Scientific Annals of Economics and Business
69 (3), 2022, 343-359
DOI: 10.47743/saeb-2022-0014

The Impact of the COVID-19 Pandemic on the Cryptocurrency Market

Nidhal Mgadmi[*], Azza Béjaoui[**], Wajdi Moussa[***], Tarek Sadraoui[§]

Abstract

The purpose of our paper is to analyze the main factors which influence fiscal balance's evolution and thereby identify solutions for configuring a sustainable fiscal policy. We have selected as independent variables some of the main macroeconomic measures, respectively public debt, unemployment rate, economy openness degree, population, consumer goods' price index, current account balance, direct foreign investments and economic growth rate. Our research method uses two econometric models applied on a sample of 22 countries, respectively 14 developed and 8 emergent. The first model is a multiple regression and studies the connection between the fiscal balance and selected independent variables, whereas the second one uses first order differences and introduces economic freedom as a dummy variable to catch the dynamic influences of selected measures upon fiscal result. The time interval considered was 1999-2013. The results generated using the two models revealed that public debt, current account balance and economic growth significantly influence the fiscal balance. As a consequence, the governments need to plan and implement a fiscal policy which resonates with economy priorities and the phase of the economic cycle, as well as ensure a proper management of the public debt, stimulate sustainable economic growth and employment.

Keywords: Covid-19 pandemic; cryptocurrency volatility; leverage effect; cryptocurrency dynamics; econometric modeling.

JEL classification: E62; G18; H62.

1. INTRODUCTION

By and large, the stock market volatility is considered as a key impactful factor which can influence a great range of decisions in finance and economics. In this regard, it can be considered as a barometer of uncertainty, stress, macroeconomic and financial risk (Zaremba *et al.*, 2020) and a substantial input in asset pricing models (Chen *et al.*, 2019). That is why

[*] Faculty of Economics and Management of Mahdia, University of Monastir, Tunisia; e-mail: *nidhalmgadmii@gmail.com*.
[**] Higher Institute of Management of Tunis, University of Tunis, Tunisia; e-mail: *bjaouiazza2@yahoo.fr*.
[***] Higher Institute of Management of Tunis, University of Tunis, Tunisia; e-mail: *wajdi.moussa@isg.rnu.tn* (corresponding author).
[§] Faculty of Economics and Management of Mahdia, University of Monastir, Tunisia; e-mail: *tarek.sadraoui@gmail.com*.

several researchers have increasingly analyzed the market volatility behavior and in particular for cryptocurrency market. For example, Katsiampa (2018) examine the dynamic behavior of Bitcoin and Ether volatilities based on a bivariate Diagonal BEKK model. They display that both cryptocurrencies' conditional volatility and correlation tend to react to major news. The linkages between the cryptocurrency markets are well-documented over the period 07/08/2015-15/01/2018. L. Fang *et al.* (2018) explore if the global economic policy uncertainty affects long-term volatilities of Bitcoin, commodities, bonds and global equities. They clearly display such influence over the period 21/09/2010-26/01/2018, except for bonds. This leads to the ability of employing information with regards to the state of global economic uncertainty in forecasting the Bitcoin volatility. Aalborg *et al.* (2018) study which variables (return, volatility, trading volume, transaction volume and change in the number of unique Bitcoin addresses) could forecast the volatility, trading volume and return of Bitcoin during the period 01/03/2012-19/03/2017. They display that the heterogeneous autoregressive model can be considered as adequate model for Bitcoin volatility. López-Cabarcos *et al.* (2021) analyze the behavior of Bitcoin and the potential impacts of S&P500 returns, VIX returns and investor sentiment on the Bitcoin volatility over the period 04/01/2016-30/09/2019. Using different GARCH-type models, Bitcoin volatility tends to be more unstable during turbulent episodes. However, VIX returns, S&P500 returns and investor sentiment have significant impact on Bitcoin volatility during stable episodes.

On the other hand, the outbreak of Covid-19 pandemic followed by the advent of the first coronavirus vaccines in early 2021 increasingly spurred and revived the analysis of return and volatility dynamics. Indeed, Baek *et al.* (2020) report that market volatility seems to be sensitive to Covid-19 news. This can attributed to unprecedented news coverage and outpouring of opinions in this age of swift sharing and spreading of information which made investors sensitive to coronavirus related news (Haroon & Rizvi, 2020). Salisu and Vinh Vo (2020) show that the negative news tend to be more influential than positive ones. In this context, Yousaf and Ali (2020) study the return and volatility transmission between Bitcoin, Ethereum and Litecoin. They show that the return spillovers significantly evolve for the Bitcoin-Ethereum, Bitcoin-Litecoin, and Ethereum-Litecoin pairs. The volatility transmission is not substantial between cryptocurrencies during the pre-Covid-19 period. They also show that the volatility spillover tends to be bidirectional between Ethereum and Litecoin. But, it is unidirectional from Bitcoin to Ethereum. Overall, they conclude that the dynamic conditional correlations among virtual currencies are higher during the Covid-19 period than the pre-Covid-19 period. James *et al.* (2021) analyze the behavior of cryptocurrency markets with the advent of heath crisis. They display different cryptocurrency market dynamics over the period 30/06/2018- 24/06/2020. They tend to be differently affected by the health crisis. Iqbal *et al.* (2021) analyze the potential effect of the severity of Covid-19 pandemic on (ten) cryptocurrencies' returns. They report that despite the whole trend path tends to be the same among virtual currencies, some differences between such assets in terms of reactions to the changes in the severity of Covid-19 are documented during the period 01/01/2020-15/06/2020. Salisu and Ogbonna (2021) analyze the role of news in predicting return volatility of cryptocurrencies during the health crisis based on the GARCH-MIDAS model. They report that fear-induced news triggered by the Covid-19 pandemic raises the return volatilities of the cryptocurrencies in comparison to the pre-Covid-19 period. Corbet *et al.* (2021) analyze the potential associations between cryptocurrency price volatility and liquidity with the advent of the Covid-19 pandemic. They display that the cryptocurrency market liquidity raises substantially after the WHO identification of a worldwide pandemic. They also identify significant and substantial interlinkages between cryptocurrency price and liquidity impacts.

Our research is related to the strand of the literature on the impact of different news related coronavirus is associated with varying (and excess) levels of market volatility. The primary objective of this paper is to analyze the volatility behavior of five cryptocurrencies' prices (Bitcoin, Ethereum, Stellar, Ripple (XRP) and Cardano) during the pre- and during Covid-19 pandemic by considering the severity of Covid-19 health crisis and the campaign of Covid-19 vaccination. For this end, we apply different econometric models on the market prices of five digital currencies.

This paper contributes to the current literature on the impact of the resolution of Covid-19 pandemic on price dynamics in different ways. First, it provides insightful information about the heterogeneity in terms of reaction of digital currencies to the announcement of bad and good announcements of Covid-19 pandemic. Indeed, it highlights the (dis)similarity in cryptocurrencies' behavior and dynamics with the Covid-19 outbreak and the vaccination campaign. We also contribute to the extant literature offering some insights on the volatility of some digital currencies, rather focusing only on Bitcoin volatility during pandemic uncertainties. In this context, our research offers some interesting findings relating to information shares during the period surrounding the different waves of Covid-19 pandemic and news on vaccines.

