Bitcoin and South African Stock Market Returns during COVID-19 Pandemic: A test of the Safe-Haven Hypothesis

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This paper tests the safe-haven property of Bitcoin for South African stocks using Full and Diagonal BEKK-GARCH models. The study uses the Johannesburg stock exchange Top40 index, and bitcoin returns data before COVID-19 (August 2018 to December 2019) and during COVID-19 (January 2020 to June 2021). The results show that bitcoin cannot be considered as safe-haven for stocks in South Africa since it is weakly correlated with stock and had a high volatility during the Pandemic. Therefore, the safe-haven hypothesis of bitcoin on South African stocks is not true for the period under study. The policy implication is that bitcoin is not an appropriate safe-haven asset on South African stocks because it lacks store of value properties.

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1. Introduction

The world experienced major health and economic shocks as the Corona virus disease of 2019 (COVID-19) swept across massive population around the world from December 2019 to mid-2020. The first worldwide awareness of the COVID-19 was made by the World Health Organization (WHO) on 30th January 2020 (WHO, 2020). Following the increase in the number of confirmed cases globally, the WHO declared COVID-19 as a pandemic on 11th March 2020. Apparently, the outbreak of Corona virus has had its toll on global stock markets. According to Ding, *et al.* (2020), there was a quick drop in Standard and Poor (S&P) index by 34 percent as well as a decrease of 46 percent, 42 percent, 31 percent and 25 percent in Brazil, Italy, Japan, and Hong Kong exchanges, respectively in the first quarter of 2020.

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In recent times, the COVID-19 pandemic happens to be the first worldwide crisis that directly transforms into financial shock since the global economic crisis of 2008 and the first cryptocurrency launch in 2009. The International Monetary Fund (IMF) has categorized cryptocurrencies as a subset of virtual currencies, which it defines as digital representations of value, issued by private developers, and denominated in their own unit of account (IMF, 2016). Cryptocurrency refers to a wide range of technological developments that are based on cryptography. Cryptography, in its simplest form, is the process of transforming information by encryption into a format that can only be decoded by someone who possesses a secret key. Cryptocurrency has attracted the attention of academics, investors, speculators, regulators, and governments throughout the world. This is because cryptocurrency uses a decentralized network of systems that is cheap, fast, and safe for online financial transactions without mediators and does not crumble at single point of failure. Bitcoin is the primary reserve asset of MicroStrategy, a leading business intelligence platform. As of the fourth quarter of 2020, Tesla holds an investment in bitcoin of over 7.7% of Tesla's $19.384 billion cash holdings (Hamid *et al.,* 2021). The cryptocurrency market has developed enormously since its inception. Bitcoin being the pioneer in the cryptocurrency market, has improved in worth from close to $0 in October 2009 to more than $60,000 in April 2021[3].

The growing popularity of cryptocurrencies has inspired numerous studies about their investment benefits, including their safe haven properties. A safe haven asset is one which is expected to maintain or increase in value during periods of economic uncertainty and market turbulence. According to Bouri *et al.* (2017a), an asset is a weak (strong) safe haven if it is uncorrelated (negatively correlated) with another asset during distress times; and is a weak (strong) hedge if it is uncorrelated (negatively correlated) with another asset on average. The dynamics of a safe haven asset works in the following way: during excessive market situations the negative correlation with the other asset, makes the value of the safe haven asset increases whereas the value of the other asset decreases, which invariably makes up for losses incurred by the investor during bad times (Baur & Lucey, 2010).

[3]https://coinmarketcap.com/currencies/bitcoin/

The Johannesburg stock exchange (JSE) is the largest stock exchange in Africa with an estimated 443 listed companies and market capitalization of US$1.05 trillion (Majapa & Gossel 2016). As of July 2023, the South Africa market capitalization reached $1.2 trillion. Coincidentally, South Africa was the most affected by COVID-19 in Africa, with more than 1.69 million infected and 56974 deaths, (Corona Virus Disease Pandemic - Statistics and Facts, 2021).

