacts of inbound tourism on Australian economy. *Annals of Tourism Research*, *88*, 103179. https://doi.org/10.1016/j.annals.2021.103179

Phuong, L. C. M. (2021). How COVID-19 impacts Vietnam's banking stocks: An event study method. *Banks and Bank Systems*, *16*(1), 92–102. https://doi.org/10.21511/bbs.16(1).2021.09

Rai, V. K., & Pandey, D. K. (2021). Does privatization of public sector banks affect stock prices? An event study approach on the Indian banking sector stocks. *Asian Journal of Accounting Research*. https://doi.org/10.1108/AJAR-06-2021-0078

Rupp, M., Schneckenburger, M., Merkel, M., Börret, R., & Harrison, D. K. (2021). Industry 4.0: A technological-oriented definition based on bibliometric analysis and literature review. *Journal of Open Innovation: Technology, Market, and Complexity*, *7*(1), 1–20. https://doi.org/10.3390/joitmc7010068

Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis*, *63*(December 2018), 322–330. https://doi.org/10.1016/j.irfa.2019.01.002

Smales, L. A. (2019). Bitcoin as a safe haven: Is it even worth considering? *Finance Research Letters*, *30*, 385–393. https://doi.org/10.1016/j.frl.2018.11.002

Tran,V.L.,Leirvik,T.,2019.Asimplebutpowerfulmeasureofmarketefficiency. *Finance Research Letters*, *29*,141–151.https://doi.org/10.1016/j.frl.2019.03.004

Ullah, S., Zaefarian, G., Ahmed, R., & Kimani, D. (2021). How to apply the event study methodology in STATA: An overview and a step-by-step guide for authors. In *Industrial Marketing Management*. Elsevier Inc. https://doi.org/10.1016/j.indmarman.2021.02.004

Umar, Z., & Gubareva, M. (2020). A time–frequency analysis of the impact of the Covid-19 induced panic on the volatility of currency and cryptocurrency markets. *Journal of Behavioral and Experimental Finance*. https://doi.org/10.1016/j.jbef.2020.100404

Urquhart, A., & Zhang, H. (2019). Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*, *63*, 49–57. https://doi.org/10.1016/j.irfa.2019.02.009

Vidal-Tomás, D. (2021). Transitions in the cryptocurrency market during the COVID-19 pandemic: A network analysis. *Finance Research Letters*, *February*. https://doi.org/10.1016/j.frl.2021.101981

Wang, G. J., Xie, C., Wen, D., & Zhao, L. (2018). When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin. *Finance Research Letters*, 1–23. https://doi.org/10.1016/j.frl.2018.12.028

Wang, P., Li, X., Shen, D., & Zhang, W. (2020). How does economic policy uncertainty affect the bitcoin market? *Research in International Business and Finance*, *March*, 1–43. https://doi.org/10.1016/j.ribaf.2020.101234

Wang, P., Zhang, W., Li, X., & Shen, D. (2019). Is cryptocurrency a hedge or a safe haven for international indices? A comprehensive and dynamic perspective. *Finance Research Letters*, 1–33. https://doi.org/10.1016/j.frl.2019.04.031