This paper is organized as follows. Section 2 presents literature review and Section 3 reports data and descriptive statistics. The empirical findings are reported in Section 4 and Section 5 concludes.

2. LITERATURE REVIEW

Overall, many researchers have interestingly focus on the volatility dynamics. For instance, Baur and Dimpfl (2018) examine the volatility dynamics of digital currencies. They show different asymmetry in comparison with equity markets. Indeed, the positive shocks increase the volatility by more than negative shocks. Katsiampa (2018) examine the volatility dynamics of Stellar Lumen, Litecoin, Ether, Ripple and Bitcoin. The empirical results clearly show that the conditional variances of such digital currencies are substantially influenced by both previous conditional volatility and past squared errors. The asymmetric past shocks significantly affect the current conditional variance for Ripple, Ether, Litecoin and Bitcoin. Katsiampa *et al.* (2019) investigate the behavior of conditional volatility of eight digital currencies as well as their volatility comovements. They show that all conditional variances are substantially influenced by past conditional volatility and squared errors. Kyriazis *et al.* (2019) study the volatility of Ripple, Bitcoin and Ethereum over the period 01/01/2018-16/09/2018. They report that the effect of the decrease of such cryptocurrencies on the returns of other digital currencies using the ARCH and GARCH models. Walther *et al.* (2019) attempt to forecast the monthly, weekly and daily volatility of Cryptocurrency index, Bitcoin, Litecoin, Ripple, Ethereum and Stellar using the GARCH-MIDAS model. They find that the global real economic activity determine the cryptocurrency volatility. Ben Cheikh *et al.* (2020) analyze the asymmetric volatility of Litecoin, Bitcoin, Ripple and Ethereum. They find an inverted asymmetric response for different cryptocurrencies. Abakah *et al.* (2020) explore the volatility persistence in cryptocurrency markets by taking into consideration the eventual structural breaks. They show that both squared and absolute returns show long memory features. T. Fang *et al.* (2020) analyze the effect of news-based implied volatility on the cryptocurrency volatility in long-term. They display that the long-term volatility of five digital currencies was significantly and negatively affected by the news-based implied volatility. Umar and Gubareva (2020) investigate the effect of the health crisis on the volatility of digital and fiat currencies. They display a great coherence between the evolution of the Covid-19 panic index and those of prices in British pound, Euro and Renminbi currencies as well as cryptocurrencies. Nevertheless, some key differences in the behavior of cryptocurrency markets. Cross *et al.* (2021) analyze the relationship between volatility formation and price of cryptocurrency (Bitcoin, Ethereum, Litecoin and Ripple). They clearly show the impact of risk premium in Ripple and Litecoin with the outbreak of the boom of 2017. They also report that the negative news effects are key factor in determining the cryptocurrency crash of 2018 for all digital currencies.

Chi and Hao (2021) investigate the behavior of cryptocurrency volatility. They display the GARCH model outperform other models and reject any substantial asymmetric volatility reaction to past returns based on GJR-GARCH model. Lahmiri and Bekiros (2021) investigate the issue of long memory in cryptocurrency and stock markets before and during the Covid-19 pandemic based on FIGARCH and ARFIMA models. They show that the level of persistence in return series of different markets during the health crisis. The return volatility of cryptocurrencies displays high degree of persistence in comparison to international financial markets during the health crisis. Catania and Grassi (2022) analyze the behavior of cryptocurrencies. They show that the prices of digital currencies are characterized by the presence of extreme values, asymmetries and nonlinearity, implying the difficulty to model and forecast such series. They develop a dynamic model which can account for long memory and asymmetry in the volatility process. Yin *et al.* (2021) investigate the role of oil market shocks in determining the cryptocurrency volatility in long term. They show that different oil market shocks such as crude oil market demand shocks negatively and significantly the long-term volatility of Bitcoin, XRP and Ethereum. So, the negative oil market seems to increase the attractiveness of digital currencies. Qiu *et al.* (2021) examine if the impact of volatility on forecasting Bitcoin realized volatility. They report that Bitcoin volatility models considering the linkage impact have better in-sample explanatory power and substantially enhance the performance of forecasts in short-term. Kakinaka and Umeno (2020) investigate the relationship between the price and volatility of cryptocurrencies and analyze the asymmetric effect of volatility during the bullish and bearish phases. They show that asymmetric responses of volatility to returns vary from those of other classical financial assets. Salisu and Ogbonna (2021) explore if the news related to the Covid-19 pandemic on the predictability of return volatility. The fear-induced news caused by the health crisis raises the cryptocurrency volatility in comparison to the pre-Covid-19 pandemic. They predictive model which includes the new impact can successfully forecast the volatility of cryptocurrency than the benchmark model. Apergis (2022) examines the importance of health crisis in determining and predicting conditional volatility returns for different digital currencies based on asymmetric GARCH model. The empirical results show that the Covid-19 pandemic significantly and positively affects the conditional return volatility. Al Guindy (2021) investigates the connectedness between the cryptocurrency volatility and investor attention. The empirical results show that investor attention increases the cryptocurrency price volatility. The empirical results display that investor attention predicts future price volatility based on VAR approach. D'Amato *et al.* (2022) investigate of the prediction of cryptocurrency (Ripple, Bitcoin and Ethereum) volatility. They develop adequate model in order to capture the cryptocurrency volatility dynamics. Elsayed *et al.* (2022) analyze the dynamic relationship of return and volatility transmission between cryptocurrency index, gold uncertainty measures. They report that cryptocurrency policy uncertainty is the key transmitter of the return spillovers to other indicators. The empirical findings are confirmed during the bull, bear and normal market phases. Bergsli *et al.* (2022) explore which model is adequate for forecasting Bitcoin volatility. They find that EGARCH and APARCH outperform other econometric models.

3. DATA AND DESCRIPTIVE STATISTICS

We gather the daily prices of Bitcoin, Ethereum, Stellar, Ripple (XRP) and Cardano in US dollars from the website https://www.coindesk.com during the period from 01/02/2019 to 07/27/2021. Such data represent mean prices using several platforms. One might then divide the sample period into two sub-periods: 01/02/2019-12/31/2019 and 01/22/2020-07/27/2021. In this respect, and following many researchers (e.g. Akhtaruzzaman *et al.*, 2020; Goodell & Goutte, 2020; Béjaoui *et al.*, 2021), the date of December 31, 2019 is used as the starting date in order to examine the impact of the Covid-19 crisis on financial markets.

The two variables 'Deaths' and 'Cases' are used to measure the severity of the Covid-19 pandemic in the United States. Indeed, the cumulative number of individuals contaminated (resp. died) by the health crisis is referred to the variable 'Cases' (resp. Deaths). On the other hand, the variable 'Vaccination' is the total number of vaccinated individuals in the United States.

