 https://doi.org/10.57017/jorit.v1.2(2).02

Safe-Haven Effectiveness of Cryptocurrency: Evidence from Stock Markets of COVID-19 Worst-Hit African Countries

Isiaka Akande RAIFU
Department of Economics, Faculty of Economics and Management Sciences
University of Ibadan, Ibadan, Nigeria
Ahamuefula Ephraim OGBONNA[1]
Centre for Econometrics and Applied Research (CEAR), Ibadan, Nigeria
& Department of Statistics, Faculty of Science
University of Ibadan, Ibadan, Nigeria

Abstract

The study assessed the hedge or safe-haven property of five cryptocurrencies for stocks of three COVID-19 worst-hit African countries. We address two main concerns bordering on the predictive capacity of African stocks for cryptocurrency returns and the safe-haven property that cryptocurrencies could offer to African stocks. A distributed lag model, with explicitly incorporated salient statistical features, was adopted based on its efficient management of parameter proliferation and estimation biases. We ascertained the model's in-sample predictability and evaluate its out-of-sample forecasts performance in comparison with the historical average model, using Clark and West statistics. While African stocks significantly predicted cryptocurrency returns, the cryptocurrency-stocks nexus revealed the diversifier and safe-haven property of cryptocurrencies for African stocks in periods of normalcy and crisis/pandemic, respectively. Our predictive model outperformed the historical average model in the out-of-sample. Our results may be sensitive to cryptocurrency-stocks nexus and sample periods but not the out-of-sample forecast horizons.

Keywords: COVID-19; cryptocurrency; distributed lag model; hedge; safe-haven.

JEL Classification: C51; C53; C58; G11; G15; G17.

Introduction

On December 31, 2019, the epidemic of a novel strain of coronavirus broke out in Wuhan City of Hubei Province in China. Given the rate of spread of the coronavirus disease (COVID-19) to other countries cum the large proportion of countries already affected, the World Health Organisation (WHO) declared it a pandemic on March 11, 2020. As of July 25, 2020, a total of 15,762,063 persons had been infected with the virus and 639,273 people had been reported dead (ECDC, 2020). To curtail or slow down the spread of the virus; governments, international organisations and corporations put several measures in place, such as washing and sanitisation of hands, wearing masks in public places, physical and social distancing, and total lockdown of the economies across the world (World Health Organisation, 2020).

These measures, especially, physical and social distancing as well as the total lockdown, have had a lot of damaging effects on socioeconomic activities almost all over the world (UNCTAD, 2020-trade, ILO, 2020-labour market; World Bank, 2020-commodity prices; UNDP, 2020-tourism and other general economic activities). Most importantly, most commodities have suffered deteriorations in prices as the economies globally are under lockdown. It is on record that as a result of the COVID pandemic, crude oil price declined by about 50% with the crude benchmark WTI recording negative values for the first time since the oil prices have been falling in the international market (World Bank, 2020). Several precious metal prices also declined spontaneously between January and March 2020. Schmidhuber, Pound and Qiao (2020) show that precious metals such as platinum, palladium, silver, copper, nickel, lead, aluminium, iron and gold fell by 41.1%, 31.8%, 28.9%, 22.3%, 17.9%, 14.3%, 12.8%, 5.5% and 3.5% between January and March 2020, respectively.

The spread of the COVI9-19 pandemic has generated unprecedented volatility across major financial markets in the world and has resulted in great losses to many investors (Baker, 2020).

[1] Corresponding Author

According to World Economic Forum (2020), total global financial assets loss is estimated to be around 12.35% between January and March, and over $9 trillion has been lost due to COVID-19 pandemic-induced fear and sentiment. As the impacts of the COVID-19 pandemic are being felt across the world, as it concerns the financial markets, a lot of investors, being rational persons, are looking for other investments to put their hard-earned money. Of all financial market assets, cryptocurrency appears to be resilient to the damaging effect of the coronavirus pandemic. Available statistics on the most traded cryptocurrency, Bitcoin, show that although the price of Bitcoin initially declined just like other commodity prices, it quickly rebounded to its pre-COVID-19 pandemic historical prices. More specifically, the World Health Organisation's declaration of COVID-19 as a pandemic on March 11th, 2020 led to a drastic fall in the price of Bitcoin from $7,935.10 to $4,826.00 the following day, March 12th, 2020, representing a decline of about 39.18%. It, however, rebounded quickly by 13.58% on the following trading day (March 14th, 2020). Since then, the price of bitcoin has been rising steadily to its historical price before the emergence of the COVID-19 pandemic.

In light of this, this study aims to address two questions:

- *First*, amidst the COVID-19 pandemic, do African stocks have the predictive capacity to predict cryptocurrency returns?
- *Second*, is cryptocurrency a safe haven or a hedge or a diversifier for investors who have suffered great losses of income in other financial market assets, especially investors from developing countries like African countries?

Since cryptocurrency became tradable, a lot of researchers, investors and financial experts have been keenly interested in knowing whether, in conjunction with other commodities, it would serve as a safe haven or a hedge for other assets (Bouri et al., 2017a, 2017b; Bouri et al., 2020; Dyhrberg, 2016; Guesmi et al., 2019; Ji et al., 2019; Okorie and Lin, 2020; Pal and Mitra, 2019; Selmi, et al., 2020; Shahzad, 2020; Smales, 2019; Urquhart and Zhang, 2019; Wang et al. 2019a, 2019b). From these strands of studies, come mixed empirical findings. For instance, Dyhrberg (2016) studied the hedging capabilities of Bitcoin and concluded that Bitcoin serves as a hedge against the US dollar and the UK stock market index.

However, Bouri et al. (2017), who investigated whether Bitcoin is a safe haven or a hedge investment against some major commodities such as stock indices, currencies, bonds, oil and gold for the US, the UK, Germany, Japan and China, found that Bitcoin does not serve as a hedge for these commodities, it only serves as a means of portfolio diversification and a safe-haven. Their findings were supported by Wang et al. (2019) who concluded that cryptocurrency is only a safe-haven but not a hedge against the international indices. While considering a safe-haven or a hedge potential of about 9 cryptocurrencies on some major US stock indices, Bouri et al. (2020) submitted that not all cryptocurrencies can serve as either a safe-haven or a hedge against the considered stock market indices. Their findings, specifically, showed that Bitcoin, Ripple and Stellar are safe-havens for all the US stock indices but not hedges. Also, Litecoin and Monero serve as safe-havens for the aggerate US equity index and selected sectors while Ethereum, Dash and Nem are hedges for a few equity sectors. There are a couple of other studies which reported that Bitcoin did not serve as a safe-haven for global assets (see Table A1 in the Appendix for the summary of literature review).

Given the above, we examine whether the cryptocurrencies, assumed to be resilient to the COVID-19 pandemic, could serve as a safe-haven, a hedge and a diversifier for the investors whose stock market values have been affected by the COVID-19 pandemic in the most affected countries in Africa. We do this by comparing and contrasting the hedging, safe-haven and diversification capacities of five cryptocurrencies before and during the COVID-19 pandemic. These five cryptocurrencies are selected based on their market capitalisation and they include Bitcoin ($204,340,866,390), Ethereum ($35,984,677,575), XRP ($10,749,160,626), Tether ($10,017,964,608) and Bitcoin cash ($5,326,532,509)[2].