Although the South African Reserve Bank position is that bitcoin and other cryptocurrencies do not meet the definition of legal tender of the country, many people and organizations are still trading on cryptocurrencies because of their many benefits. The majority of bitcoin related transactions in South Africa center around investment with average daily circulating supply of 19.6 million bitcoins and market capitalization of $1.2 trillion. There are several cryptocurrency exchanges and trading platforms operating in the country that are regulated by the Financial Sector Conduct Authority (Budree & Nyathi, 2023). In spite of having the largest stock exchange and being the most affected by the COVID-19 pandemic in Africa, there appears to be little or no empirical evidence on the safe haven property of cryptocurrencies in the South Africa (SA) stock market. Related studies have focused mainly on stocks in Asia, Europe, and America. Therefore, this paper closes this gap by focusing on the major stock market in Africa, JSE.

The aim of this paper is to test the 'safe haven' hypothesis of bitcoin on the SA stock market during the COVID-19 pandemic and estimate the optimum bitcoin holding weight in a portfolio of bitcoin and SA stock. The significance of this study is that the results will provide policy makers and investors with the platform to know whether bitcoin can be used as safe haven asset in a period of economic chaos similar to the COVID-19 pandemic. The findings will also benefit investors and portfolio managers who seek asset diversification to gain insight on the potential and capabilities of this asset.

The rest of the paper is structured as follows: Section 2 presents a review of the literature, while Section 3 espouses the data and method used in achieving the objectives of the study. Section 4 discusses the results, while section 5 concludes the paper with policy recommendations.

2. Literature Review

There is a growing literature on safe haven properties of cryptocurrency. Bitcoin is the first and one of the major forms of cryptocurrency. In this section, literature on the subject under review is presented in two spheres, namely theoretical literature, and empirical literature.

2.1 Theoretical Literature

Several theories have been used in the literature to examine the relationship between bitcoin, other cryptocurrencies, and stocks. These theories include, the bivariate cross-quantilogram theory in Shahzad *et al.* (2019), and multivariate dynamic copulas in Nguyen *et al.* (2020) among others. Interestingly, researchers have promoted discussions on whether cryptocurrencies can offer hedging and safe haven abilities for stocks, using different theoretical frameworks. For example, GARCH models were used by Dyhrberg (2016) to investigate the financial asset potential of bitcoin. The asymmetric GARCH model was used to assess the effectiveness of bitcoin in financial risk management for risk-averse investors anticipating market downturns. The GARCH model incorporates squared conditional variance terms as additional explanatory variables. Bitcoin, Dyhrberg claims, has a place on the financial markets and in portfolio management since it falls somewhere between gold and the US dollar on a scale ranging from pure medium of exchange advantages to pure store of value advantages. Tiwari *et al.* (2019) studied the structure of time-varying conditional correlation between cryptocurrency and stock markets using the copula-ADCC-EGARCH model. Time-varying correlations were used to evaluate the hedge asset property of cryptocurrency against the S&P 500 stock market.

Caferra & Vidal-Tomás (2021), applied the wavelet coherence approach and Markov switching autoregressive model to study the behaviour of cryptocurrencies and stock markets. The model was used to establish the functional relationship between cryptocurrencies and the real economy. Ly *et al.* (2022) proposed a hybrid of ARMA-GARCH, static and dynamic copulas and dynamic state-space models with Kalman filter to investigate the dependence structure, extreme co-movement, risk spillover and integration relationship among five major markets. Jia *et al.* (2023) used quantile-on-quantile and quantile regression methods for analysis of the nexus between the gold market, bitcoin, and stock market returns. Quantile regression models the relationship between a set of predictor variables and specific percentiles of a target dependent variable, most often the median. Banerjee *et al.* (2022) applied nonlinear technique of transfer entropy to develop a relationship between cryptocurrencies by market capitalization and COVID-19 news sentiments. Transfer entropy is a non-parametric statistic measuring the amount of directed transfer of information between two random processes.

