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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 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 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, 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

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1. 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 Organizations (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 organizations and corporations put several measures in place, such as washing and sanitization of hands, wearing of mask in public places, physical and social distancing, and total lockdown of the economies across the world (World Health Organization, 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 the 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 recorded 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 COVID-19 pandemic has generated unprecedented volatility across major financial markets in the world and has resulted in great losses to many investors (Baker, 2020). 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-earning money. Of all financial market assets, cryptocurrency appears to be resilient to the damaging effect of coronavirus pandemic. Available statistics on the most traded cryptocurrency, Bitcoin, shows that although the price of Bitcoin initially declined just like any other commodity prices, however, it quickly rebounds to its pre-COVID-19 pandemic historical prices. More specifically, the World Health Organization declaration of COVID-19 as a pandemic in 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%, 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 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 the 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. 2017 a, b; 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. 2019 a, b). 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

aggregate US equity index and selected sectors while Ethereum, Dash and Nem are hedges for 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 a 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 capitalization 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).¹ 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)).² 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-earning money as the prices of their stocks shrunk drastically. For instance, in Nigeria, the largest economy in Africa, the market capitalization 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, between March 5, 2020, when the first case of COVID-19 was reported in South Africa and March 23th, 2020, the prices of the top 40 traded stocks declined by 17.06%. In Egypt, the first case of Coronavirus was confirmed on February 14th, 2020. This announcement only had a marginal effect on the stock prices as it declined by 1.00% in the following trading day (February 16th, 2020). However, as from the day the WHO declared the COVID-19 a pandemic (March 11th, 2020), the stock price nosedived significant, declining by 10.04% between March 11th, 2020 and April 5th, 2020.

¹ <https://coinmarketcap.com/currencies/bitcoin-cash/>

² <https://www.ecdc.europa.eu/en/geographical-distribution-2019-ncov-cases/14/08/2020>

Following this introduction, the rest of the study is structured as follows. Method is presented in section 2. Section 3 focuses on data sources and descriptions. The empirical results are presented in section 4 while section 5 concludes.

2. 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, Sharma, 2018; Salisu et al., 2019 a,b,c,d & e; Salisu et al., 2020a & b; among others). The choice of model is informed by 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,b,c,d & e; Salisu et al., 2020a & b; among others). 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 ($\hat{\sigma}_\varepsilon$) from an arch model. Failure to adequately account for these salient features are 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),

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

where cryptocurrency returns at a given time t is defined as $r_t = \ln(P_t/P_{t-1})$ and P_t denotes the price of cryptocurrency; α is the model intercept; stk_{t-i} is the i^{th} lag of stock returns (stk_t), $i=1,2,\dots,k$ and $k=5$; β_i 's are slope coefficients corresponding to the $i=1,2,\dots,k$ lags of the predictor variable; $(stk_t - stk_{t-1})$ and its associated slope parameter (γ) are incorporated to correct for endogeneity bias and persistence 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. 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 considered to determine if cryptocurrency offer 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 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

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

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 $MSE_1 - (MSE_2 - adj.)$, 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 significance or non-significance of the difference in the forecast errors of the restricted and unrestricted models.

Positive and significant t-statistic would imply preference of the unrestricted model over the restricted model in the prediction of cryptocurrency returns.

3. 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 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 the investing.com and they covered the period from January 2019 to July 2020. The cryptocurrencies are selected based on their market capitalization. The data³ was partitioned into three, namely: the full period, the pre-declaration of COVID-19 pandemic as a pandemic and post-declaration. The descriptive statistic 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 declines in prices in Nigeria. Despite the negative returns of the stock price in Nigeria, the standard deviation of the asset prices (cryptocurrencies and stocks show that stock returns are more volatile in South Africa and Egypt than Nigeria as the returns of stock prices deviate more in the two countries. The returns of the 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 at this period. The only cryptocurrency that experienced negative returns is Ripple. In post-declaration of COVID-19 as a pandemic, SAT 40 and EGX70 returns on average are positive, while the returns of NSE30 is, on the average, negative. In the case of cryptocurrencies after the declaration of COVID-19 as 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

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

are more volatile post-COVID-19 declaration than pre-declaration as shown by the values of standard deviation. Similarly, cryptocurrencies are more volatile than the 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 too peaked or leptokurtic. This is even corroborated by the results of Jarque-Bera which show that distribution is not normally distributed across the sample because Jarque-Bera statistics are statistically significant throughout the sample classifications.