Table no. 1 – Descriptive Statistics of Different Variables

Part 1. *The Pre-Covid-19 Crisis Period*

	BITCOIN	ETHEREUM	STELLAR	XRP	CARDANO
Mean	7363.024	181.0410	0.0876	0.3097	0.0554
Median	7836.885	173.7894	0.0840	0.3078	0.0467
Maximum	12575.90	324.1309	0.1520	0.4722	0.0963
Minimum	3360.534	103.2856	0.0433	0.1813	0.0314
Standard Deviation	2654.154	50.5868	0.0256	0.0606	0.0185
Skewness	-0.0940	0.8140	0.2565	0.4787	0.7978
Kurtosis	1.7557	3.0111	1.9732	3.1847	2.2134
Jarque-Bera	24.0172	40.2050	19.9830	14.4230	48.0002
p-value	0.0000	0.0000	0.0000	0.0007	0.0000
Observations	364	364	364	364	364

Part 2. *During the Covid-19 Crisis Period*

	BITCOIN	ETHEREUM	STELLAR	XRP	CARDANO	CASES	DEATHS	VACCINATION
Mean	23640.09	973.5581	0.1984	0.4425	0.4837	1,5E+07	287769.1	6,9E+07
Median	13033.52	411.2160	0.0989	0.2779	0.1280	8599971	225526.0	1.0000
Maximum	63346.79	4132.758	0.7045	1.8098	2.2464	3,5E+07	611414.0	3.43E+08
Minimum	4944.702	107.8983	0.0344	0.1386	0.0237	1.0000	1.0000	1.0000
Standard Deviation	17498.67	946.4969	0.1691	0.3508	0.5804	1,3E+07	215348.3	1.15E+08
Skewness	0.8044	1.0895	1.0811	1.9034	1.0122	0.3437	0.2365	1.3818
Kurtosis	2.1958	3.2113	3.0462	6.1239	2.4437	1.4148	1.5756	3.248243
Jarque-Bera	74.5440	110.4346	107.7813	558.7950	101.5755	68.7868	51.9065	177.4156
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	553	553	553	553	553	553	553	553

Table no. 1 reports the descriptive statistics of data related to cryptocurrencies' prices during the two periods of pre-Covid-19 pandemic (01/02/2019-12/31/2019) and during the Covid-19 pandemic (01/22/2020-07/27/2021). Table no. 1 (part 2) also presents the statistical indicators of variables 'Cases', 'Deaths' and 'Vaccination'. These statistics comprise the mean, minimum, maximum, standard deviation, kurtosis, skewness, Jarque-Bera statistic and respective probabilities. All the statistics values clearly display the change of cryptocurrencies' prices with the outbreak of Covid-19 crisis. In this regard, the mean prices of different digital currencies have risen from pre- to during the Covid-19 crisis period. For instance, the mean price of Bitcoin has increased from 7363.024 over the period 01/02/2019-12/31/2019 to 23640.09 during the period 01/22/2020-07/27/2021. As well, the standard deviation of cryptocurrencies' prices tends to increase after the advent of Covid-19 pandemic. This reflects high fluctuations of cryptocurrency markets. The daily prices of virtual currencies are positively skewed during the pre-health crisis period (except for Bitcoin) and during the Covid-19 pandemic. This clearly displays that right tail of different distributions, implying that positive values or profits are more likely. The platykurtic feature of price distribution is more pronounced during the Covid-19 crisis than the pre-Covid-19 pandemic for all digital currencies. The Jarque-Bera statistics are significant at low levels. Therefore, the daily prices seem not to be normally distributed.

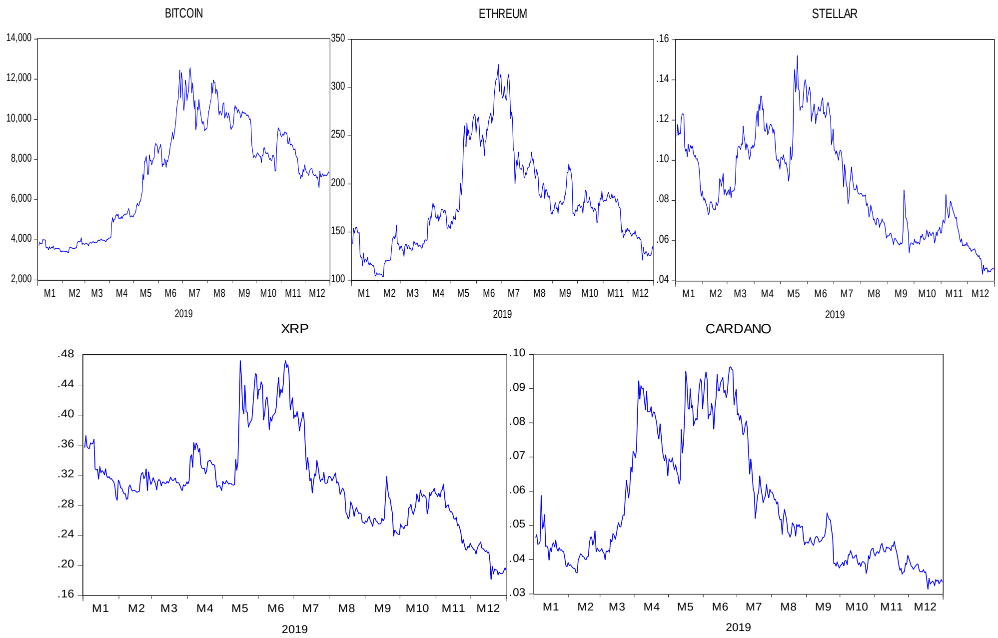


Figure no. 1 – Evolution of the Cryptocurrencies' Prices during the Pre-Covid-19 Crisis Period (01/02/2019-12/31/2019)