2.2. Empirical Literature

There is growing research on cryptocurrencies before, during and after the COVID-19 pandemic in recent times. Bouri *et al.* (2017b) studied the relationship between the down movements in the S&P500 and its ten equities sectors (financials, information technology, telecom services, industrials, basic materials, consumer discretionary, energy, consumer staples, utilities, and health care) and eight cryptocurrencies (bitcoin, Ethereum, ripple, Litecoin, stellar, dash, Nem, and Monero). While their findings concurred that many cryptocurrencies had the potential to be valuable digital assets, there was substantial variability in many situations. They claimed that bitcoin, ripple, and stellar are uncorrelated with all US equities indices, Litecoin and Monero are safe havens for the overvalued US equity index and a few sectors since they are uncorrelated.

Wang *et al.* (2019a) used daily record of bitcoin and six other economic assets, namely: bonds, monetary asset, foreign exchange, gold, stocks, and commodity futures to examine the mean and volatility dynamics between bitcoin and the six economic assets in China. The study adapted a VAR-GARCH-BEKK[4] model to determine whether bitcoin can be used as a safe-haven asset or as a hedging asset. The results of the analysis show that only monetary asset is uncorrelated with bitcoin, whereas bitcoin is positively correlated with bonds, stocks and Shanghai Interbank Offer Rate (SHIBOR). Hence, bitcoin is a safe haven when severe price changes occur in the financial market and a hedged for stocks, bonds, and SHIBOR. Gil-Alana, *et al.* (2020) profess that cryptocurrencies are different from traditional financial and economic assets, and investors should include them to diversify their portfolios.

[4]Baba, Engle, Kraft and Kroner

Moreover, bitcoin's safe-haven properties are even better than gold and other commodities (Shahzad *et al.,* 2020). Similarly, Mariana *et al.* (2021) found out that the two largest cryptocurrencies, bitcoin and Ethereum are suitable as short-term safe havens for S&P 500. Contrary opinion was given by Bouri *et al.* (2017a). They discovered that bitcoin is not a good hedge and is therefore suitable only for reasons of portfolio diversification.

Soloviev *et al.* (2020) established the comparative possibility of constructing indicators of critical crash phenomena in the volatile market of cryptocurrencies and developed stock market using random matrix measures of complexity to detect dynamics in a complex time series. The study observed the statistical properties of cross-correlation coefficient using daily returns of price time series. The results show that the largest eigenvalues can act as indicators to fall in both markets. Ferreira *et al.* (2020) investigated the serial correlation structure of six cryptocurrencies, namely: bitcoin, dash, stellar, Litecoin, Monero and ripple, with a long data record with the use of detrended cross correlation and detrending moving average cross-correlation coefficients. The result shows that these cryptocurrencies behave differently from the stock markets which are much closer to the random walk dynamics.

Li and Meng (2022) used time frequency methods to give an overall new pragmatic depiction of the dynamic association between cryptocurrencies and renewable energy stock market from different investment spheres to offer fresh insight since long-run and short-run investors show different investment patterns as can be seen in Jiang *et al.* (2017). The contribution of Li and Meng (2022) to existing literature was the use of novel methods in constructing a framework for providing fresh evidence on the cryptocurrency-stock returns dependence from different investment horizons which supplement related time domain studies. It was shown that hedging effectiveness in portfolio design is relatively weak in the long run and in this case, investors can gain more profit through short term transactions.

Gambarelli *et al.* (2023) examined the hedging effectiveness of cryptocurrencies and cryptocurrency portfolio for European equities in a period characterized by low and high volatility phases. The study analyzes the European blue-chip index for the period between March 2018 and September 2022 which includes both the bitcoin all-time high of about 69,000 USD reached in November 2021 and the sharp drop that occurred in the first half of 2022. One of the key findings of the study was that among the cryptocurrency assets under study, only the US dollar-pegged coin Tether proved to be a safe haven for the European stock market in two out of the three bearish market phases. Bitcoin and Etherium were found to be the most closely correlated with stock market returns in bear market phases.