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 is 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 price which is more pronounced after the declaration of COVID-19, a pandemic.

Table 1: Summary Statistics of the Cryptocurrencies and Stock Returns

Statistics	Cryptocurrency Returns					Stock Returns		
	Bitcoin	Bitcoin Cash	Ethereum	Ripple	Tether	EGX70	NSE30	SAT40
	<i>Full Sample</i>							
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***
Observations	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***
	<i>Pre-COVID-19 Declaration as a Pandemic</i>							
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
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***
	<i>Post-COVID-19 Declaration as a Pandemic</i>							
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: Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

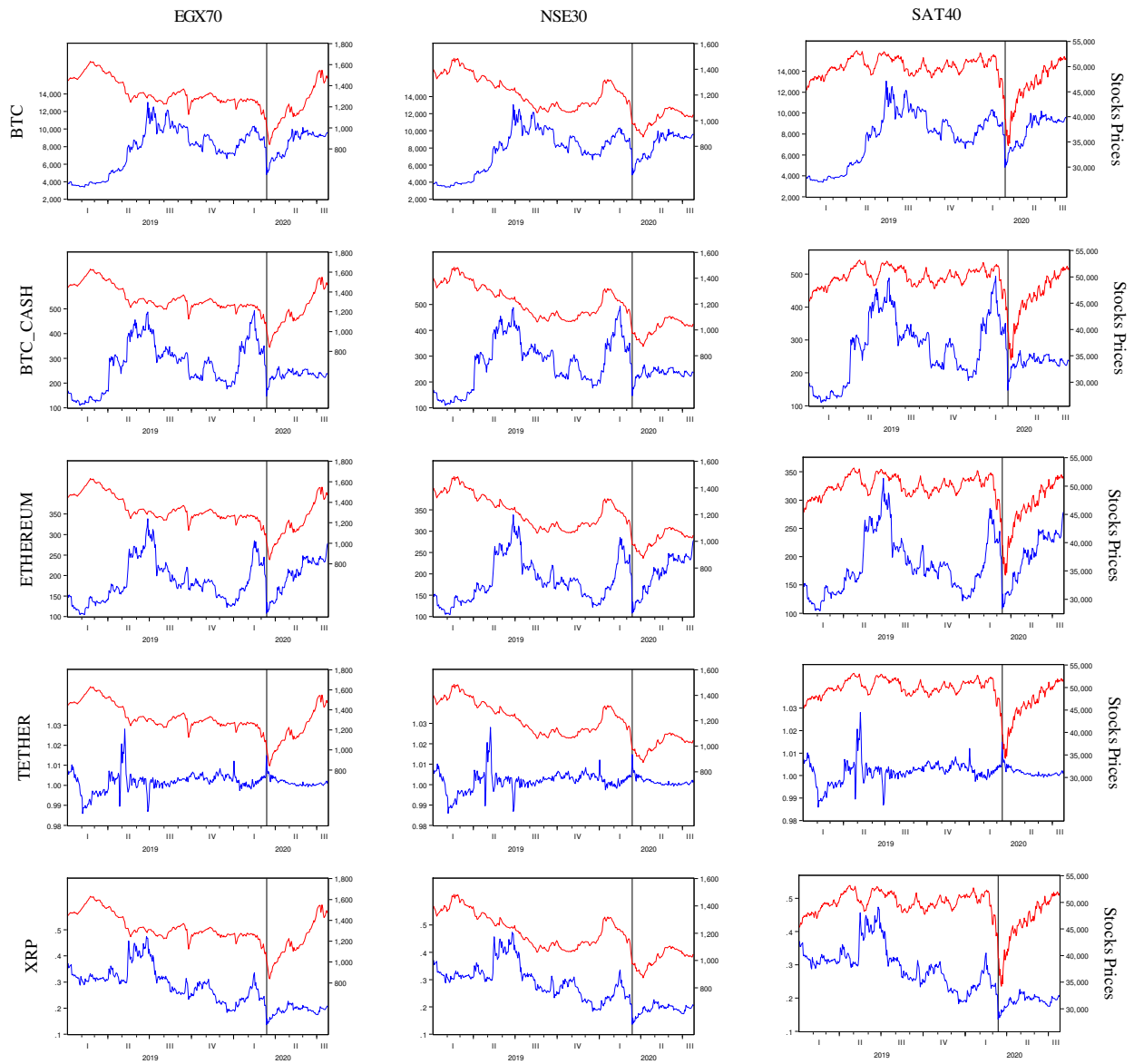


Figure 1: Bi-variate Plot of Cryptocurrencies and Stock Prices

4. 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 condition. In periods of economic down or financial crisis or pandemic, 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 January 2019 to 24th July 2020), pre-COVID-19 (1st January 2019 to 11th March 2020) and post-COVID-19 (11th March 2020 to 24th 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 3, respectively.

4.1 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 stocks. 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
<i>Full Sample Data</i>					
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]
<i>Pre-COVID-19 Declaration as a Pandemic</i>					
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]
<i>Post-COVID-19 Declaration as a Pandemic</i>					
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 coefficient 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 results are 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 property in the case of Nigerian stocks, while Tether is a diversifier. 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

	<i>Full Sample Data</i>		<i>Pre-COVID-19 Declaration as a Pandemic</i>		<i>Post-COVID-19 Declaration as a Pandemic</i>	
	<i>h = 5</i>	<i>h = 10</i>	<i>h = 5</i>	<i>h = 10</i>	<i>h = 5</i>	<i>h = 10</i>
<i>Bitcoin</i>						
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]
<i>Bitcoin Cash</i>						
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]
<i>Ethereum</i>						
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]
<i>Tether</i>						
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]