We used three stock market indices of three (Egypt, Nigeria and South Africa) out of the five most affected countries in Africa (South Africa (579,140), Egypt (96,220), Nigeria (48,445), Ghana (42,063) and Morocco (39,241)[3]. We focus on the aforementioned three countries for three reasons. First, their stock market indices are readily available on daily basis and those data can be extracted from a common database such as yahoo finance or investor.com. Second, during the current pandemic, a lot of investors have lost their hard-earned money as the prices of their stocks shrunk drastically. For instance, in Nigeria, the largest economy in Africa, the market capitalisation has dipped by 16.88 billion as of June 2020 (Adesina, 2020). All share index also fell from 26,415.54 points in February 27th, 2020 to 23,021.01 points on April 30th, 2020, representing about 12.85% decline. Similarly,

[2] https://coinmarketcap.com/currencies/bitcoin-cash/

[3] https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases/14/08/2020

between March 5th, 2020, when the first case of COVID-19 was reported in South Africa and March 23rd 2020, the prices of the top 40 traded stocks declined by 17.06%. In Egypt, the first case of Coronavirus was confirmed on 14th of February, 2020. This announcement only had a marginal effect on the stock prices as the prices declined by 1.00% on the following trading day (February 16th, 2020). However, as from the day WHO declared COVID-19 a pandemic (11th of March, 2020), the stock price nosedived significantly, declining by 10.04% between 11th of March, 2020 and 5th of April, 2020.

Following this introduction, the rest of the study is structured as follows. The method is presented in Section 1. Section 2 focuses on data sources and descriptions. The empirical results are presented in Section 3 while the last section concludes.

1. Methodology

A distributed lag model, that explicitly accounts for salient statistical features inherent in the data set, following Westerlund and Narayan (2012, 2015) approach, is adopted to assess the cryptocurrency returns - stock returns nexus. The merits of this approach lie in how efficiently parameter proliferation and estimation biases are controlled. Extant literature is awash with several empirical studies (see Narayan and Gupta, 2015; Narayan, Phan and Sharma, 2018; Salisu et al., 2019a, 2019b, 2019c, 2019d, 2019e; Salisu et al., 2020a, 2020b).

The choice of model is informed by the observed data features, which include autocorrelation, conditional heteroscedasticity, endogeneity and persistence, see Bannigidadmath and Narayan (2015), Narayan and Gupta, (2015), Phan et al. (2015), Narayan et al. (2016), Devpura et al. (2018), Narayan et al. (2018) Salisu and Oloko (2015), Salisu et al. (2018), Salisu et al. (2019a, 2019b, 2019c, 2019d, 2019e), Salisu et al. (2020a, 2020b). As a way to account for the day-of-the-week effect that characterizes most high-frequency financial series, five lags of the stock returns are incorporated into the distributed lag model. In the same vein, the inherent conditional heteroscedasticity is accounted for by pre-weighting the model variables with the standard deviation of the residuals $\left(\hat{\sigma}_{\varepsilon}\right)$ from an arch model. Failure to adequately account for these salient features is likely to result in biased estimates, which may be misleading (Zhang et al., 2017; Yaya and Ogbonna, 2019; Salisu and Vo, 2020). The distributed lag model is defined in equation (1):

$$r_t = \alpha + \sum_{i=1}^{k} \beta_i stk_{t-i} + \gamma\left(stk_t - stk_{t-1}\right) + \varepsilon_t \quad (1)$$

where: cryptocurrency returns at a given time t is defined as $r_t = \ln\left(P_t / P_{t-1}\right)$ and P_t denotes the price of cryptocurrency; α is the model intercept; stk_{t-i} is the i^{th} lag of stock returns $\left(stk_t\right)$, *i* = 1, 2, …, *k* and *k*=5; β_i's are slope coefficients corresponding to the *i* = 1, 2, …, k lags of the predictor variable; $\left(stk_t - stk_{t-1}\right)$ and its associated slope parameter $\left(\gamma\right)$ are incorporated to correct for endogeneity bias and persistence (*p*) in stock returns; while ε_t is the error term.

The model in equation (1) specifies cryptocurrency returns as a function of the lags of stock returns. While the estimates of the parameters associated with the lags of stock returns are statistically examined, we would be particularly interested in the joint significance of the incorporated lags. The latter reveals stock returns' predictability for cryptocurrency returns, a feat from which the hedge, safe-haven or diversifier property of cryptocurrency can be ascertained. We, therefore, evaluate the joint significance of the five lags of stock returns under a null hypothesis of no predictability $\left(H_0 : \sum_{i=1}^{k} \beta_i = 0\right)$ using the Wald test statistic. The rejection of the null hypothesis is indicative of the joint significance of the lags stock returns and consequently predictability of the stock returns for cryptocurrency returns. Also, the sign and period being considered would be simultaneously used to determine if cryptocurrency offers hedge or safe-haven or diversifier properties for African stocks. Also, in a bid to account for time variation in the model parameters, the estimation is done under a rolling window framework.

For model comparison, we also estimate a historical average model as a benchmark model, where the cryptocurrency returns are regressed on constant only. A pairwise comparison statistic, Clark and West (CW, 2007) test, is considered given that the benchmark model is nested within the distributed lag model specified in equation (1). The testing framework determines, in a more formal manner, if the difference between the forecast errors in a restricted (benchmark historical average) model and an unrestricted (our predictive distributed lag) model is not statistically different from zero. The Clark and West test equation is:

$$\hat{f}_{t+h} = \left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2 - \left[\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2 - \left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2\right] \tag{2}$$

where: h represents the forecast horizon; $\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$ and $\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$ respectively represent the squared errors from the restricted and unrestricted model; while $\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$ is the adjusted squared error that corrects for large model forecast noise.

Also, the sample average $\hat{f}_{t+h}$ is defined as $MSE_1 - \left(MSE_2 - adj.\right)$

where: $MSE_1 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$; $MSE_2 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$; $adj. = P^{-1}\sum\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$ and P is the number of averaged forecasts.

Subsequently, $\hat{f}_{t+h}$ is regressed on a constant, and the *t*-statistic of the estimated constant determines the significance or non-significance of the difference in the forecast errors of the restricted and unrestricted models. Positive and significant t-statistic would imply a preference for the unrestricted model over the restricted model in the prediction of cryptocurrency returns.

2. Data Sources and Preliminary Findings

To implement the objective of this study, we collected daily data on stock prices of the three most affected countries by COVID-19 pandemic in Africa. The three African countries include South Africa, Egypt and Nigeria. We also collected the daily data of the most traded cryptocurrencies which include Bitcoin, Bitcoin Cash, Ethereum, Ripple and Tether. The daily stock prices of South Africa (SAT 40); Egypt (EGX 70) and Nigeria (NSE30) and cryptocurrencies were collected from a financial database (www.investing.com) and they covered the period from January 2019 to July 2020. The cryptocurrencies are selected based on their market capitalisation.