In Lee and Zhang (2023), the dynamic link between cryptocurrency prices, green bonds, and sustainable equities as well as whether green bonds and sustainable equities provide hedges against environmental unsustainability caused by cryptocurrencies were examined. The paper analyzed the causal relationship across quartiles using Granger-causality in quantiles analysis proposed by Troster (2018). The results show positive granger-causality from green sustainable equity to cryptocurrency prices and a negative Granger-causality from cryptocurrency prices to green sustainable investment under the lower and upper quantiles.

In summary most of the studies examined the dynamics of cryptocurrencies and equities in developed economies and most sample periods span between 2012 and before the COVID-19 pandemic which was characterized by heavy markets downturns. To the best of our knowledge, there are no studies focused on the dynamics of bitcoin and stocks in Africa during the period of COVID-19 pandemic. This paper fills the gap in the existing body of literature as it tests the safe haven properties of bitcoin using data from South African stock market before and during COVID-19 pandemic.

3. Data and Methodology

3.1 Data

The data for this study contains 728 observations of Johannesburg stock exchange Top 40 index and bitcoin returns. The sample period ranged from 1st August 2018 through 30th June 2021 and grouped into ‘pre-COVID-19’ (1st August 2018 to 31st December 2019) and ‘during COVID-19’ (1st January 2020 to 30th June 2021). Though the WHO formally declared the COVID-19 a pandemic in March 2020, the outbreak started in December 2019. This gives a justification for the period demarcated as ‘before COVID-19’ and ‘during COVID-19’. The bitcoin data in USD is obtained from Coindesk[5] while JSE data is obtained online[6]. Johannesburg stock exchange Top40 index is a capitalization weighted index. Companies included in this index are the 40 largest companies by market capitalization included in the JSE All Shares Index.

3.2 Model Specification

The bivariate BEKK-GARCH models (full and diagonal) were selected to study the volatility dynamics and safe haven capability of bitcoin over SA stock. From similar studies, (Arouri *et al.,* 2015; Wang *et al.,* 2019b), multivariate generalized autoregressive conditionally heteroscedastic (MGARCH) models have proven to be efficient in the study of cryptocurrency dynamics.

Among the numerous specifications of MGARCH models, the most widely used are the Constant Conditional Correlations (CCC) model introduced by Bollerslev (1990) and extended by Jeantheau (1998), the Baba, Engle, Kraft, and Kroner (BEKK) model of Engle and Kroner (1995), and the Dynamic Conditional Correlations (DCC) models proposed by Tse and Tsui (2002) and Engle (2002). MGARCH models are used to study the relations between the volatilities and co-volatilities of several markets. Also, MGARCH models permit time-varying conditional covariances as well as variances. The variances can be of substantial practical use for both modeling and forecasting, especially in finance and investment evaluations.

The bivariate BEKK-GARCH models utilize less parameter to study the relationship between the volatilities of two markets over time; they could capture the interdependence between bitcoins and stock market returns in mean and variance. A key advantage of the BEKK-GARCH model is that it does not force any constraint on the conditional correlation structure between series. The models are presented below:

Let $Y_t = (r_t^s, r_t^c)$ represents returns on stock market index and bitcoin price index vector where s and c represent stock and cryptocurrency, respectively and $H_t = \begin{bmatrix} h_t^s & h_t^{sc} \\ h_t^{sc} & h_t^c \end{bmatrix}$ represents the conditional variance-covariance matrix of stock and bit-

[5]https://coindesk.com
[6]https://investing.com

coin returns. It is assumed that the conditional mean of our models is a bivariate AR(1) process defined as follows:

$$Y_t = \mu + \Phi Y_{t-1} + \varepsilon_t$$

$$\varepsilon_t = H_t^{\frac{1}{2}} z_t \tag{1}$$

where μ is a constant vector of terms in the AR; Φ represents a (2 x 2) matrix of coefficients; $\varepsilon_t = (\varepsilon_t^s, \varepsilon_t^c)$ is a vector of the error terms; $z_t = (z_t^s, z_t^c)$ is a sequence of independently and identically distributed random errors with $E(z_t) = 0$ and $Var(z_t) = I_2$. The parameters of this model are estimated by quasi-maximum likelihood estimation (QMLS) since it is robust to any departure from normality conditions; see Bauwens *et al.* (2006). Another method of estimating these parameters is the equation-by-equation method proposed by Francq and Zakoïan (2016).

