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Does Analyzing the Dynamics of Digital Currencies Help to Determine the Safe-Haven Crypto-Currency during the Covid-19 Outbreak?

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Abstract:

Purpose: *In this paper, we attempt to investigate the dynamic behavior of the crypto-currencies in order to better apprehend their possible safe-haven proprieties during the health crisis.*
Design/methodology/approach: *From a methodological standpoint, we develop a unified framework to jointly model the dynamic association between some crypto-currencies and the intensity of Covid-19 pandemic.*
Findings: *The empirical findings clearly indicate asymmetric dynamics of digital currencies when facing against an extremely stressful and unpredictable event. This also indicates the different reactions of cryptocurrency markets to the increase of Covid-19 intensity during the period 01/09/2019-01/01/2021.*
Practical implications: *Therefore, a better understanding of the joint dynamics between the Covid-19 intensity and digital currencies involves figuring out the safe-haven features of some digital currencies. Overall, such findings can be interesting for helping the market participants who want to learn much more about the safe-haven role of crypto-currencies.*

Keywords: *Market dynamics, cointegration approach, safe-haven.*

Paper type: *Research article.*

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1. Introduction

Overwhelmingly, the advent of Covid-19 health crisis has drastically affected the international markets. For instance, Iqbal *et al.* (2021) indicate that SetP500 and Dow Jones had suffered from a 30% decrease in values during March 2020. Other stock markets such as markets in Europe, UK, Australia and Asia have also displayed similar patterns (Zhang *et al.*, 2020). Al-Awadhi *et al.* (2020) display the severity of the Covid-19 pandemic in terms of confirmed cases and deaths negatively and substantially affect Chinese companies' stock returns. Ashraf (2020) clearly show that the financial markets significantly and negatively respond to the Covid-19 pandemic and such response evolves depending on the phase of such pandemic.

Cognizant worrying trends of the financial markets, other researchers have increasingly focused on the safe-haven features of some assets (e.g., gold, crypto-currency). In this respect, Umar and Gubareva (2020) and Mariana *et al.* (2020), among others, investigate the safe-haven proprieties of crypto-currency (in particular Bitcoin) market during the outbreak of Covid-19 health crisis. For instance, Umar and Gubareva (2020) analyze the effect of the Covid-19 fueled panic on the volatility of major fiat and crypto-currency markets over the period 1/2020-5/2020.

They show the cross-currency hedge strategies could not implement during the Covid-19 pandemic. They also report some key differences in currency markets behavior. Mariana *et al.* (2020) test if Ethereum and Bitcoin can be safe-havens for stocks during the Covid-19 pandemic. They show that crypto-currency returns seem to be negatively correlated with SetP500 returns. They also display that Ethereum and Bitcoin can be considered as short-term safe-havens. Conlon et al. (2020) analyze safe-haven capabilities of some crypto-currencies (Bitcoin, Ethereum and Tether) against stock markets. They report that Bitcoin and Ethereum are not a safe haven for the majority of international equity markets.

However, Tether can play as safe-haven asset against the international indices. Dutta *et al.* (2020) examine the safe-haven proprieties of Bitcoin and gold against the crude oil markets during the Covid-19 pandemic. They report that gold is a safe haven asset for global crude oil markets. On the other hand, Bitcoin acts only as a diversifier for crude oil. Mokni and Ajmi (2021) report the causal analysis between crypto-currencies (Bitcoin, Ethereum, Litecoin, Ripple and Bitcoin Cash) and the US dollar during the Covid-19 health crisis.

They report a significant causal relationship between the two markets during such pandemic. They also indicate that the US dollar loses its predictive power in favor of crypto-currencies, which can play a hedging role against the US dollar variations. Conlon and McGee (2020) explore the safe-haven proprieties of Bitcoin against the SetP500 market over the period 3/21/2019-3/20/2020. They report that Bitcoin cannot play as a safe haven, rather diminishing in price in lockstep with the SetP500 as the crisis develops. When held alongside the SetP500, even a small allocation to Bitcoin significantly increases portfolio downside risk.

Ji et al. (2020) examine the safe-haven role of some assets (gold, crypto-currency, foreign exchange and commodities) during the Covid-19 pandemic. They display that the role of safe haven becomes less effective for major assets while gold and soybean commodity futures remain robust as safe-haven assets during this pandemic. Corbet *et al.* (2020c) analyze the relationship between the Chinese financial markets and crypto-currency market during the Covid-19 health crisis. The volatility relationship between the main Chinese stock markets and Bitcoin tend to change significantly during such period.

This paper lies to the aforementioned literature and tries to analyze the dynamic behavior of the crypto-currencies in order to better apprehend their possible safe-haven proprieties during the health crisis. From a methodological standpoint, we develop a unified framework to jointly model the dynamic association between some crypto-currencies and the intensity of Covid-19 pandemic.