The data[4] was partitioned into three, namely: the full period, the pre-declaration of COVID-19 pandemic and the post-declaration. The descriptive statistics of the stock returns and cryptocurrencies' returns are presented in Table 1. We considered the summary statistics which include mean, standard deviation, skewness, kurtosis and Jarque-Bera. For the overall sample, the average returns of cryptocurrencies are positive as indicated in the table. Similarly, the average returns of SAT 40 and EGX 70 are also positive. Conversely, the returns of NSE30 are negative, suggesting stocks have suffered some sort of decline in prices in Nigeria.

Despite the negative returns of the stock price in Nigeria, the standard deviations of the asset prices (cryptocurrencies and stocks) show that stock returns are more volatile in South Africa and Egypt than in Nigeria as the returns of stock prices deviate more in the two countries. The returns of cryptocurrencies are also volatile. Before the declaration of COVID-19 as a pandemic, the stock prices in South Africa, Egypt and Nigeria have been declining; hence, the negative returns of all the stocks pre-declaration. However, most of the returns of the cryptocurrencies remain positive during this period. The only cryptocurrency that experienced negative returns is Ripple. In the period of post-declaration of COVID-19 as a pandemic, SAT 40 and EGX70 returns on average are positive, while the returns of NSE30 are, on average, negative. In the case of cryptocurrencies after the declaration of COVID-19 as a pandemic globally, it is observed that the average returns of Bitcoin Cash and Ripple are positive. However, the average returns of Bitcoin, Ethereum and Tether remain positive for the full sample and sub-sample data (pre- and post-declaration of COVID-19 as a pandemic). Besides, the stock returns are more volatile post-COVID-19 declaration than pre-declaration as shown by the values of standard deviations. Similarly, cryptocurrencies are more volatile than stock prices, though some yielded positive returns in all the samples. The skewness results reveal that the returns of stocks and cryptocurrencies are skewed, while the high values of returns of the assets suggest that the distribution is leptokurtic (more peaked than the normal distribution). This is even corroborated by the results of Jarque-Bera, which show that the distribution is not normally distributed across the sample because the Jarque-Bera statistics are statistically significant throughout the sample classifications.

[4] The complete data can be found in https://mfr.osf.io/render?url=https%3A%2F%2Fosf.io%2F7jdhz%2Fdownload

Table 1. Summary statistics of the cryptocurrencies and stock returns

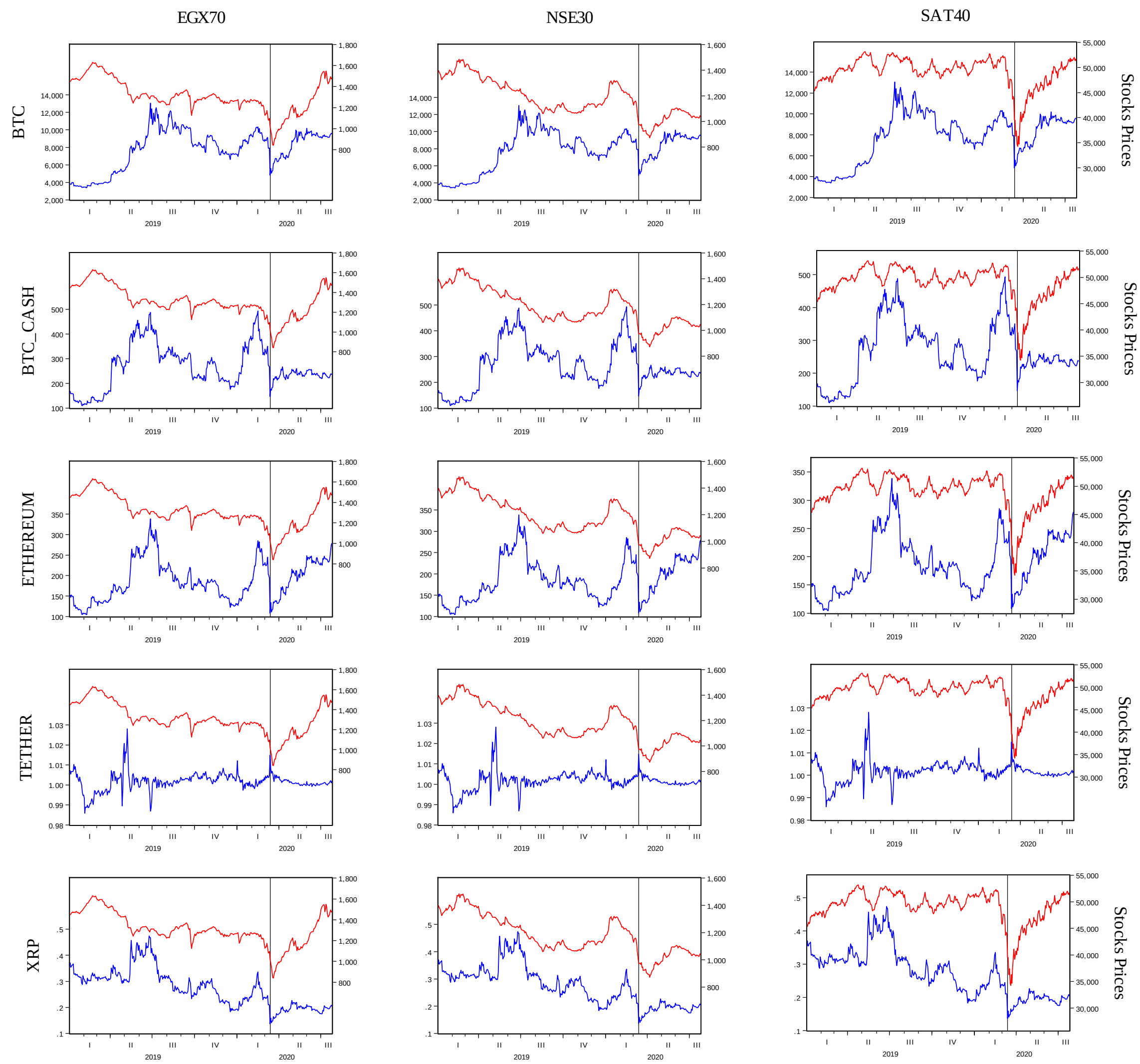
Statistics	Cryptocurrency returns					Stock returns		
	Bitcoin	Bitcoin Cash	Ethereum	Ripple	Tether	EGX70	NSE30	SAT40
Full Sample								
Mean	0.22	0.08	0.15	-0.15	0	0.01	-0.07	0.03
Std. Dev.	4.83	6.62	5.78	4.9	0.24	1.41	1.02	1.54
Skewness	-2.49	-1.02	-2.56	-1.29	0.08	-1.33	-0.23	-1.23
Kurtosis	31.96	23.04	30.61	18.12	17.44	7.61	8.1	14.33
Jarque-Bera	14,645.00***	6,880.90***	13,371.01***	3,992.17***	3,535.04***	479.65***	444.69***	2,279.42***
Obs.	407	407	407	407	407	407	407	407
Arch(1)	0.23	1.75	0.99	2.21	39.54***	18.97***	11.01***	8.68***
Arch(5)	0.88	1.69	0.91	1.33	32.23***	20.47***	5.01***	54.37***
Arch(10)	0.46	0.9	0.5	0.72	19.33***	10.37***	5.84***	30.85***
Q(5)	3.51	4.94	10.02*	2.29	30.55***	14.62**	18.53***	16.79***
Q(10)	6.28	14.94	11.97	4.75	44.00***	20.61**	28.52***	41.20***
$Q^2(5)$	4.79	7.69	5.2	6.95	145.73***	135.86***	28.43***	281.83***
$Q^2(10)$	5	7.91	5.73	7.44	218.29***	164.63***	74.91***	466.41***
Pre-COVID-19 Declaration as a Pandemic								
Mean	0.23	0.15	0.09	-0.18	0	-0.09	-0.09	-0.01
Std. Dev.	4.16	6.33	4.85	4.54	0.27	1.1	0.94	1.02
Skewness	0.25	1.02	-0.26	0.33	-0.05	-1.59	0.1	-1.51
Kurtosis	7.21	9.61	6.04	6.51	15.04	9.49	9.37	11.33
Jarque-Bera	231.00***	616.26***	122.68***	164.76***	1,866.70***	672.08***	522.32***	1,010.12***
Observations	309	309	309	309	309	309	309	309
Arch(1)	2.31	2.11	1.44	5.57**	30.99***	36.40***	9.11***	3.32*
Arch(5)	3.17***	0.55	0.55	1.42	27.73***	16.68***	2.40**	20.06***
Arch(10)	1.79*	0.38	0.47	1.1	16.66***	8.35***	1.37	39.05***
Q(5)	1.13	1.58	0.55	4.29	23.97***	12.92**	1.35	4.81
Q(10)	2.63	7.03	2.21	5.4	37.19***	14.22	5.34	8.8