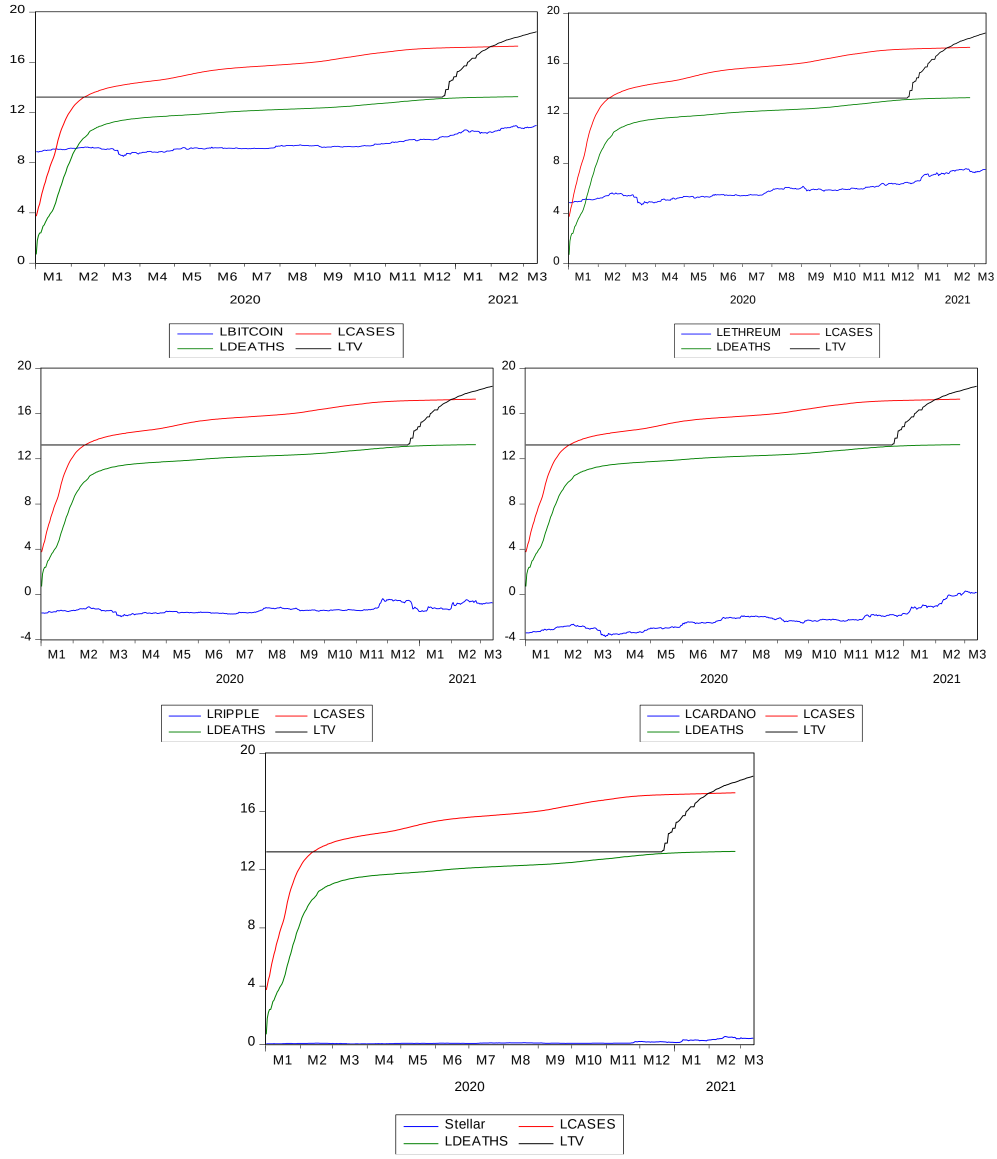


Figure no. 2 – Evolution of the Cryptocurrencies' Prices, Cases, Deaths and Vaccination during the Covid-19 Crisis Period (01/22/2020-07/27/2021)

Figures no. 1 and no. 2 display the evolution of digital currencies during two sub-periods. Overall, the daily prices of digital currencies tend to change overwhelmingly over time. In this regard, cyclical fluctuations and volatility clustering issue tend to be well-documented. In this regard and as the intensity of Covid-19 pandemic (measured by the variables 'Cases' and 'Deaths') and the 'Vaccination' increase, the prices of cryptocurrencies tend to react in a more pronounced manner.

Afterwards, we analyze the linear relationships between different variables during the two sub-periods. From Table no. 2, the linkages between the cryptocurrencies' prices are characterized by some salient patterns in terms of amplitude and nature. In particular, such associations are seemingly different with the outbreak of Covid-19 pandemic. For instance, the correlation coefficient between Bitcoin and Stellar prices changes from -0.2235 during the pre-Covid-19 crisis period to 0.951648 after the outbreak of Covid-19 pandemic.

Table no. 2 – Linear Relationships between Variables

Variance-Covariance Matrix

Part 1. *The Pre-Covid-19 Crisis Period*

	BITCOIN	ETHEREUM	STELLAR	XRP	CARDANO
BITCOIN	7025181	101691.0	-15.1526	9.6424	9.2550
ETEHREUM	101691.0	2551.994	0.5241	2.0055	0.6573
STELLAR	-15.1526	0.5241	0.0006	0.0013	0.0003
XRP	9.6424	2.0055	0.0013	0.0036	0.0009
CARDANO	9.2550	0.6573	0.0003	0.0009	0.0003

Part 2. *During the Covid-19 Crisis Period*

	BITCOIN	ETHEREUM	STELLAR	XRP	CARDANO	CASES	DEATHS	VACCINATION
BITCOIN	**3.06E+08**	14636818	2811.504	4645.474	8675.130	2.10E+11	3.37E+09	1.34E+12
ETHEREUM	14636818	**894236.4**	148.6066	290.6175	527.5166	1.15E+10	1.86E+08	9.51E+10
STELLAR	2811.504	148.6066	**0.0285**	0.0509	0.086926	1943838	31338.72	13364309
XRP	4645.474	290.6175	0.0509	**0.1228**	0.169029	3438628	55818.63	30653198
CARDANO	8675.130	527.5166	0.0869	0.1690	**0.336364**	6877988	112240.4	61240688
CASES	2.10E+11	1.15E+10	1943838	3438628	6877988	**1.72E+14**	2.80E+12	1.24E+15
DEATHS	3.37E+09	1.86E+08	31338.72	55818.63	112240.4	2.80E+12	**4.63E+10**	2.03E+13
VACCINATION	1.34E+12	9.51E+10	13364309	30653198	61240688	1.24E+15	2.03E+13	**1.32E+16**

Correlation Matrix

Part 1. *The Pre-Covid-19 Crisis Period*

	BITCOIN	ETHEREUM	STELLAR	XRP	CARDANO
BITCOIN	1.0000	0.7594	-0.2235	0.0600	0.1886
ETHEREUM	0.7594	1.0000	0.4057	0.6553	0.7029
STELLAR	-0.2235	0.4057	1.0000	0.9011	0.8408
XRP	0.0600	0.6553	0.9011	1.0000	0.8408
CARDANO	0.1886	0.7029	0.8408	0.8408	1.0000

Part 2. *During The Covid-19 Crisis Period*

	BITCOIN	ETHEREUM	STELLAR	XRP	CARDANO	CASES	DEATHS	VACCINATION
BITCOIN	1.0000	0.8853	0.9516	0.7579	0.8555	0.9135	0.8968	0.6657
ETHEREUM	0.8853	1.0000	0.9299	0.8766	0.9618	0.9242	0.9133	0.8743
STELLAR	0.9516	0.9299	1.0000	0.8607	0.8869	0.8767	0.8619	0.6874
XRP	0.7579	0.8766	0.8607	1.0000	0.8313	0.7476	0.7400	0.7600
CARDANO	0.8555	0.9618	0.8869	0.8313	1.0000	0.9038	0.8994	0.9178
CASES	0.9135	0.9242	0.8767	0.7476	0.9038	1.0000	0.5910	0.3229
DEATHS	0.8968	0.9133	0.8619	0.7400	0.8994	0.5910	1.0000	0.4202
VACCINATION	0.6657	0.8743	0.6874	0.7600	0.9178	0.3229	0.4202	1.0000

Next, we examine the issue of non-stationarity (in level and first difference) for different variables based on the Dickey-Fuller (1979, 1981) tests. To this end, one might determine the optimal number of lags for each variable. The estimation results for the two sub-periods are presented in Table no. 3.