The optimal lag for our models were determined to be lag one for both the conditional mean and GARCH (p, q) process using AIC information. Therefore, the conditional variance-covariance matrix of stock and bitcoin returns is presented as:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2}$$

where C is a (nxn) upper triangular matrix, A and B are (nxn) coefficient matrices. $C'C$ is the decomposition of the intercept matrix. Each element in H_t depends on the corresponding element in $\varepsilon_{t-1}\varepsilon'_{t-1}$ and H_{t-1}. Past shocks and volatility are allowed to directly spill over from one market to another, and they are captured by coefficients of A and B matrices, respectively.

Simplifying further, the conditional variance and covariance processes for the full-BEKK-GARCH model takes the following form:

$$\begin{bmatrix} h_t^s & h_t^{sc} \\ h_t^{sc} & h_t^c \end{bmatrix} = \begin{bmatrix} c_s & c_{sc} \\ c_{cs} & c_c \end{bmatrix} + \begin{bmatrix} a_s(\varepsilon_{t-1}^s)^2 + a_{sc}\varepsilon_{t-1}^c\varepsilon_{t-1}^s & a_s\varepsilon_{t-1}^s\varepsilon_{t-1}^c + a_{sc}(\varepsilon_{t-1}^c)^2 \\ a_{sc}(\varepsilon_{t-1}^s)^2 + a_c\varepsilon_{t-1}^c\varepsilon_{t-1}^s & a_{cs}\varepsilon_{t-1}^s\varepsilon_{t-1}^c + a_c(\varepsilon_{t-1}^c)^2 \end{bmatrix} \begin{bmatrix} a_s & a_{cs} \\ a_{sc} & a_c \end{bmatrix} +$$
$$\begin{bmatrix} b_s h_{t-1}^s + b_{sc}h_{t-1}^{sc} & b_s h_{t-1}^{sc} + b_{sc}h_{t-1}^c \\ b_{cs}h_{t-1}^s + b_c h_{t-1}^{sc} & b_{cs}h_{t-1}^{sc} + b_c h_{t-1}^c \end{bmatrix} \begin{bmatrix} b_s & b_{cs} \\ b_{sc} & b_c \end{bmatrix}$$

$$h_t^s = c_s + a_s^2(\varepsilon_{t-1}^s)^2 + a_{sc}^2(\varepsilon_{t-1}^c)^2 + 2a_s a_{sc}\varepsilon_{t-1}^c\varepsilon_{t-1}^s + b_s^2 h_{t-1}^s + b_{sc}^2 h_{t-1}^c + 2b_s b_{sc}h_{t-1}^{sc}$$

$$h_t^c = c_c + a_{cs}^2(\varepsilon_{t-1}^s)^2 + a_c^2(\varepsilon_{t-1}^c)^2 + 2a_c a_{cs}\varepsilon_{t-1}^c\varepsilon_{t-1}^s + b_{cs}^2 h_{t-1}^s + b_c^2 h_{t-1}^c + 2b_c b_{cs} h_{t-1}^{sc}$$

$$h_t^{sc} = c_{sc} + a_{cs}a_s(\varepsilon_{t-1}^s)^2 + a_c a_{sc}(\varepsilon_{t-1}^c)^2 + (a_{cs}a_{sc} + a_c a_s)\varepsilon_{t-1}^c\varepsilon_{t-1}^s$$
$$+(b_{cs}b_{sc} + b_c b_s)h_{t-1}^{sc} + b_{cs}b_s h_{t-1}^s + b_c b_{sc} h_{t-1}^c$$