Statistics	Cryptocurrency returns					Stock returns		
	Bitcoin	Bitcoin Cash	Ethereum	Ripple	Tether	EGX70	NSE30	SAT40
$Q^2(5)$	18.45***	2.87	2.27	7.4	119.41***	100.07***	8.83	36.84***
$Q^2(10)$	21.54**	3.64	3.88	10.83	175.62***	102.12***	10.48	99.15***
Post-COVID-19 Declaration as a Pandemic								
Mean	0.19	-0.15	0.34	-0.04	0	0.32	-0.02	0.15
Std. Dev.	6.55	7.47	8.07	5.93	0.15	2.07	1.23	2.56
Skewness	-4.4	-4.95	-3.83	-3.57	2.57	-1.31	-0.74	-0.93
Kurtosis	36.19	43.23	31.88	28.79	28.87	4.89	5.84	7.09
Jarque-Bera	4,814.50***	7,007.58***	3,644.47***	2,923.15***	2,841.19***	42.69***	41.85***	82.38***
Observations	98	98	98	98	98	98	98	98
Arch(1)	0.2	0.04	0.13	0.15	50.87***	2.12	0.18	2.15
Arch(5)	9.12***	34.70***	3.14**	3.97***	33.67***	3.43***	3.33***	21.80***
Arch(10)	1.27	0.67	0.6	1.05	2.60***	1.5	1.05	11.04***
Q(5)	4.94	6.38	6.95	4.3	15.33***	3.45	20.88***	3.57
Q(10)	7.37	7.99	8	6.93	24.84***	10.25	28.77***	17.63*
$Q^2(5)$	0.62	0.71	0.37	0.42	4.58	15.04**	11.09*	60.70***
$Q^2(10)$	0.64	0.72	0.39	0.52	5.51	16.97*	20.38**	87.81***

Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

We also report the results of ARCH LM tests and Ljung-Box Q-statistics tests in Table 1. While the ARCH LM test helps us explore the conditional heteroscedasticity of the variables, the Ljung-Box Q-statistics test guides us to detect the presence of correlation in the variables. The null hypothesis of ARCH LM test is that there is no ARCH effect; that is, there is no heteroscedasticity problem or no volatility; while the alternative hypothesis is that there is ARCH effect, implying that there exists heteroscedasticity problem or volatility. When the values of ARCH LM tests are not statistically significant at least at 5% level of significance, this implies that there is no ARCH effect, otherwise, there is ARCH effect and the estimation method that accounts for ARCH effect would be preferable to the one that does not account for it. Our results show that ARCH effects are a common phenomenon for stock returns, especially in the full sample and scanty before and after the declaration of coronavirus as a pandemic. Concerning the Ljung-Box Q-statistics, it is equally evident that stock prices are serially correlated. The final results presented here in this section are the graphical illustration of the relationship or co-movement between cryptocurrencies and stock prices. As shown in Figure 1, there is co-movement between cryptocurrencies and stock prices, which is more pronounced after the declaration of COVID-19, a pandemic.

Figure 1. Bi-variate plot of cryptocurrencies and stock prices



3. Empirical Results

Here, we present the empirical results of the observed nexus between the returns of selected cryptocurrencies (Bitcoin, Bitcoin Cash, Ethereum, Tether and Ripple) and three major African stocks. This is in a bid to ascertain whether the selected cryptocurrencies serve as hedges or safe-havens or diversifiers for the stock returns being considered. We follow Baur and Lucey (2010), Baur and McDermott (2010) and Baur et al. (2017) definitions to ascertain if a given cryptocurrency is to be considered as a hedge, a safe-haven or a diversifier for stocks. Here, cryptocurrency would be considered a hedge for stocks if the latter weakly or strongly negatively influences the former during the period of normal economic conditions. In periods of economic downturn or financial crisis or pandemics, a weak or strong negative relationship between a given cryptocurrency and stocks implies that cryptocurrency is a safe-haven. In another stance, a given cryptocurrency would be considered a diversifier for stocks if the observed nexus is weakly or strongly positive, especially during periods of normal economic conditions.

We examine the cryptocurrency-stocks nexus under three different sample intervals; full sample (1st of January, 2019 to 24th of July, 2020), pre-COVID-19 (1st January 2019 to 11th March, 2020) and post-COVID-19 (11th of March, 2020 to 24th of July, 2020) declaration as a pandemic. We referred to the first two sample intervals as periods of normal economic conditions, while the last sample interval is assumed to be the period of economic downturn. The stocks, comprising separately of the top-performing firms in Egypt (EGX70), Nigeria (NSE30) and South Africa (SAT40), are selected given that these countries represent the powerhouse of the African economy, as well as its financial hub. Following Westerlund and Narayan (2012, 2015), we employ a distributed lag model that accounts for inherent salient statistical features such as persistence, endogeneity and conditional heteroscedasticity. Our choice model is also compared to a benchmark historical average model, as a way to ascertain its predictive performance. We, therefore, present the in-sample predictability and the out-of-sample forecast performance of our choice model in Tables 2 and Table 3, respectively.

3.1. In-Sample Predictability

The in-sample predictability of stocks for cryptocurrency returns reported in Table 2 is presented under three different panels, for each cryptocurrency and African stock. The first panel contains predictability results when the full sample is considered; the second panel contains predictability results when the period considered is the pre-COVID-19 declaration as a pandemic; while the last panel contains predictability results when the period considered is the post-COVID-19 declaration as a pandemic. The reported predictability values are the joint coefficients and associated standard errors of the five lags of the returns of the corresponding stock, and their joint significance is determined by the conventional Wald test.