Table no. 3 – Estimation Results for Dickey-Fuller (1979-1981) Tests

Part 1. *The Pre-Covid-19 Crisis Period*

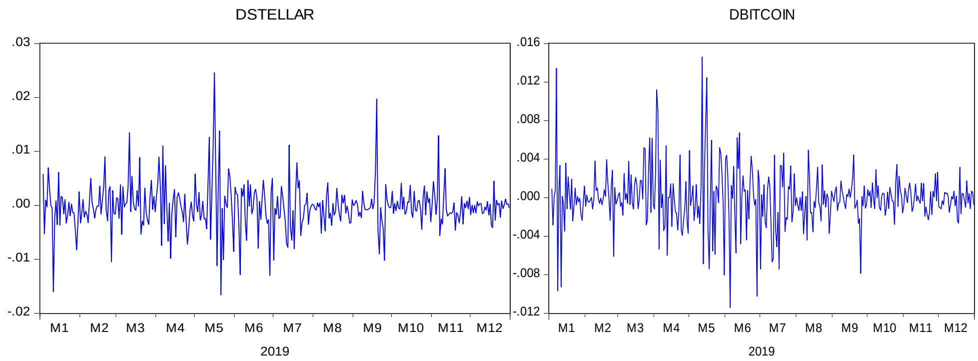
	Lags	In Level			In First Difference		
		T-Statistics	Critical Values	Models	T-Statistics	Critical Values o	Models
BITCOIN	1	0.0452	-1.9416	M1	-19.7223	-1.9417	M1
ETHEREUM	1	-0.4232	-1.9416	M1	-19.2181	-1.9417	M1
STELLAR	2	-2.1706	-3.4222	M3	-14.8197	-3.4223	M3
XRP	1	-0.9767	-1.9416	M1	-18.7109	-1.9417	M1
CARDANO	2	-0.6355	-3.4222	M1	-15.3524	-3.4223	M1

Part 2. *During The Covid-19 Crisis Period*

	Lags	In Level			In First Difference		
		T-Statistics	Critical Values	Models	T-Statistics	Critical Values	Models
BITCOIN	1	0.2838	-1.9413	M1	-24.2219	-1.9413	M1
ETHEREUM	3	-2.3707	-3.4180	M3	-12.3439	-3.4180	M3
STELLAR	1	-0.5977	-1.9413	M1	-23.7047	-1.9413	M1
XRP	2	-2.4872	-3.4179	M3	-15.8600	-3.4180	M3
CARDANO	2	-2.0194	-3.4179	M3	-15.2591	-3.4180	M3
Cases	6	-3.2056	-3.4180	M3	-11.1351	-3.4180	M3
Deaths	5	-1.7010	-3.4180	M3	-12.4307	-3.4180	M3
Vaccination	3	-0.3417	-3.4180	M3	-4.6995	-3.4180	M3

From the part 1 of Table no. 3, the optimal number of lags for Bitcoin, Ethereum and Ripple is equal to 1. The results from the Dickey-Fuller (1979) test show that the prices of such digital currencies are not stationary in level. After a first difference, they become stable because their T-statistics of first difference variables are lower than the tabulated values based on MacKinnon (1992). The optimal number of lags seems to be equal to 2 for Stellar and Cardano. The prices of Stellar and Cardano are non-stationary in level based on the Dickey-Fuller-Augmented (1981) test. After first difference, they become stationary given that their T-Statistics are lower than the critical value of MacKinnon (1996).

From the part 2 of Table no. 3, the optimal number of lags for Bitcoin and Stellar is equal to 1. The T-statistics for the prices of Bitcoin and Stellar are higher than the critical value of MacKinnon (1992). Hence, they are non-stationary in level. After a first difference, they become stationary. The optimal number of lags for the other digital currencies is greater than 1. They also become stationary after one difference.



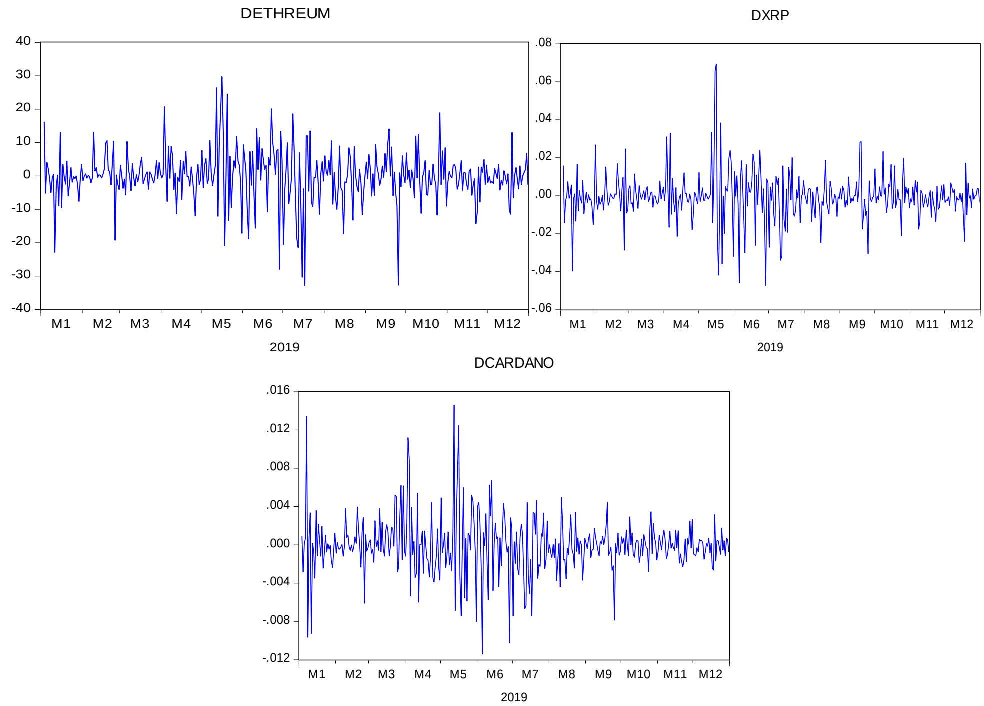


Figure no. 3 – Evolution of the First Difference Cryptocurrencies' Prices (in first difference) during the Pre-Covid-19 Crisis Period (01/02/2019-12/31/2019)

After a first difference, Figures no. 3 and no. 4 illustrate the evolution of cryptocurrencies' prices and variables during the two sub-periods. It is worth noting that cyclical fluctuations of time series volatility clustering behavior are well-documented. In particular, such features tend to be more pronounced with the increase of the people vaccinated. From the foregoing, it is interesting to analyze the volatility behavior over time.

4. EMPIRICAL VALIDATION

In this section, we attempt to analyze the volatility of the five cryptocurrencies' prices (Bitcoin, Ethereum, Stellar, Ripple (XRP) and Cardano) during the two sub-periods based on different models. The use of different models provides information about different aspects of behavior of volatility and leads to better dynamics of cryptocurrency markets. It is also important to report some features of volatility with regard to positive and negative shocks.

4.1 Volatility Behavior of Cryptocurrencies' Prices before the Health Crisis

Different models (ARMA(p,q), ARCH, GARCH, EGARCH and TGARCH models) are used successively used to explore the behavior of cryptocurrencies' volatility during the period 01/02/2019-12/31/2019. Table no. 4 reports the estimation results of different models are reported in Table no. 4.