<i>Ripple</i>						
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% and 10% respectively. The Clark and West statistics tests 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 from 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 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 stocks data employed. Imperative, stocks provide some valuable information for the prediction of cryptocurrency returns; hence, the existence of a nexus that gives room for the latter as a hedge or safe-haven or a diversifier for the former.

4.2 Implication of Findings

The implications of our findings are very straight forward. In the full sample and pre-declaration periods, investors in Egypt and South Africa would prefer a mixture of investment 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 COVID-19 pandemic, investors in Egypt,

South Africa and Nigeria would use cryptocurrencies as a safe-haven. In other words, investors would prefer to invest in cryptocurrencies assumed to be resilient to COVID-19 pandemic rather than investing in stocks, which prices suffer great deteriorations. Some 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.

5. 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 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, sample periods but not out-of-sample forecast horizons.

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Data Availability Statement

The data that support the findings of this study are openly available in Open Science Framework repository at <https://mfr.osf.io/render?url=https%3A%2F%2Fosf.io%2F7jdhz%2Fdownload>.

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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 services, 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 aggregate 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 Five Cryptocurrencies: Bitcoin, Ethereum, XRP, Bitcoin Cash and Litecoin, Bottom Five Cryptocurrencies: Solve, Elastos, Redd Coin, Bit Capital Vendor and Stratis	<i>VAR – MGARCH – GJR – BEKK</i> 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 and the 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, 2020	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 (CHF), 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 and 30 international indices	<i>DCC-GARCH model</i>	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 and Economic Policy EPU	GARCH model and quantile regression with dummy variables	Both gold and bitcoin serve not as a safe-haven or a hedge for economic policy uncertainty