Table 2. In-Sample predictability results

	Bitcoin	Bitcoin Cash	Ethereum	Tether	Ripple
Full Sample Data					
EGX70	0.4467***[0.1040]	0.7799***[0.0378]	0.6303***[0.0371]	0.0049**[0.0023]	0.9178***[0.0630]
NSE30	0.7172***[0.0694]	-0.0961[0.1200]	-0.2812***[0.0818]	-0.0204***[0.0024]	0.9025***[0.0642]
SAT40	1.0655***[0.0615]	0.5639***[0.0541]	0.7873***[0.1308]	-0.0109***[0.0021]	1.2778***[0.0761]
Pre-COVID-19 Declaration as a Pandemic					
EGX70	1.2102***[0.0500]	1.0358***[0.0862]	0.9790***[0.0525]	-1.97E-05[0.0046]	1.1068***[0.0589]
NSE30	-0.2416***[0.0410]	-0.2447*[0.1416]	0.1478**[0.0579]	-0.0080[0.0063]	0.3633***[0.0280]
SAT40	0.3178***[0.0469]	0.5878***[0.1401]	0.2642**[0.1137]	0.0164***[0.0037]	-0.0795[0.0853]
Post-COVID-19 Declaration as a Pandemic					
EGX70	-0.6391***[0.0409]	-0.6162***[0.1005]	-0.5056***[0.1718]	0.0088***[0.0030]	-0.2280**[0.1007]
NSE30	-0.6063**[0.2287]	-1.4496***[0.0700]	-1.1825***[0.2975]	0.0055***[0.0013]	-1.3187***[0.1515]
SAT40	-0.8837***[0.0951]	-1.4907***[0.3074]	-0.6860**[0.3361]	-0.0017[0.0020]	-0.1689[0.3149]

Note: Figures in square brackets are the standard error of the estimates, while ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

For the full sample interval, we find positive and statistically significant coefficients in all the Bitcoin-stocks and Ripple-stocks nexuses. In the cases of the other cryptocurrencies, we find positively significant coefficients associated with EGX70 (for Bitcoin Cash, Ethereum and Tether) and SAT40 (for Bitcoin cash and Ethereum); while significantly negative coefficients are found in the case of NSE30 (for Ethereum and Tether) and SAT40 (for Tether). The Bitcoin cash-NSE30 nexus is negative but not statistically significant. From the foregoing, we find evidence that, under periods of normal economic conditions, cryptocurrencies could serve as diversifiers for EGX70 (all five cryptocurrencies), NSE30 (Bitcoin and Ripple) and SAT40 (all cryptocurrencies except Tether). On the other hand, Ethereum and Tether seem to be hedging options for NSE30, while Tether could serve as a hedge for SAT40. In other words, while all five cryptocurrencies serve as good diversifiers in the case of Egypt, only four and two cryptocurrencies are found to be good diversifiers in the cases of South Africa (Bitcoin, Bitcoin Cash, Ethereum and Ripple) and Nigeria (Bitcoin and Ripple), respectively.

The pre-declaration of COVID-19 as a pandemic sample result is slightly different from the full sample, as we find some consistency in the stance of cryptocurrencies mostly serving as diversifiers in Egypt (in all except Tether) and South Africa (in all except Ripple), and as hedges in Nigeria (Bitcoin and Bitcoin Cash). The observed disparity could have resulted from the fact that the post-COVID-19 declaration sample period is also contained in the full sample. Interestingly, we observed that the positive coefficients are all statistically significant, while the negative coefficients are mostly not statistically significant. Imperatively, we could assert that the considered cryptocurrencies are diversifiers for African stocks, especially concerning Egypt and South Africa. On the other hand, the post-COVID-19 declaration as pandemic evidence shows that most of the cryptocurrencies act as safe-havens for stock market returns in Egypt (except Tether), South Africa and Nigeria (except Tether). For Egypt stocks, there exists a relatively strong safe-haven property in Bitcoin, Bitcoin Cash and Ethereum, and a weak safe-haven property in Ripple. Similarly, Bitcoin, Bitcoin Cash, Ethereum and Ripple have strong haven properties in the case of Nigerian stocks, while Tether is diversified. In South Africa, all cryptocurrencies act as safe-havens for stock returns, though the degrees of their safe-haven properties vary. Bitcoin, Bitcoin Cash and Ethereum act as strong safe-havens for SAT40, while the estimated coefficients under Tether and Ripple are not statistically significant.

Table 3. Out-of-sample forecast performance using Clark and West statistics

Cryptocurrency Stock market	Full Sample Data		Pre-COVID-19 Declaration as a Pandemic		Post-COVID-19 Declaration as a Pandemic	
	h = 5	h = 10	h = 5	h = 10	h = 5	h = 10
Bitcoin						
EGX70	1.939* [1.056]	1.923* [1.043]	0.490 [0.472]	0.449 [0.471]	5.847*** [1.958]	5.738*** [1.858]
NSE30	1.255 [1.491]	1.235 [1.473]	0.437* [0.256]	0.274 [0.299]	2.939** [1.274]	2.857** [1.207]
SAT40	3.246*** [1.056]	3.213*** [1.043]	0.356 [0.239]	0.246 [0.266]	9.876** [4.539]	9.485** [4.298]
Bitcoin Cash						
EGX70	1.769 [1.258]	1.780 [1.242]	2.190** [0.955]	2.145** [0.956]	1.273 [1.167]	1.344 [1.108]
NSE30	1.607* [0.882]	1.587* [0.872]	2.040** [1.015]	1.599 [1.089]	4.693** [2.157]	4.530** [2.044]
SAT40	4.837** [2.202]	4.775** [2.175]	0.824 [0.771]	1.422 [1.039]	10.739** [5.208]	10.282** [4.932]
Ethereum						
EGX70	2.250* [1.261]	2.302* [1.246]	1.369* [0.784]	1.234 [0.813]	5.959* [3.134]	6.124** [2.996]
NSE30	-0.123 [1.137]	-0.105 [1.123]	0.437 [0.373]	0.246 [0.430]	6.100* [3.309]	5.924* [3.136]
SAT40	5.974*** [2.192]	5.914*** [2.165]	0.326 [0.407]	0.340 [0.402]	10.765** [4.427]	10.718** [4.191]
Tether						
EGX70	0.000 [0.000]	0.000 [0.000]	0.001 [0.0010]	0.001 [0.0010]	0.001* [0.0004]	0.001* [0.0004]
NSE30	0.001 [0.001]	0.001 [0.001]	0.003** [0.0014]	0.003** [0.0014]	0.001** [0.0003]	0.001** [0.0003]
SAT40	0.002 [0.001]	0.002 [0.001]	0.0004 [0.0010]	0.0003 [0.0010]	0.003** [0.0014]	0.003** [0.001]
Ripple						
EGX70	1.591 [1.220]	1.576 [1.205]	0.633 [0.444]	0.681 [0.438]	1.298* [0.6848]	1.348** [0.653]
NSE30	0.969 [1.147]	0.955 [1.133]	0.111 [0.325]	-0.033 [0.359]	3.719*** [1.3082]	3.575*** [1.245]
SAT40	3.281*** [1.163]	3.270*** [1.148]	1.371*** [0.471]	1.563*** [0.511]	6.926** [2.9671]	6.763** [2.811]

Note: Figures in square brackets are the standard error of the estimates, while ***, ** and * indicate statistical significance at 1%, 5%, 10% respectively. The Clark-West statistics test the hypothesis no significant difference between the benchmark model and our predictive model, with positive and significant values indicating preference in favour of the latter.