More specifically, the Co-integration approach and error correction model are used in the short- and long-term analysis. The paper is organized as follows. Section 2 reports a set of empirical studies and Section 3 reports, methodology, data, descriptive statistics and empirical results. Section 4 concludes.

2. Literature Review

Overall, researchers attempt to analyze and revisit the safe-haven features of crypto-currencies with the outbreak of Covid-19 pandemic. For instance, Conlon and McGee (2020) explore the safe-haven proprieties of Bitcoin during the health crisis. They display that Bitcoin cannot be a safe-haven asset, instead decreasing in price in lockstep with the SetP500 as the health crisis develops. Corbet *et al.* (2020a) show that the volatility relationship between the Chinese stock markets and Bitcoin substantially changes over the period 11/03/2019-10/03/2020. The dynamic associations during the turbulent periods call for portfolio design through the diversification benefits.

Wang *et al.* (2021) investigate the time-frequency domain connectedness and hedging proprieties among five hedges (Bitcoin, commodities, crude oil, gold and the U.S. dollar index) and four stock indices (developed and emerging markets). They show the time-changing associations between stock markets and hedges. In particular, the linkages between Bitcoin and stock indices tend to be the smallest among all hedges, especially for the short horizon. Pho *et al.* (2021) analyze the diversification proprieties of Bitcoin and gold against Chinese portfolios over the period 2010-2020. They display that gold seems to be a better portfolio diversifier than Bitcoin given that it helps to better diminish portfolio risk.

Goodell and Goutte (2021) analyze the co-movements between Bitcoin and the severity of Covid-19 pandemic over 13/12/2019-29/04/2020. They show that the levels of Covid-19 pandemic in terms of daily data of Covid-19 world deaths lead to an increase in Bitcoin prices. This can have insightful implications on the safe-haven proprieties of Bitcoin during the turbulent periods. Będowska-Sójkaa and Klibe (2021) analyze the safe-haven of gold and two digital currencies (Bitcoin and Ether).

Safe havens seem to be the financial assets which help investors to protect their portfolios during turbulent periods. They show that only gold can be employed as a strong safe-haven against the stock market indices. Ether seems to act more often as a weak safe-haven against DAX or SetP500, whereas Bitcoin can play such role against FTSE250, STOXX600 and SetP500.

Guo *et al.* (2021) analyze and compare the contagion phenomenon of Bitcoin and other assets before and after the Covid-19 pandemic. They clearly display that the contagion effect between Bitcoin and developed markets seems to be strengthened during the Covid-19 pandemic. They also show that gold has contagion impact with Bitcoin whereas gold, US dollar and bond market are the contagion receivers of Bitcoin during the shock of health crisis. Disli *et al.* (2021) attempt to evaluate the safe-haven proprieties of crypto-currency, crude oil and gold during the Covid-19 pandemic. They display that Bitcoin, gold and oil exhibit low coherency with each stock index until the onset of the Covid-19.

However, with the outbreak of the health crisis, the return spillover is more intense across financial assets, and a significant pairwise return connectedness between each equity index and hedging asset is well-documented. Raheem (2021) examines the safe haven proprieties of crypto-currencies such as Bitcoin with the advent of Covid-19 pandemic. They display the safe haven prowess of Bitcoin against measures of uncertainty (VIX, EPU, and Oil Shock). They also show that Bitcoin can act as safe-haven asset before the outbreak of Covid-19 pandemic. Nonetheless, such proprieties disappear after the Covid-19 announcement.