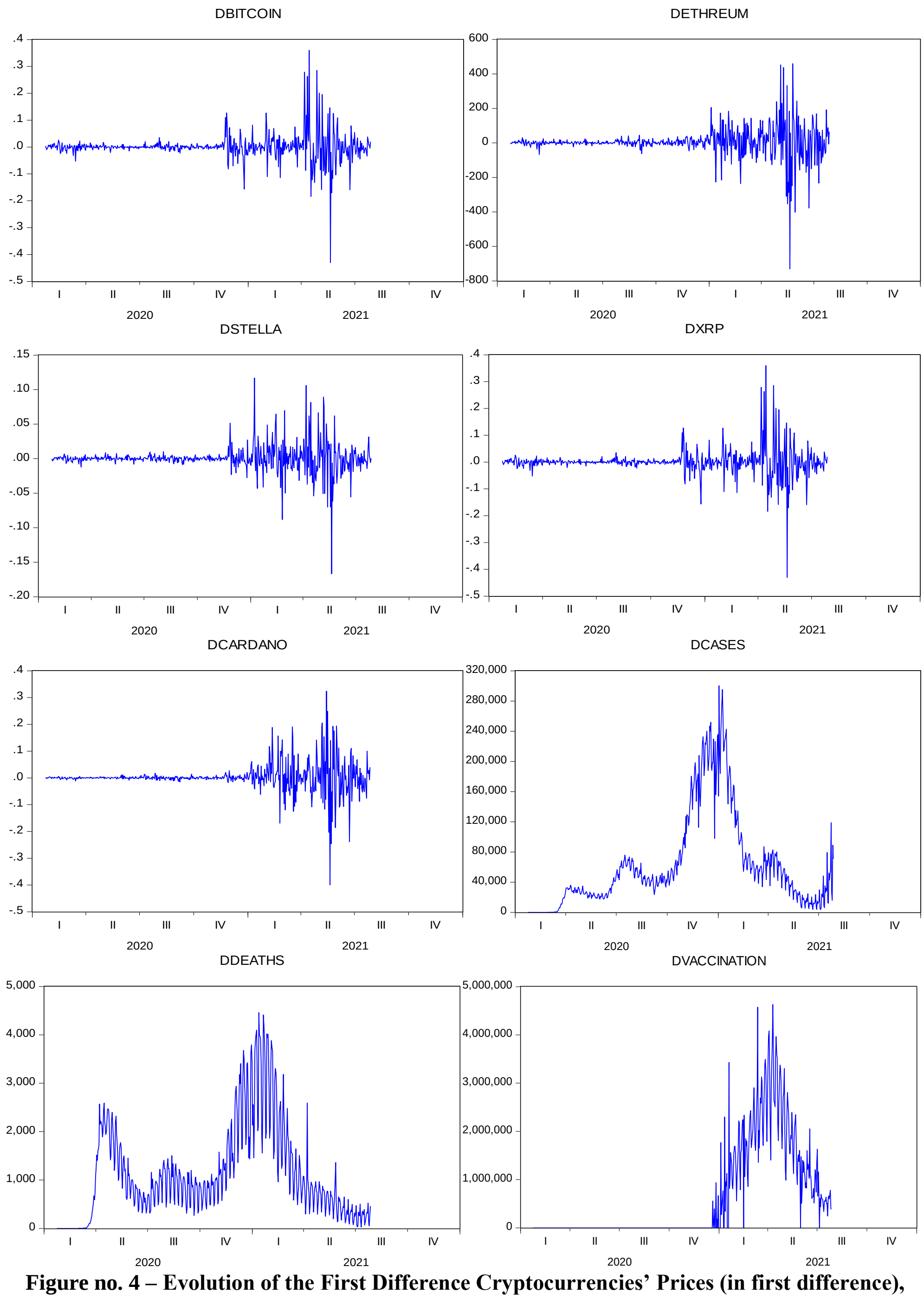


Figure no. 4 – Evolution of the First Difference Cryptocurrencies' Prices (in first difference), Cases, Deaths and Vaccination during the Covid-19 Crisis Period (01/22/2020-07/27/2021)

Table no. 4 – Estimation Results of Different Models

ARMA (p, q) Model

	Δ BITCOIN	Δ ETEHREUM	Δ STELLAR	Δ XRP	Δ CARDANO
Intercept	9.3371	-0.0601	-0.0001	-0.0004	-3.81×10^{-5}
AR(1)	-0.0381	-0.0056	0.0074	0.0160	-0.0631
Models	AR(1)	AR(1)	AR(1)	AR(1)	AR(1)
White Test	17.7852	4.7190	20.7002	53.2438	22.8972
Signification	0.0001	0.0945	0.0000	0.0000	0.0000
ARCH	17.5905	4.6192	10.9667	57.1243	15.7114
Signification	0.0000	0.0323	0.0010	0.0000	0.0001

ARCH Model

	Δ BITCOIN	Δ ETEHREUM	Δ STELLAR	Δ XRP	Δ CARDANO
Intercept	13081.77	31.1057	8.14×10^{-6}	7.3810^{-5}	1.70×10^{-6}
RESID(-1)^2	**0.4649**	0.2522	**0.6270**	0.3353	0.2481
RESID(-2)^2	0.3634	0.1067	0.1075	0.0527	0.3311
RESID(-3)^2	0.1433	0.1791		0.1497	0.0666
RESID(-4)^2	0.223157				0.4592

GARCH Model

	Δ BITCOIN	Δ ETEHREUM	Δ STELLAR	Δ XRP	Δ CARDANO
Intercept	6758.397	3.4181	1.82×10^{-6}	1.70×10^{-5}	1.70×10^{-7}
RESID(-1)^2	**0.5357**	**0.1383**	**0.4345**	0.1766	0.1301
GARCH(-1)	**0.5225**	-0.0491	**0.5705**	**0.7085**	**0.8545**
GARCH(-2)		**0.8618**			

TGARCH Model

	Δ BITCOIN	Δ ETEHREUM	Δ STELLAR	Δ XRP	Δ CARDANO
OMEGA	4.45E-08	0.0170	1.68E-06	1.29E-05	4.45E-08
ALPHA1	0.0989	0.0341	0.6008	0.2209	0.0989
GAMMA1	-0.0851	-0.0631	-0.4425	-0.1704	-0.0851
BETA1	0.9344	1.0022	0.6090	0.7748	0.9344

EGARCH Model

	Δ BITCOIN	Δ ETEHREUM	Δ STELLAR	Δ XRP	Δ CARDANO
Mu	1.4361	0.0238	-1.8464	-1.3414	-0.3580
Omega	0.6696	-0.0291	0.5084	0.2587	0.1738
Alpha	-0.0560*	0.1025	0.2119	0.1672	0.0702
Beta	0.8287	0.9985	0.8674	0.8710	0.9809

We first model each variable (in first difference) based on the ARMA model. From Table no. 4, the optimal number of lags to model the first difference cryptocurrencies' price is equal to 1. We report the presence of a heteroscedasticity issue for each digital currency given that the calculated value of White's test is statistically significant at the 1% significance level.

We then examine the ARCH effect for each cryptocurrency. From Table no. 4, Bitcoin and Cardano prices (in difference) can be modeled by ARCH(4) model. This can be attributed to a strong information asymmetry due the costs of obtaining information by investors. The Ethereum and Ripple prices (in first difference) are modeled by ARCH(3) model while the first difference Stellar price is specified by ARCH(2) model. Thus, one might model different variables using the GARCH model. The empirical results are also reported in Table no. 4. In this regard, the volatility of each cryptocurrency price (in first difference) is significant given that the sum of the coefficients of the estimated squared residuals and those of the GARCH is equal to 1. The volatility of each cryptocurrency price (in first difference) can be explained by the information asymmetry detected by the ARCH models and the bad and good news arrived in the cryptocurrency markets.

Next, we model the cryptocurrency prices (in first difference) without any prior constraint on the parameters of the EGARCH equation based on the logarithmic variance instead of the variance itself. The estimation results using the maximum likelihood technique are also reported in Table no. 4. The estimated coefficients of the EGARCH model are statistically significant for different cryptocurrencies. In addition, the magnitude of volatility is very noticeable given that the estimated alpha coefficients are statistically positive and significant except for Bitcoin. Hence, a leverage effect can be documented in cryptocurrencies' prices.