Following the in-sample predictability results, we further evaluate our predictive model's out-of-sample performance in comparison with a benchmark historical average model. This is in a bid to ascertain the capability of our predictive model to mirror the variation in cryptocurrency returns over the benchmark. It is also to serve as a diagnostic check, as preference in favour of our predictive model would imply the relevance of stocks as a good predictor for cryptocurrency returns and consequently, a confirmation of a nexus between both to warrant the adoption of one as a hedge, safe-haven or diversifier for the other. We consider a pairwise model performance evaluation statistic Clark and West (2007) that tests the hypothesis of no significant difference between the benchmark model and our predictive model; with positive and significant values indicating preference in favour of the latter. We consider for robustness, two out-of-sample forecast horizons (h = 5 and h = 10).

In the full sample, we find our predictive model to significantly outperform the benchmark across the cryptocurrencies (except for Tether) and forecast horizons in most cases when the EGX70 and SAT40 were considered as predictors and just a few in the case of NSE30. The stance is also different for the pre-and post-declaration periods, with more consistency observed in the latter; regardless of the cryptocurrency or stocks or forecast horizons being considered. In other words, the performance stance may be sensitive to sample periods, but under the post-declaration period, the out-performance is not sensitive to the cryptocurrency or stock data employed. Imperative, stocks provide some valuable information for the prediction of cryptocurrency returns; hence, the existence of a nexus gives room for the latter as a hedge or safe-haven or a diversifier for the former.

3.2. Implication of Findings

The implications of our findings are very straightforward. In the full sample and pre-declaration periods, investors in Egypt and South Africa would prefer a mixture of investments in different assets, to lower the risk of putting their money in one investment basket. In other words, the purpose is to smoothen unsystematic risks in an asset or a portfolio, with the belief that some investments would perform better, thereby neutralising the effects of investments that perform poorly. In the case of Nigeria, investors may just use cryptocurrencies to offset the unfavourable movement in the prices of stocks. During the period of the COVID-19 pandemic, investors in Egypt, South Arica and Nigeria would use cryptocurrencies as a safe-haven. In other words, investors would prefer to invest in cryptocurrencies assumed to be resilient to the COVID-19 pandemic rather than investing in stocks in which prices suffer great deterioration.

A couple of studies have found that cryptocurrencies could serve as a diversifier, a hedge and a safe-haven for stocks. This, however, varies from the stock market to the stock market, or from one country (a group of countries) to another country (a group of countries). Stensås et al. (2019) finds that Bitcoin serves as a hedge for investors in developing countries, whereas it acts as a diversifier in developed countries. In this current pandemic, Conlon et al (2020) queried whether cryptocurrencies could act as a safe-haven for the equity market in the US. Their findings reveal that among the cryptocurrencies used (Bitcoin, Ethereum and Tether), only Tether acts as a safe-haven. Omane-Adjepong and Alagidede (2020) examined whether some precious metals, including only Bitcoin, could act as a safe-haven in Africa's emerging stock market. They conclude that the precious metals considered and Bitcoin do not serve as safe-havens for investors in Africa's stock market. It is important to say that the question of whether cryptocurrencies or precious metals would act as a diversifier or a hedge or a safe-haven for investors depends on data classification, transformation and the estimation methods deployed by the researchers.

Conclusion

We set out to assess the hedge or safe-haven property of five cryptocurrencies (Bitcoin, Bitcoin Cash, Ethereum, Ripple and Tether) for stocks of three African countries (Egypt, Nigeria and South Africa) that were worst hit by the COVID-19 pandemic. Two main concerns/questions are addressed in this study: First, do African stocks have the predictive capacity for cryptocurrency returns? Second, can cryptocurrencies be considered safe-havens or hedges or diversifiers for African stocks? In a bid to provide answers to the raised questions, we adopted a distributed lag model; wherein we explicitly accounted for salient statistical features of the data, in the similitude of Westerlund and Narayan (2012, 2015) approach and hinging on the merits and efficient management of parameter proliferation and estimation biases. The data sample spans January 2019 and July 2020, covering periods before and during (with a focus on the first wave) the pandemic. We examined the cryptocurrency-stock returns nexus under three sample categorizations: Full, Pre- and Post- declaration of COVID-19 as a pandemic, while ascertaining the in-sample predictability as well as the out-of-sample forecast evaluation. For the latter, our predictive model is compared with a benchmark historical average model using the Clark and West statistics. Two different forecast horizons are considered, for robustness.

On the in-sample predictability, we find the predictability of cryptocurrencies using African stocks as predictors in our predictive distributed lag model. The selected cryptocurrencies were found to be majorly diversifiers (safe-haven) in periods of normalcy (crisis/pandemic). Our predictive distributed lag model consistently yielded better out-of-sample forecasts than the benchmark historical average model (especially in the cases of the full and post-declaration sample data). The forecast out-performances are upheld regardless of the forecast horizon being considered. Overall, our results are sensitive to cryptocurrency-stocks nexus and sample periods but not out-of-sample forecast horizons.

References

[1] Baker, S., Bloom, N., Davis, S. J., Kost, K., Sammon, M., and Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *Covid Economics: Vetted and Real-Time Papers*, 1(3). https://doi.org/10.1093/rapstu/raaa008

[2] Bannigidadmath, D., and Narayan, P. (2015). Stock return predictability and determinants of predictability and profits. *Emerg. Market. Rev*. 26, 153–173. https://doi.org/10.1016/j.ememar.2015.12.003

[3] Baur, D. G., and Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217-229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

[4] Baur, D. G., and McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance,* 34(8), 1886-1898. https://doi.org/10.1016/j.jbankfin.2009.12.008

[5] Bouri, E., Jalkh, N., Molnár, P., and Roubaud, D. (2017a). Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Applied Economics*, 49(50), 5063-5073. https://doi.org/10.1080/00036846.2017.1299102

[6] Bouri, E., Molnár, P., Azzi, G., Roubaud, D., and Hagfors, L. I. (2017b). 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

[7] Bouri, E., Shahzad, S. J. H., and Roubaud, D. (2020). Cryptocurrencies as hedges and safe havens for US equity sectors. *The Quarterly Review of Economics and Finance*, 75, 294-307. https://doi.org/10.1016/j.qref.2019.05.001

[8] Clark, T.E. and West, K.D. (2007). Approximately normal tests for equal predictive accuracy in nested models. *Journal of Econometrics*, 138, 291–311. https://doi.org/10.1016/j.jeconom.2006.05.023

[9] Conlon, T., Corbet, S., and 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*, 101248. https://doi.org/10.1016/j.ribaf.2020.101248

[10] Devpura, N., Narayan, P. K. and Sharma, S. S. (2018). Is stock return predictability time varying? *Journal of Int Finan Markets, Instutions and Money* 52, 152–172. https://doi.org/10.1016/j.intfin.2017.06.001

[11] Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, 16, 139-144. https://doi.org/10.1016/j.frl.2015.10.025