3. Data and Descriptive Statistics

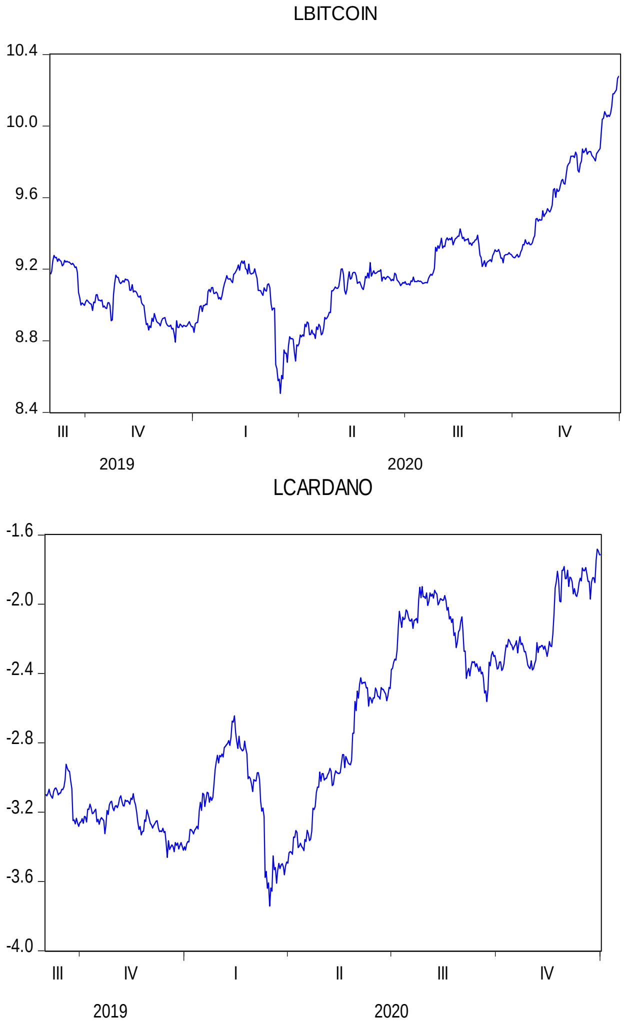
We gather data from the website yahoofinance.fr for eight digital currencies namely: Bitcoin, Cardano, Chainlink, Ethereum, Litecoin, Ripple, Sellar and Tether. In particular, we use the prices of crypto-currencies on daily frequency. As well, the proxies for the intensity of the Covid-19 pandemic are the “Cases” and “Deaths”.

The variable “Cases” refers to the total (cumulative) number of people affected by the Covid-19 pandemic (i.e., the total (cumulative) confirmed cases). The variable “Deaths” corresponds to the total (cumulative) number of people died by the Covid-19 pandemic.

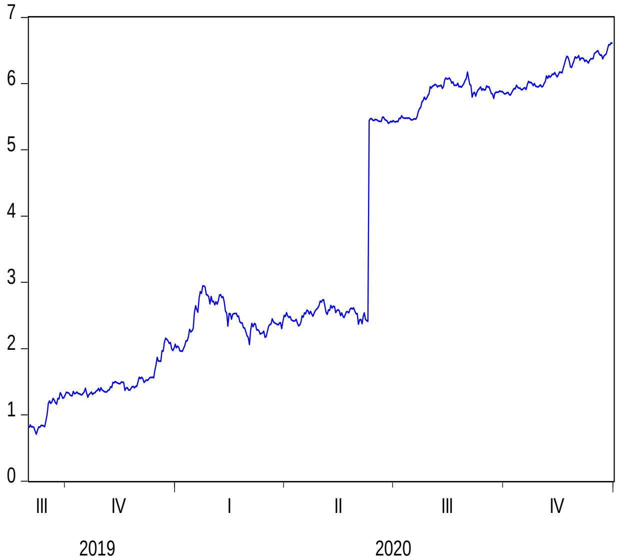
Such data is gathered from the website https://www.worldometers.info/. The period spans from 01/09/2019-01/01/2021. Needles to say, such period is characterized by the outbreak of Covid-19 pandemic.

Figure 1 illustrates the evolution of cryptocurrencies' logarithmic prices over time. At a first glance, each cryptocurrency' price tend to evolve differently before and during the Covid-19 pandemic. In particular, individual behavior of cryptocurrency market seems to dominate as the severity of Covid-19 pandemic (measured by Cases and Deaths) increases. Different bullish and bearish phases appear to characterize each cryptocurrency market cycle. However, in spite of the increase of cases and deaths around the World, there is no synchronization between digital currencies.

Figure 1. *Evolution of Crytocurrencies' Prices and the Covid-19 Cases and Deaths over Time*