One might model the volatility's behavior based on the TGARCH model. The estimated coefficients are strictly positive and significant. The volatility parameter is negative and low for different variables. The transition speed is less than 1 for different variables.

4.2 Cryptocurrency Volatility during the Covid-19 Health Crisis

In this sub-section, we analyze the impact of the severity of Covid-19 pandemic (Cases and Deaths) and the total number of people vaccinated against virus (Vaccination) on cryptocurrencies' prices using the Ordinary Least squares method (Eq. 1). Table reports the estimation results of model during 01/22/2020-07/27/2021.

$$Log(Y_t) = \alpha + \beta Log(Cases_t) + \delta Log(Deaths_t) + \phi Log(Vaccination_t) + \varepsilon_t \tag{1}$$

Table no. 5 – Estimation Results of Model

	LBITCOIN	LETEHREUM	LSTELLAR	LXRP	LCARDANO
Intercept	8.6509*	4.6148*	-3.0653*	-1.8203*	-3.2923*
LCases	0.1307*	0.2177*	0.0628	0.1295*	0.0379
LDeaths	-0.1137*	-0.1872*	-0.0339	-0.1327*	0.0211
LVaccination	0.0675*	0.0898*	0.0759*	0.0488*	0.1255*
R^2	0.8874	0.9012	0.8523	0.6161	0.8829
White	320.2047	315.1918	157.9837	226.1991	354.5085
Signification	0.0000	0.0000	0.0000	0.0000	0.0000
Estimation Results of ARCH Model on Residuals					
Intercept	0.0006*	0.0011*	0.0018*	0.0007*	0.0017*
RESID(-1)^2	1.0386*	1.0537*	1.0149*	1.2134*	1.0004*
Estimation Results of GARCH Model on Residuals					
Intercept	0.0007*	0.0013*	0.0020*	0.0003*	0.0012*
RESID(-1)^2	1.0420*	1.0850*	1.0280*	0.7840*	0.8948*
GARCH(-1)	-0.0445	-0.0357	-0.0132	0.2986*	0.1219*
Estimation Results of EGARCH Model on Residuals					
Mu	-1.5884*	-1.9692*	-1.9083*	-1.6624*	-1.6842*
Omega	1.3076*	1.5456*	1.5231*	1.4435*	1.4432*
Alpha	-0.0209	-0.0172	0.0022	-0.0556	-0.0426
Beta	0.904784*	0.8421*	0.8470*	0.8889*	0.8829*
Estimation Results of TGARCH Model on Residuals					
Omega	0.0006*	0.0012*	0.0019*	0.0003*	0.0011*
Alpha1	1.0179*	1.1493*	1.0540*	0.8454*	0.9796*
Gamma1	0.0505	-0.0408	-0.0283	-0.1323	-0.1483
Beta1	-0.0038	-0.0523	-0.0119	0.2983*	0.1202*

Note: * denotes statistical significance at the 10% level

From Table no. 5, we report that the cumulative number of contaminated people (Cases) has a positive and significant influence on different cryptocurrencies' prices. On the other hand, people who die by Covid-19 pandemic affect negatively the prices of cryptocurrencies, except for Cardano. However, the variable 'Vaccination' influences significantly and positively the prices of different cryptocurrencies. This clearly indicates that cryptocurrency markets consider the increase of total number of people vaccinated against virus as good news. As a result, investors become more confident to invest in cryptocurrency markets.

From Table no. 5, the stationarity of residuals in level for different cryptocurrencies based on Dickey-Fuller (1979, 1981) test is well-documented. Using White test, we confirm the presence of the heteroskedasticity issue in residuals given that White statistic is statistically significant. The information asymmetry for residuals is evidenced using the linear ARCH model given that the estimated squared residual coefficients are statistically significant. We then examine the volatility behavior of different residuals based on GARCH-type model for different cryptocurrencies. Such salient facts such as persistence and leverage effect characterize the residuals series.

5. CONCLUSION

In this paper, we attempt to analyze the volatility behavior of five cryptocurrencies' prices (Bitcoin, Ethereum, Ripple, Stellar and Cardano) before and during the Covid-19 pandemic market using different models. The empirical results clearly show that the change of the volatility behavior of cryptocurrencies, in particular with the increase of the total number of individuals vaccinated against the virus. We also show some key features in the volatility behavior such as the leverage effect. Not surprisingly, the intensity of contagious disease followed by the announcement of the increase of vaccinated people coupled with sharing different information about vaccines tend to increasingly influence the volatility's dynamics. Thus, using different models can highlight different facets of volatility dynamics. The empirical findings also show that the total number of deaths has a negative and significant impact on cryptocurrencies' prices, except for Cardano. Nevertheless, the total number of affected people (Cases) influences positively and significantly different cryptocurrencies' prices. As well, the cumulative number of vaccinated individuals affects positively and significantly the prices of different cryptocurrencies. This leads investors to become more confident in investing on cryptocurrency markets.

Overall, the outbreak of pandemics seems to play a crucial role in the dynamic behavior of financial markets and portfolio risk management. In this regard, our findings could be of great interest to portfolio managers and investors who search for to invest in digital markets and collect information during turbulent phases. Thus, participants to cryptocurrency market could use social media platforms to better make decisions by using information regarding Bitcoin dynamics.

Overwhelmingly, the outbreak of health crisis can offer insightful interesting lessons to explore the dynamic behavior of cryptocurrency markets. Such unexpected crisis which is characterized by the disclosure of huge amount of news related to the virus spreading and the reliability of different vaccines coupled with increasingly economic and political uncertainty encourage to better examine the behavior such markets. In this regard, our results can serve market participants who want to understand the potential reactions of cryptocurrency markets and search for better making decisions during turbulent episodes.

References

Aalborg, H. A., Molnar, P., & de Vries, J. E. (2018). What can explain the price, volatility and trading volume of Bitcoin? *Finance Research Letters, 29*(June), 255-265. http://dx.doi.org/10.1016/j.frl.2018.08.010

Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics & Finance, 69*, 680-691. http://dx.doi.org/10.1016/j.iref.2020.06.035

Akhtaruzzaman, M., Sensoy, A., & Corbet, S. (2020). The influence of Bitcoin on portfolio diversification and design. *Finance Research Letters, 37*, 101344. http://dx.doi.org/10.1016/j.frl.2019.101344

Al Guindy, M. (2021). Cryptocurrency price volatility and investor attention. *International Review of Economics & Finance, 76*, 556-570. http://dx.doi.org/10.1016/j.iref.2021.06.007

Apergis, N. (2022). COVID-19 and cryptocurrency volatility: Evidence from asymmetric modelling. *Finance Research Letters, 47*, 102659. http://dx.doi.org/10.1016/j.frl.2021.102659

Baek, S., Mohanty, S. K., & Glambosky, M. (2020). COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters, 37*, 101748. http://dx.doi.org/10.1016/j.frl.2020.101748

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters, 173*, 148-151. http://dx.doi.org/10.1016/j.econlet.2018.10.008