[12] ECDC (2020). COVID-19 situation updates worldwide, as of 18th of July, 2020. https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases

[13] Goodell, J. W., and Goutte, S. (2021). Diversifying with cryptocurrencies during COVID-19. International Review of Financial Analysis, 76, 101781. https://doi.org/10.1016/j.irfa.2021.101781

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

[15] I.L.O. Monitor (2020). Brief: Impact of lockdown measures on the informal economy. https://www.ilo.org/global/topics/employment-promotion/informal economy/publications/WCMS_743523/lang--en/index.htm

[16] I.L.O. Monitor (2020). COVID-19 and the world of work. Monitor 27th of May, 2020. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/documents/briefingnote/wcms_749399.pdf

[17] I.L.O. Monitor (2020). COVID-19 and the world of work. 2nd Edition Updated estimates and analysis https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/documents/briefingnote/wcms_740877.pdf

[18] Ji, Q., Bouri, E., Lau, C. K. M., and Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *Int Rev of Financ Analysis*, 63, 257-272. https://doi.org/10.1016/ j.irfa.2018.12.002

[19] Narayan, P. K. and Gupta, R. (2015). Has oil price predicted stock returns for over a century? *Energy Economics,* 48, 18–23. https://doi.org/10.1016/j.eneco.2014.11.018

[20] Narayan, P., Phan, D., Sharma, S. (2018). Does Islamic stock sensitivity to oil prices have economic significance? *Pac. Basin Finance J.*, 53, 497–512. https://doi.org/10.1016/j.pacfin.2018.04.003

[21] Narayan, P.K., Phan, D.H.B., Sharma, S.S. and Westerlund, J. (2016). Are Islamic stock returns predictable? A global perspective. *Pac. Basin Finance J.,* 40(A), 210–223. https://doi.org/10.1016/j.pacfin.2016.08.008

[22] Okorie, D. I. (2020). Could stock hedge Bitcoin risk(s) and vice versa. *Digital Finance*, 2(1), 117-136. https://link.springer.com/article/10.1007/s42521-019-000110#:~:text=The%20Exogenous%20Dynamic%20Conditional%20Correlation,stocks'%20risks%20and%20vice%20versa

[23] Okorie, D. I., and Lin, B. (2020). Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. *Energy Economics*, 87, 104703. https://doi.org/10.1016/j.eneco.2020.104703

[24] Omane-Adjepong, M., and Alagidede, I. (2021). Exploration of safe havens for Africa's stock markets: A test case under COVID-19 crisis. *Finance Research Letters*, 38, 101877. https://doi.org/10.1016/j.frl.2020.101877

[25] Pal, D., and 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

[26] Phan, D.H.B., Sharma, S.S., and Narayan, P.K. (2015). Stock return forecasting: Some new evidence, *Int. Rev. Financ. Anal.,* 40, 38–51. https://doi.org/10.1016/j.irfa.2015.05.002

[27] Salisu, A. A. and Oloko, T. F. (2015). Modelling oil price-US stock nexus: A VARMA-BEKK-AGARCH approach. *Energy Economics*, 50, 1-12. https://doi.org/10.1016/j.eneco.2015.03.031

[28] Salisu, A. A., Isah, K.O. Akanni, L.O. (2019a). Improving the predictability of stock returns with Bitcoin prices. *North American Journal of Economics and Finance,* 48, 857-867. https://doi.org/10.1016/j.najef.2018. 08.010

[29] Salisu, A. A., Swaray, R., and Oloko, T. F. (2019b). Improving the predictability of the oil–US stock nexus: The role of macroeconomic variables. *Economic Modelling,* 76, 153-171. https://doi.org/10.1016/j.econmod.2018.07.029

[30] Salisu, A. A., Raheem, I. D. and Ndako, U. D. (2019c). A sectoral analysis of asymmetric nexus between oil price and stock returns. *International Review of Economics and Finance,* 61, 241–259. https://doi.org/10.1016/j.iref.2019.02.005

[31] Salisu, A. A., Adekunle, W., Alimi, W. A. and Zachariach, E. (2019d). Predicting exchange rate with commodity prices: New evidence from Westerlund and Narayan (2015) estimator with structural breaks and asymmetries. *Resources Policy*, 62, 33–56. https://doi.org/10.1016/j.resourpol.2019.03.006

[32] Salisu, A. A., Isah, K. O. and Raheem, I. D. (2019e). Testing the predictability of commodity prices in stock returns of G7 countries: Evidence from a new approach. *Resources Policy*, 64, 101520. https://doi.org/10.1016/j.resourpol.2019.101520

[33] Salisu, A. A., Ogbonna, A. E. and Omosebi, P. A. (2018). Does the choice of estimator matter for forecasting? A revisit - Centre for Econometric and Allied Research, *University of Ibadan Working Papers Series* (CWPS) 0053. https://ideas.repec.org/p/cui/wpaper/0053.html

[34] Salisu, A. A. and Vo, V. X. (2020). Predicting stock returns in the presence of COVID-19 pandemic: The role of health news. *Int Rev of Fin Analysis*, 71, 101546 https://doi.org/10.1016/j.irfa. 2020.101546

[35] Salisu, A. A., Ogbonna, A. E., and Adewuyi, A. (2020a). Google trends and the predictability of precious metals. *Resources Policy*, 65, 101542. https://doi.org/10.1016/j.resourpol.2019.101542

[36] Salisu, A. A., Ogbonna, A. E. and Adediran, I. (2020b) Stock-induced Google trends and the predictability of sectoral stock returns. *Journal of Forecasting,* 1–19. https://doi.org/10.1002/for.2722

[37] Schmidhuber, J., Pound, J., and Qiao, B. (2020). COVID-19: Channels of Transmission to Food and Agriculture. Roma, FAO. https://doi.org/10.4060/ca8430en

[38] Selmi, R., Mensi, W., Hammoudeh, S., and Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics*, 74, 787-801. https://doi.org/10.1016/j.eneco.2018.07.007

[39] Shahzad, S. J. H., Bouri, E., Roubaud, D., and Kristoufek, L. (2020). Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling,* 87, 212-224. https://doi.org/10.1016/j.econmod.2019.07.023

[40] 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

[41] Stensås, A., Nygaard, M. F., Kyaw, K., Treepongkaruna, S. (2019). Can Bitcoin be a diversifier, hedge or safe haven tool? *Cogent Economics & Finance,* 7(1), 1593072. https://doi.org/10.1080/23322039. 2019.1593072

[42] UNCTAD (2020). Global trade impact of Coronavirus (COVID-19) epidemic. Trade and Development Update, March. https://unctad.org/system/files/official-document/ditcinf2020d1.pdf

[43] UNDP (2020). Brief#2: Putting the UN framework for socio-economic response to Covid-19 into action: insights. Brief prepared by the United Nations development programme, June. https://reliefweb.int/report/world/brief-2-putting-un-framework-socio-economic-response-covid-19-action-insights-june2020#:~:text=Over%20the%20next%2012%20to,across%20five%20pillars%20of%20action

[44] Urquhart, A., and 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

[45] Wang, G., Tang, Y., Xie, C., and Chen, S. (2019). Is bitcoin a safe haven or a hedging asset? Evidence from China. *J Manag Sci and Engineering*, 4(3), 173-188. https://doi.org/10.1016/ j.jmse.2019.09.001