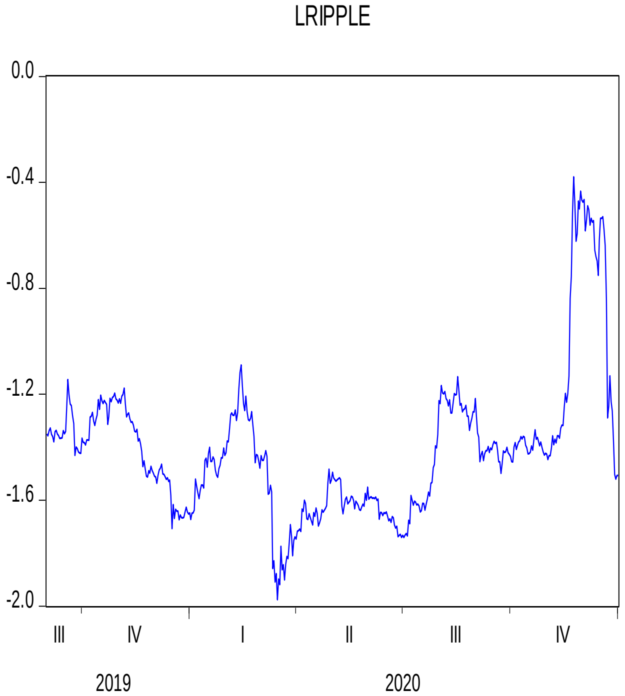


LCHAINLINK

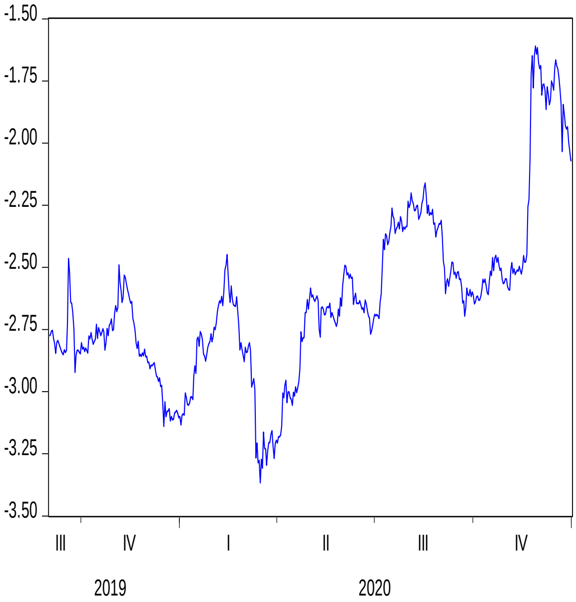


LETHEREUM

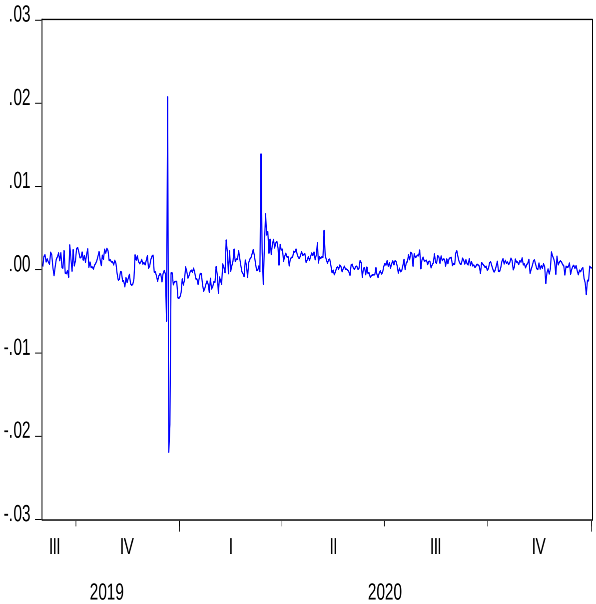

LLITECOIN
5.0
4.8
4.6
4.4
4.2
4.0
3.8
3.6
3.4
III
IV
I
II
III
IV
2019
2020

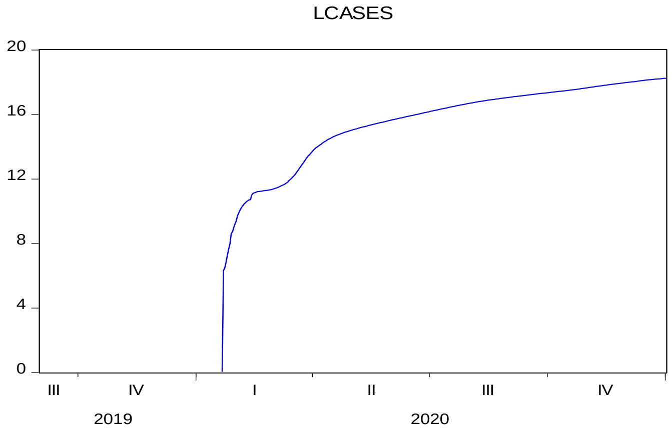

LRIPPLE
0.0
-0.4
-0.8
-1.2
-1.6
-2.0
III
IV
I
II
III
IV
2019
2020

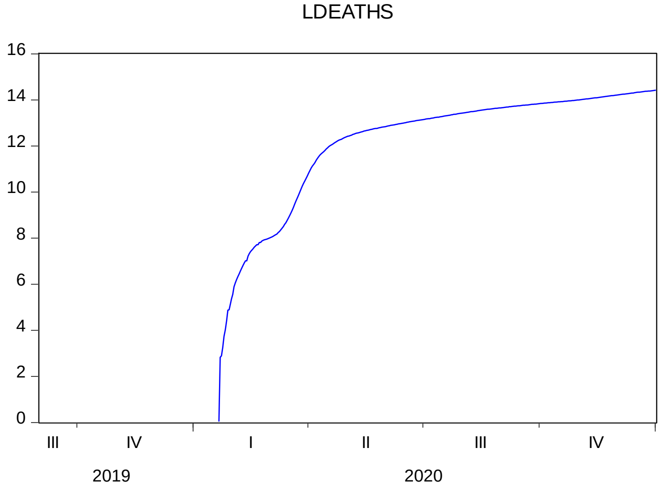
LSELLAR



LTETHER







Source: *Own study.*

Table 1 reports presents the descriptive statistics for eight selected crypto-currencies including: Mean, Median, Maximum, Minimum, Skewness, Kurtosis and Jarque-Bera test. From Table 1, the mean logarithmic price varies from Cardano (-2.73) to Bitcoin (9.20) over the period 01/09/2019-01/01/2021. Tether seems to be the least risky asset (0.002) whereas Chainlink is considers as the riskiest digital asset.

Afterwards, the average values of LCases and LDeaths are 10.98 and 8.64, respectively. The prices for all crypto-currencies seem to be positively skewed, except for Ripple and Sellar during the period 01/09/2019-01/01/2021. This implies that the right tail is particularly extreme (i.e., positive values or gains are much more likely). The asymmetric pattern among digital currencies in terms of kurtosis is well-documented. For instance, the value of kurtosis is equal 57.77 for Tether whereas it is about 1.29 for Chainlink. The Jarque-Bera statistics tend to be significant even at very low levels. Therefore, the daily prices are not normally distributed.

Table 1. *Descriptive Statistics for Different Cryptoccurencies*

	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera	N
LBITCOIN	9.2037	9.1479	10.2788	8.5060	0.3110	1.1491	4.5464	156.3595	489
LCARDANO	-2.7305	-2.8736	-1.6825	-3.7421	0.5394	0.2270	1.6685	40.3186	489
LCHAINLINK	3.6575	2.5907	6.6148	0.7059	2.0100	0.2018	1.2939	62.6225	489
LETHEREUM	5.5000	5.4019	6.6148	4.6811	0.4597	0.5369	2.2662	34.4701	489