Béjaoui, A., Mgadmi, N., Moussa, W., & Sadraoui, T. (2021). A short-and long-term analysis of the nexus between Bitcoin, social media and Covid-19 outbreak. *Heliyon, 7*(7), e07539. http://dx.doi.org/10.1016/j.heliyon.2021.e07539

Ben Cheikh, N., Ben Zaied, Y., & Chevallier, J. (2020). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters, 35*, 101293. http://dx.doi.org/10.1016/j.frl.2019.09.008

Bergsli, L. Ø., Lind, A. F., Molnár, P., & Polasik, M. (2022). Forecasting volatility of Bitcoin. *Research in International Business and Finance, 59*, 101540. http://dx.doi.org/10.1016/j.ribaf.2021.101540

Catania, L., & Grassi, S. (2022). Forecasting cryptocurrency volatility. *International Journal of Forecasting, 38*(3), 878-894. http://dx.doi.org/10.1016/j.ijforecast.2021.06.005

Chen, L., Pelger, M., & Zhu, J. (2019). Deep Learning in Asset Pricing. *arXiv:1904.00745*. http://dx.doi.org/10.48550/arXiv.1904.00745

Chi, Y., & Hao, W. (2021). Volatility models for cryptocurrencies and applications in the options market. *Journal of International Financial Markets, Institutions and Money, 75*, 101421. http://dx.doi.org/10.1016/j.intfin.2021.101421

Corbet, S., Hou, Y., Hu, Y., Lucey, B., & Oxley, L. (2021). Aye Corona! The contagion effects of being named Corona during the COVID-19 pandemic. *Finance Research Letters, 38*, 101591. http://dx.doi.org/10.1016/j.frl.2020.101591

Cross, J. L., Hou, C., & Trinh, K. (2021). Returns, volatility and the cryptocurrency bubble of 2017–18. *Economic Modelling, 104*, 105643. http://dx.doi.org/10.1016/j.econmod.2021.105643

D'Amato, V., Levantesi, S., & Piscopo, G. (2022). Deep learning in predicting cryptocurrency volatility. *Physica A, 596*, 127158. http://dx.doi.org/10.1016/j.physa.2022.127158

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*, 427-431. http://dx.doi.org/10.1080/01621459.1979.10482531

Dickey, D. A., & Fuller, W. A. (1981). Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. *Econometrica, 49*(4), 1057-1072. http://dx.doi.org/10.2307/1912517

Elsayed, A. H., Gozgor, G., & Lau, C. K. M. (2022). Risk transmissions between bitcoin and traditional financial assets during the COVID-19 era: The role of global uncertainties. *International Review of Financial Analysis, 81*, 102069. http://dx.doi.org/10.1016/j.irfa.2022.102069

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2018). Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? *International Review of Financial Analysis, 61*(January), 29-36. http://dx.doi.org/10.1016/j.irfa.2018.12.010

Fang, T., Su, Z., & Yin, L. (2020). Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis, 71*, 101566. http://dx.doi.org/10.1016/j.irfa.2020.101566

Goodell, J. W., & Goutte, S. (2020). Co-movement of Covid-19 and Bitcoin: Evidence from wavelet coherence analysis. *Finance Research Letters, 38*, 1-6. http://dx.doi.org/10.1016/j.frl.2020.101625

Haroon, O., & Rizvi, S. A. R. (2020). COVID-19: Media coverage and financial markets behavior-A sectoral inquiry. *Journal of Behavioral and Experimental Finance, 27*, 100343. http://dx.doi.org/10.1016/j.jbef.2020.100343

Iqbal, N., Fareed, Z., Wan, G., & Shahzad, F. (2021). Asymmetric nexus between Covid-19 outbreak in the world and cryptocurrency market. *International Review of Financial Analysis, 73*, 101-613. http://dx.doi.org/10.1016/j.irfa.2020.101613

James, N., Menzies, M., & Chan, J. (2021). Changes to the extreme and erratic behaviour of cryptocurrencies during COVID-19. *Physica A, 565*(March), 1-19. http://dx.doi.org/10.1016/j.physa.2020.125581

Kakinaka, S., & Umeno, K. (2020). Characterizing Cryptocurrency Market with Lévy's Stable Distributions. *Journal of the Physical Society of Japan, 89*(2), 024802. http://dx.doi.org/10.7566/JPSJ.89.024802

Katsiampa, P. (2018). Volatility co-movement between Bitcoin and Ether. *Finance Research Letters, 30*(September), 221-227. http://dx.doi.org/10.1016/j.frl.2018.10.005

Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters, 29*, 68-74. http://dx.doi.org/10.1016/j.frl.2019.03.009

Kyriazis, N. A., Daskalou, K., Arampatzis, M., Prassa, P., & Papaioannou, E. (2019). Estimating the volatility of cryptocurrencies during bearish markets by employing GARCH models. *Heliyon, 5*(8), e02239. http://dx.doi.org/10.1016/j.heliyon.2019.e02239

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*, 111221. http://dx.doi.org/10.1016/j.chaos.2021.111221

López-Cabarcos, M. Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., & Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. Are they connected? *Finance Research Letters, 38*, 101399. http://dx.doi.org/10.1016/j.frl.2019.101399

MacKinnon, J. G. (1992). Model Specification Tests and Artificial Regressions. *Journal of Economic Literature, 30*(1), 102-146.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics, 11*, 601-618. http://dx.doi.org/10.1002/(SICI)1099-1255(199611)11:6<601::AID-JAE417>3.0.CO;2-T

Qiu, Y., Wang, Y., & Xie, T. (2021). Forecasting Bitcoin realized volatility by measuring the spillover effect among cryptocurrencies. *Economics Letters, 208*, 110092. http://dx.doi.org/10.1016/j.econlet.2021.110092

Salisu, A. A., & Ogbonna, A. E. (2021). The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect. *Global Finance Journal*, 100641. http://dx.doi.org/10.1016/j.gfj.2021.100641

Salisu, A. A., & Vinh Vo, X. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *International Review of Financial Analysis, 71*, 101546. http://dx.doi.org/10.1016/j.irfa.2020.101546

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, 28*, 100404. http://dx.doi.org/10.1016/j.jbef.2020.100404

Walther, T., Klein, T., & Bouri, E. (2019). Exogenous drivers of Bitcoin and Cryptocurrency volatility – A mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money, 63*, 101133. http://dx.doi.org/10.1016/j.intfin.2019.101133

Yin, L., Nie, J., & Han, L. (2021). Understanding cryptocurrency volatility: The role of oil market shocks. *International Review of Economics & Finance, 72*, 233-253. http://dx.doi.org/10.1016/j.iref.2020.11.013

Yousaf, I., & Ali, S. (2020). The COVID-19 outbreak and high frequency information transmission between major cryptocurrencies: Evidence from the VAR-DCC-GARCH approach. *Borsa Istanbul Review, 20*(December), S1-S10. http://dx.doi.org/10.1016/j.bir.2020.10.003

Zaremba, A., Kizys, R., Aharon, D. Y., & Demir, E. (2020). Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. *Finance Research Letters, 35*(July), 101597. http://dx.doi.org/10.1016/j.frl.2020.101597

To cite this article: Mgadmi, N., Béjaoui, A., Moussa, W., Sadraoui, T. (2022). The Impact of the COVID-19 Pandemic on the Cryptocurrency Market. *Scientific Annals of Economics and Business*, 69(3), 343-359. https://doi.org/10.47743/saeb-2022-0014

Copyright