[46] Wang, P., Zhang, W., Li, X., and Shen, D. (2019). Is cryptocurrency a hedge or a safe haven for international indices? A comprehensive and dynamic perspective. *Finance Research Letters,* 31, 1-18. https://doi.org/10.1016/j.frl.2019.04.031

[47] Westerlund, J., and Narayan, P. (2015). Testing for predictability in conditionally heteroskedastic stock returns. *Journal of Financial Econometrics*, 13(2), 342-375. https://doi.org/10.1093/jjfinec/nbu001

[48] Westerlund, J., and Narayan, P. K. (2012). Does the choice of estimator matter when forecasting returns? *Journal of Banking & Finance*, 36(9), 2632-2640. https://doi.org/10.1016/j.jbankfin.2012.06.005

[49] World Bank (2020). Commodity markets outlook: Implications of COVID-19 for commodities. A World Bank Report April. https://openknowledge.worldbank.org/bitstream/handle/10986/33624/CMO-April-2020.pdf

[50] World Economic Forum (2020). Mad March: how the stock market is being hit by COVID-19. https://www.weforum.org/agenda/2020/03/stock-market-volatility-coronavirus/

[51] World Health Organisation (2020). Coronavirus disease (COVID-19 advice for the public. Update 8th of December, 2020. https://www.who.int/publications/m/item/weekly-epidemiological-update-8-december-2020

[52] Wu, S., Tong, M., Yang, Z., and Derbali, A. (2019). Does gold or bitcoin hedge economic policy uncertainty? *Finance Research Letters, 31*, 171-178. https://doi.org/10.1016/j.frl.2019.04.001

[53] Yaya, O. S. and Ogbonna, A. E. (2019). Do we Experience Day-of-the-week Effects in Returns and Volatility of Cryptocurrency? *MPRA Paper 91429*. https://mpra.ub.uni-muenchen.de/91429/1/MPRA_paper_91429.pdf

[54] Zhang, J., Lai, Y. and Lin, J. (2017). The day-of-the-Week effects of stock markets in different countries. *Finance Research Letters*, 20, 47-62. https://doi.org/10.1016/j.frl.2016.09.006

Cite this article

Raifu, I. A. and Ogbonna, A. E. (2022). Safe-Haven Effectiveness of Cryptocurrency: Evidence from Stock Markets of COVID-19 Worst-Hit African Countries. *Journal of Research, Innovation and Technologies*, Volume I, 2(2), 107 - 120. https://doi.org/10.57017/jorit.v1.2(2).02

Article's history:

Received 21st of September, 2022; Revised 19th of October, 2022;
Accepted for publication 20th of November, 2022;
Published 30th of December, 2022.

APPENDIX

Table A1. Table of literature review

S/N	Authors	Topic	Data	Methodology	Findings
1	Bouri et al. (2020)	Cryptocurrencies as hedges and safe-havens for US equity sectors	▪ Bitcoin, Ethereum, Ripple, Litecoin, Stellar. Dash, Nem and Monero, S&P 500 and its 10 equity sectors: financials, information technology, telecom ser-vices, industrials, basic materials, consumer discretionary, energy, consumer staples, utilities, and health care.	Cross-quantilogram approach of Han et al. (2016)	▪ Bitcoin, Ripple and Stellar are safe-havens for all US equity indices, while Litecoin and Monero are safe-havens for the aggerate US equity index and selected sectors. ▪ Ethereum, Dash and Nem are hedges for few equity sectors
2	Okorie and Lin (2020)	Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy	▪ Top 5 Cryptocurrencies: Bitcoin, Ethereum, XRP, Bitcoin Cash; ▪ Litecoin, ▪ Bottom 5 Cryptocurrencies: Solve, Elastos, Redd Coin, Bit Capital Vendor and Stratis.	VAR – MGAECH and GJR – BEKK model techniques	▪ The hedging capacities of crude oil assets on Ethereum are temporary. ▪ The crude oil asset hedging potentials for Solve, Elastos and Bit Capital Vendor are very long.
3	Bouri et al. (2018)	On the hedge and safe-haven properties of Bitcoin: Is it really more than a diversifier?	▪ Cryptocurrency: Bitcoin; ▪ Stock indices: bonds, oil, gold, the general commodity index; ▪ US dollar index.	DCC-GARCH Model	▪ Bitcoin is a poor hedge and is suitable for diversification purposes only. It can also be used as a safe-haven for other commodities.
4	Goodell and Goutte (2021)	Diversifying with cryptocurrencies during COVID-19	▪ Cryptocurrencies: Bitcoin, Ethereum, Tether, XRP, and EOS; ▪ Equity: MSCI World, FTSE China, TA 35 Israel, NIFTY India, Jakarta Philippine, KOSPI Korea, FTSE Italy, IBEX 35 Spain, CAC 40 France, DAX All, Bovespan Brazil, SP500 US, EUROSTOXX and FTSE RU.	Principal Components and Neural Network	▪ Bitcoin co-moves with MSCI World with positive connection.
5	Shahzad et al. (2019)	Safe-haven, hedge and diversification for G7 stock markets: Gold versus Bitcoin	▪ Bitcoin and gold; ▪ G7 stock markets.	AGDCC-GARCH	▪ Gold is a safe-haven and hedge for several G7 stock indices. ▪ Bitcoin is a safe-haven and hedge in Canada.
6	Okorie (2020)	Could stock hedge Bitcoin risk(s) and vice versa?	▪ Bitcoin and S&P500.	Exogenous DCC and BEKK methods	▪ The S&P500 hedges Bitcoin risk; ▪ Bitcoin also hedges S&P500 stocks' risks.
7	Selmi et al. (2018)	Is Bitcoin a hedge, a safe-haven or a diversifier for oil price movements? A comparison with gold	▪ Bitcoin and Gold; ▪ Oil prices.	Quantile-on-quantile regression approach	▪ Bitcoin and gold serve as hedges, safe-havens and diversifier against extreme oil price movements.
8	Urquhart and Zhang (2019)	Is Bitcoin a hedge or safe-haven for currencies? An intraday analysis	▪ Bitcoin; ▪ Currencies: Swiss Franc (CH)F, Euro (EUR), Pound Sterling (GBP), Australian Dollar (AUD), Canadian Dollar (CAD) and Japanese Yen (JPY).	Asymmetric DCC	▪ Bitcoin serves intraday hedge for CHF, EUR and GBP. It also acts as a diversifier for the AUD, CAD and JPY.
9	Wang et al. (2019)	Is cryptocurrency a hedge or a safe-haven for international indices? A comprehensive and dynamic perspective	▪ 973 cryptocurrencies; ▪ 30 international indices.	DCC-GARCH model	▪ Cryptocurrency serves as a safe-haven and not hedge for most of the international indices.
10	Wu et al. (2019)	Does gold or Bitcoin hedge economic policy uncertainty?	▪ Gold, bitcoin; ▪ Economic PoliciEPU.	GARCH model and quantile regression with dummy variab.	▪ Both gold and bitcoin serve not as a safe-haven or a hedge for economic policy uncertainty.