LLITECOIN	3.9923	3.9618	4.8644	3.4673	0.2563	0.9957	4.0445	103.0401	489
LRIPPLE	-1.4042	-1.4244	-0.3792	-1.9760	0.2780	1.5415	6.2257	405.6899	489
LSELLAR	-2.6303	-2.6546	-1.6101	-3.3671	0.3445	0.8230	3.9599	73.9867	489
LTETHER	0.0005	0.0006	0.0207	-0.0219	0.0021	-1.6387	57.4038	60524.39	489
LCASES	10.9772	15.0531	18.2469	0.0000	7.3896	-0.6775	1.6722	73.3380	489
LDEATHS	8.6373	12.4207	14.4194	0.0000	5.9627	-0.5967	1.5608	71.2190	489

Note: *N refers to the number of observations.*
Source: *Own study.*

Table 2 reports the results from the unit root tests without trend break, i.e., the Dickey-Fuller (1979-1981) tests in level and in first difference. As well, the optimal number of lags for logarithmic prices of crypto-currencies is reported in Table 2.

Table 2. *Results from Dickey-Fuller (1979-1981) Tests*

	Lags	In Level			In First Difference		
		T-Statistics	Critical value of 5%	Model	T-Statistics	Critical value of 5%	Model
LBITCOIN	1	-0.6353	-3.4190	M3	-22.0928	-3.4190	M3
LCARDANO	1	-2.1109	-3.4190	M3	-23.1363	-3.4190	M3
LCHAINLINK	1	-2.4010	-3.4190	M3	-21.9357	-3.4190	M3
LETHEREUM	1	-1.9343	-3.4190	M3	-23.1330	-3.4190	M3
LLITECOIN	1	-1.1736	-3.4190	M3	-23.0852	-3.4190	M3
LRIPPLE	2	-2.2595	-2.8672	M2	-14.2655	-2.8672	M2
LSELLAR	1	-2.3356	-3.4190	M3	-22.1099	-3.4190	M3
LTETHER	1	-1.8407	-2.8672	M2	-25.6449	-2.8672	M2
LCASES	1	-1.1494	-2.8672	M2	-21.0669	-2.8672	M2
LDEATHS	3	-1.2033	-2.8672	M2	-8.4115	-2.8672	M2

Source: *Own study.*

From Table 2, the results from applying the Dickey-Fuller type (1979) test on logarithmic prices of the crypto-currencies, except for Ripple. Such time series seem to be non-stationary in level because the t-Statistics are greater than the critical values of Fuller (1976) and Mackinnon (1992). So, the specification with constant and trend (M3) seems to characterize these time series.