For diagonal-BEKK-GARCH (1,1), A and B in (2) are diagonal matrices and the conditional variance-covariance matrix of stock and bitcoin is as follows:

$$\begin{bmatrix} h_t^s & h_t^{sc} \\ h_t^{sc} & h_t^c \end{bmatrix} = \begin{bmatrix} c_s + a_s^2(\varepsilon_{t-1}^s)^2 + b_s^2 h_{t-1}^s & c_{sc} + a_s a_c \varepsilon_{t-1}^s \varepsilon_{t-1}^c + b_s b_c h_{t-1}^{sc} \\ c_{sc} + a_s a_c \varepsilon_{t-1}^s \varepsilon_{t-1}^c + b_s b_c h_{t-1}^{sc} & c_c + a_c^2(\varepsilon_{t-1}^c)^2 + b_c^2 h_{t-1}^c \end{bmatrix}$$

The following conditions makes the diagonal-BEKK-GARCH model covariance stationary: $a_s^2 + b_s^2 < 1, a_c^2 + b_c^2 < 1$,and $|a_s a_c + b_s b_c| < 1$.

Furthermore, from Kroner and Ng (1998), the optimum holding weight (w_t^{cs}) of cryptocurrency per unit dollar portfolio of stock/ bitcoin at time t is obtained as follows:

$$w_t^{cs} = \frac{h_{t-}^s h_t^{sc}}{h_t^s - 2h_t^{sc} + h_t^c} \tag{3}$$

where h_t^c , h_t^s and h_t^{sc} are the conditional volatility of the bitcoin returns, SA stock market index returns and the conditional covariance between bitcoin and stock returns at time t, respectively.

The mean-variance portfolio optimization method requires the following restriction on the optimum weight of cryptocurrency:

$$w_t^{cs} = \begin{cases} 0,\ if\ w_t^{cs} < 0 \\ w_t^{cs}, if\theta \le w_t^{cs} \le 1 \\ 1,\ if\ w_t^{cs} > 1 \end{cases} \tag{4}$$

3.3 Estimation Procedure

The general multivariate model can be written as:

$$y_t = \mu + \Pi(L)y_{t-1} + \phi x_{t-1} + \Lambda vech(H_t) + \varepsilon_t \tag{5}$$

where y_t is a (N x 1) vector of weakly stationary variables (that is, asset returns),

$\Pi(L) = \Pi_1 + \Pi_2 L + \ldots + \Pi_k L^{k-1}$, x_{t-1} contains predetermined variables. ε_t is the vector of innovation with respect to the information set formed exclusively of past realization of y_t. Λ is a (N x N(N+1)/2) such that $H_t = E_{t-1}(\varepsilon_t \varepsilon_t')$.

Given Equation (5), the log-likelihood function for $\{\varepsilon_T, \ldots, \varepsilon_1\}$ obtained under the assumption of conditional multivariate normality is:

$$L_T(\varepsilon_T, \ldots, \varepsilon_1; \theta) = -\frac{1}{2}\left[TN\ln 2\pi + \sum_{t=1}^{T}(\ln|H_t| \ \ + \varepsilon_t' H_t^{-1} \varepsilon_t)\right] \tag{6}$$

The conditional likelihood function for the univariate ARCH model, which is employed in maximum likelihood or quasi-maximum likelihood estimation, is directly equivalent to (6). Because maximum likelihood under normalcy is commonly employed, it is crucial to look at its qualities in a broader context. The assumption of conditional normalcy can be rather constraining in general. The symmetry required by normality is difficult to justify, and even conditional distributions' tails frequently appear wider than those of normal distributions.

Let $(y_t, x_t) : t = 1, 2, \ldots$ be a sequence of observable random vectors with y_t $(N \times 1)$ and x_t $(L \times 1)$. The vector y_t contains the "endogenous" variables and x_t contains contemporaneous "exogenous" variables. Let $w_t = (x_t, y_{t-1}, x_{t-1}, \ldots, y_1, x_1)$. The conditional mean and variance functions are jointly parametrized by a finite dimensional vector θ such that $\{\mu_t(w_t, \theta), \theta \in \theta\}$ $\{H_t(w_t, \theta), \theta \in \theta\}$ where θ is a subset of R^P and μ_t and H_t are known functions of w_t and θ.