Given that the optimal number for Ripple's logarithmic price is equal to 2, it is worth noting to use the Augmented Dickey-Fuller (1981) test to examine the presence of a unit root in level and not stationary from the model with constant and without linear trend (M2). Using the Dickey-Fuller (1979) test, the variable LCases is not stationary in level under the specification with constant and without linear trend. Based on Augmented Dickey-Fuller (1981) test, the variable LDeaths is not stationary under the M2 specification.

Afterwards, one might use the Co-integration approach to investigate the relationships between the intensity of Covid-19 pandemic and the crypto-currency markets. In particular, one might use the double-step method of Engle and Granger (1987) to perform the univariate Co-integrating based on the ordinary least squares (OLS) technique. Such vector is a posteriori accepted under the stationarity of residuals. If, these residuals are stationary in level, we nest this vector or the long-term relationship within an error correction model (ECM).

This ECM encompasses the short-term equilibrium where the different variables are stationary in first difference and the long-term equilibrium where these variables are stationary by the linear combination when the target of the relationship is stationary in level. Table 3 reports the empirical results for different crypto-currencies.

Table 3. *Estimation Results of Long-Term Relationship*

	LCASES		LDEATHS	
Variable	Coefficient	Signification	Coefficients	Signification
LBITCOIN	-8.0571	0.0000	-4.3413	0.0025
LCARDANO	-7.4122	0.0000	-6.1176	0.0000
LCHAINLINK	1.5273	0.0000	0.9850	0.0000
LETHEREUM	1.8240	0.0000	1.4807	0.0000
LLITECOIN	-4.2948	0.0038	-6.4224	0.0000
LRIPPLE	-1.4510	0.0000	-1.2027	0.0000
LSELLAR	1.1465	0.0000	1.0394	0.0000
LTETHER	2.4817	0.0007	2.0864	0.0001
C	-1.4222	0.2709	-1.7173	0.0775
R^2	0.8047		0.8302	
F-Statistics	247.2407 (0.0000)		293.4008 (0.0000)	
Durbin-Watson	0.0889		0.1039	
Unit Root Test of Residuals of Long- Term relationship				
Lags	3		3	
Models	Without constant and without linear trend		Without constant and without linear trend	
T-Statistics	-2.2110		-2.3677	
Critical values of 5%	-1.9414		-2.8672	

Source: *Own study.*

From Table 3, the estimation results of long-term relationships between the variables related to the intensity of Covid-19 pandemic and logarithmic price of crypto-currency. At first glance, all the relationships between crypto-currency's logarithmic price, the total confirmed cases (LCases) and the cumulative number of people died by the Covid-19 pandemic seem to be statistically significant.

Nonetheless, the nature of such relationship differs from crypto-currency to another. For instance, the relationship between LCases (LDeaths) and Bitcoin's logarithmic price appears to be negative whereas the association between Sellar's logarithmic price and LCases (LDeaths) is positive. Overall, the adjustment quality of model seems to be good given that the determination coefficient is about 81%. From Table, the stationarity in level is well-documented for the residuals of long-term relationship based on the Augmented Dickey-Fuller- (1981) test.

We then model the long-term relationship between the crypto-currency returns (dLCryptocurrency) and the different variables of the severity of Covid-19 pandemic based on an error correction model (ECM). The estimation results of the ECM using the OLS technique are given in Table 4.

***Table 4.** Estimation Results of ECM*

Variable	Coefficients	Standard Deviation	T-Statistics	Signification
$dLBITCOIN_t$	-0.3530	0.7759	-0.4549	0.6494
$dLCARDANO_t$	0.2488	0.5123	0.4856	0.6274
$dLCHAINLINK_t$	0.0374	0.0914	0.4097	0.6821
$dLETHEREUM_t$	-0.3749	0.7186	-0.5217	0.6021
$dLLITECOIN_t$	0.5569	0.6122	0.9095	0.3635
$dLRIPPLE_t$	0.1083	0.4379	0.2474	0.8047
$dLSELLAR_t$	-0.3073	0.4451	-0.6903	0.4903
$dLTETHER_t$	-1.0698	4.8653	-0.2198	0.8261
$Residuals_{t-1}$	**0.0022**	**0.0041**	**0.5475**	**0.5843**
C	0.0378	0.0133	2.8293	0.0049
R^2	0.0039			
F-Statistics	0.2094 (0.9930)			
Durbin-Watson	1.9182			

***Source:** Own study.*

From Table 4, the estimation results of the ECM provide statistically insignificant coefficients. Also, the long-term goodness-of-fit is insignificant. Hence, there is not a long-term between crypto-currency returns and the variables related to the intensity of Covid-19 pandemic. In a multivariate framework, one might study the impact of the variables related to Covid-19 pandemic on eight crypto-currency prices using an autoregressive vector (VAR) model for different lags. The estimation results are presented in Table 5.

***Table 5.** Optimal Number of VAR Lags*

X_{1t} = ($LCases_t$, $LBitcoin_t$, $LCardano_t$, $LChainlink_t$, $LEthereum_t$, $LLitecoin_t$, $LRipple_t$, $LSellar_t$, $LTether_t$)						
Lags	LogL	LR	FPE	AIC	SC	HQ
0	1732.849	NA	6.23×10^{-15}	-7.1677	-7.0896	-7.1370
1	8676.868	13599.31	2.52×10^{-27}*	-35.7042*	-34.9228*	-35.3971*
2	8728.307	98.81263	2.85×10^{-27}	-35.5813	-34.0967	-34.9978
3	8787.285	111.0908	3.13×10^{-27}	-35.4897	-33.3019	-34.6298
4	8844.581	105.7769*	3.46×10^{-27}	-35.3911	-32.5002	-34.2549
X_{1t} = ($LDeaths_t$, $LBitcoin_t$, $LCardano_t$, $LChainlink_t$, $LEthereum_t$, $LLitecoin_t$, $LRipple_t$, $LSellar_t$, $LTether_t$)						
Lags	LogL	LR	FPE	AIC	SC	HQ
0	1869.888	NA	3.53×10^{-15}	-7.7375	-7.6594	-7.7068
1	9051.595	14064.80	5.31×10^{-28}*	-37.2623*	-36.4810*	-36.9552*
2	9103.335	99.3910	6.00×10^{-28}	-37.1406	-35.6561	-36.5571
3	9166.542	119.0559	6.46×10^{-28}	-37.0667	-34.8789	-36.2068
4	9228.733	114.8143*	7.00×10^{-28}	-36.9885	-34.0975	-35.8522

***Source:** Own study.*

From Table 5, there is relationship between crypto-currency's logarithmic prices using VAR (1) framework based on information criteria. The order of lags for the VAR framework is equal to 4 according to the likelihood ratio test.

Afterwards, we consider the trace and maximum eigenvalues of Johansen (1990) tests in order to determine the number of Co-integration relationship between the variables related to the severity of Covid-19 pandemic and the crypto-currency's logarithmic prices. The results of Johansen (1990) tests are summarized Table 6.

***Table 6.** Results from Johansen (1990) Tests*

	Test λ_{trace}				**Test** λ_{max}				
X_{1t} = ($LCases_t$, $LBitcoin_t$, $LCardano_t$, $LChainlink_t$, $LEthereum_t$, $LLitecoin_t$, $LRipple_t$, $LSellar_t$, $LTether_t$)									
Null Hypothesis	r=0	$r\leq 1$	$r\leq 2$	$r\leq 3$	r=0	r=1	r=2	r=3	
Altrnative Hypothesis	$r\geq 1$	$r\geq 2$	$r\geq 3$	r=4	r=1	r=2	r=3	r=4	
T-Statistics	*267.3819*	*161.4458*	116.5207	78.0993	*105.9361*	44.9250	38.4213	32.2481	

Critical Values at 5% Level	*197.3709*	*159.5297*	125.6154	95.7536	*58.4335*	52.3626	46.2314	40.0775	
Variables	LCases$_t$	LBitcoin$_t$	LCardano$_t$	LChainlink$_t$	LEthereum$_t$	LLitecoin$_t$	LRipple$_t$	LSellar$_t$	LTether$_t$
Normalized Cointegrating Vector for LCases	**1.0000**	**-5.34360**	**-7.2963**	**-3.6523**	**3.4472**	**1.7321**	**-2.9367**	**6.6135**	**-9.2585**
T-Statistics		**14.8877**	**10.4349**	**2.0217**	**12.4681**	**11.2621**	**10.4237**	**13.8250**	**8.4592**
X_{2t} = (LDeaths$_t$, LBitcoin$_t$, LCardano$_t$, LChainlink$_t$,LEthereum$_t$,LLitecoin$_t$,LRipple$_t$,LSellar$_t$,LTether$_t$)									
Null Hypothesis	$r=0$	$r\leq 1$	$r\leq 2$	$r\leq 3$	$r=0$	$r=1$	$r=2$	$r=3$	
Altrnative Hypothesis	$r\geq 1$	$r\geq 2$	$r\geq 3$	$r=4$	$r=1$	$r=2$	$r=3$	$r=4$	
T-Statistics	*340.2736*	*221.1935*	*133.5968*	93.7363	*119.0802*	*87.5966*	34.8604	28.0618	
Critical Values at 5% Level	*197.3709*	*159.5297*	*125.6154*	95.7536	*58.4335*	*52.3626*	46.2314	40.0775	
Variables	LDeaths$_t$	LBitcoin$_t$	LCardano$_t$	LChainlink$_t$	LEthereum$_t$	LLitecoin$_t$	LRipple$_t$	LSellar$_t$	LTether$_t$
Normalized Cointegrating Vector for LDeaths	**1.0000**	**7.3581**	**-4.6958**	**9.8408**	**-3.1125**	**-2.7460**	**-2.0367**	**5.7954**	**7.6012**
T-Statistics		**14.7846**	**10.6553**	**19.4054**	**11.1816**	**10.7613**	**9.7619**	**13.7415**	**7.9654**

Source: *Own study.*

From Table 6, the results from Johansen (1990) tests show the existence two Co-integration relationships between the cumulative number of people affected by the Covid-19 pandemic and crypto-currency's logarithmic prices based on trace tests and maximum eigenvalues. As well, there are two Co-integration relationships between the total number of people died by the Covid-19 pandemic and virtual currency's logarithmic prices from the maximum eigenvalue test and three long-term relationships from the trace test.

There is a positive association between some crypto-currencies' logarithmic prices (Bitcoin, Cardano, Chainlink, Ripple and Tether) and the cumulative number of individuals affected by the virus. However, a negative relationship between the cumulative number of deaths and some crypto-currencies' logarithmic prices (Bitcoin, Chainlink, Sellar and Tether) is well-documented.

Thereafter, the error correction vector (VECM) is used to investigate the relationship between different variables. Such model is performed based on the maximum likelihood technique. The linear fit of each long-term relationship through matrices are reported in Table 7.

From Table 7, the multivariate relationships between crypto-currency returns and the variables related to the intensity of Covid-19 pandemic do not show a long-term equilibrium given that the adjustment speed is not statistically significant. Hence, there is not a mechanism to correct the deviation of the target of crypto-currency returns. This may be attributed to the governmental measures such as lockdown, social distancing and vaccination of people in attempt to slow the spread of the Covid-19 pandemic. This can ultimately make investors less nervous and more confident about investing crypto-currency markets.

Table 7. *Linear Adjustment Matrices*

	LCases		LDeaths	
Variables	Coefficients	T-Statistics	Coefficients	T-Statistics
dLCases	-0.0076	-0.5636	-	
dLDeaths	-		-0.0021	-0.3358
dLBITCOIN	0.0008	0.4983	0.0008	0.5331
dLCARDANO	7.68×10^{-5}	0.0322	0.0001	0.0741
dLCHAINLINK	0.0014	0.2055	0.0013	0.1973
dLETHEREUM	0.0020	0.9557	0.0021	0.9935
dLLITECOIN	0.0029	1.3432	0.0031	1.3885
dLRIPPLE	0.0035	1.5204	0.0035	1.5382
dLSELLAR	0.0028	1.1896	0.0029	1.2196
dLTETHER	-0.0013	-14.3599	-0.0013	-14.3348

Source: *Own study.*

4. Conclusion

In this paper, we attempt to investigate the dynamic behavior of digital currencies to determine the potential safe-haven features with the outbreak of Covid-19 pandemic. Cognizant the economic and financial costs of such health risk, investors have increasingly endeavored to search for suitable safe-haven to include it in their portfolios. So, it urges to re-assess the role of safe-haven of some well-known crypto-currencies and discover other digital currencies given such unprecedented event.

As a matter of fact, the financial literature stipulates that the safe-haven proprieties of assets can seemingly change over time and according the nature of dramatic event. In this regard, Ji *et al.* (2020) argue that investors who search for the suitable safe-haven asset(s) should not dismiss the underlying features/driving forces of market turmoil. Based on this crux, we use the prices of eight crypto-currencies (Bitcoin, Cardano, Chainlink, Ethereum, Litecoin, Ripple, Sellar and Tether) over the period 01/09/2019-01/01/2021.

From a methodological standpoint, we develop a unified framework to jointly model the dynamic connectedness between some crypto-currencies and the intensity of Covid-19 pandemic. More specifically, the Co-integration approach and error correction model are used in the short and long term analysis. The empirical results clearly show differences between the digital currencies in their responses to the changing levels of the severity of Covid-19 pandemic. The nature of such relationship seems to differ from crypto-currency to another. Therefore, a better understanding of the joint dynamics between the intensity of pandemic and digital currencies leads to better understand the safe-haven capabilities of some digital currencies. The dis (similar) pattern of associations between the dynamic behavior of digital currencies and the severity of Covid-19 pandemic could thus an important impact on investor portfolio.

Overall, the empirical findings can be interesting for investors and researchers to better apprehend the behavior of digital currencies and find out their ongoing safe-haven features, especially during episodes of great panic, high tension and stress due to the traumatic events such as health crisis.

Further studies can explore such dynamics and features with the inflow of huge amount of (fake news and valuable information) news from social media channels with regards to the virus spreading and the reliability of different vaccines.

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