In the analysis, the validity of most of the inference procedures is proven under the null hypothesis that the first two conditional moments are correctly specified, for some $\theta_0 \in \theta$,

$$E(y_t/w_t) = \mu_t(w_t, \theta_0) \tag{7}$$

$$Var(y_t/w_t) = H_t(w_t, \theta_0) \tag{8}$$

where $E(y_t/w_t)$ implies expectation of y_t given w_t ; $Var(y_t/w_t)$ signifies variance of y_t given w_t.

The procedure most often used to estimate θ_0 is maximization of a likelihood function that is constructed under the assumption that $y_t/w_t \sim N(\mu_t, H_t)$. The approach taken here is the same, but the subsequent analysis does not assume that y_t has a conditional normal distribution. The quasi-conditional log-likelihood is:

$$l_t(\theta; y_t,\ w_t) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t(w_t, \theta)| - \frac{1}{2}(\ y_t - \mu_t((w_t, \theta))' H_t^{-1}(w_t, \theta)(y_t - \mu_t((w_t, \theta)) \tag{9}$$

Letting $\varepsilon_t(y_t, w_t, \theta_0) \equiv y_t - \mu_t((w_t, \theta)$ denote $N \times 1$ residual function, and in more concise notation

$$l_t(\theta) = -\frac{N}{2}\ln(2\pi) - \frac{1}{2}\ln|H_t(\theta)| - \frac{1}{2}(\ \varepsilon_t'(\theta) H_t^{-1}(\theta)\varepsilon_t(\theta) \tag{10}$$

$$L_T(\theta) = \sum_{t=1}^{T} l_t(\theta) \tag{11}$$

Most applied work on GARCH models use the Berndt, Hall, Hall and Hausman (BHHH) algorithm to maximize $l_t(\theta)$.

The estimation procedure is divided into two parts: the pre-estimation and the estimation tests. In the pre-estimation tests, the Ljung-Box Q test for the existence of autocorrelations in the variables and squared returns, the Augmented Dickey-Fuller test and the bivariate portmanteau test for conditional heteroscedasticity were carried out to give direction on the type of models to be estimated. In the estimation test, the values of log likelihood ratio, AIC and SIC of the entertained models were used in selecting the appropriate model.

4. Results and Discussion

4.1 Descriptive Statistics

Table 1 shows the descriptive statistics for the bitcoin and stock return series. Bitcoin provided higher mean daily returns of 0.0042 against stock mean daily returns of 0.0002 during the Pandemic. It is obvious that bitcoin is highly volatile from the standard deviations of return series of 0.037 before COVID-19 and 0.0489 during the Pandemic. The skewness, kurtosis, and Jarque-Bera statistics indicate that the distributional assumption of normality is violated.

Table 1: Descriptive statistics

	Before COVID-19		During COVID-19	
	BTC˙R	JSE˙R	BTC˙R	JSE˙R
Mean (%)	-0.0006	-2.77E-05	0.0042	0.0002
Std. Dev.	0.0370	0.0102	0.0489	0.0165
Skewness	0.1904	-0.2702	-2.4846	-1.0881
Kurtosis	6.1395	3.9876	28.704	11.439
J-B	147.1136	18.6460	10709.27	1186.968

4.2 Pre-Estimation Results

The Ljung-Box Q test indicates the existence of autocorrelations in the variables and the Ljung-Box Q test of squared returns also showed that autocorrelations existed in the square of the variables. This suggests that the variables have volatility clustering and therefore requires a GARCH-type model for estimation. It can be seen from the Augmented Dickey-Fuller (ADF) statistics that the variables are stationary therefore, further analysis can be carried out on them. The bivariate portmanteau test for the return series before the pandemic rejects the null hypothesis of no bivariate-conditional heteroscedasticity at 10% significant level, though weak it also gives credence to the use of the GARCH-BEKK models. On the other hand, the bivariate portmanteau test during the pandemic rejects the null hypothesis of no bivariate-conditional heteroscedasticity at 1% significant level which provides strong evidence of ARCH effects in the return series.

Table 2: Pre-Estimation Tests Results

	Before COVID-19		During COVID-19	
	BTC_R	JSE_R	BTC_R	JSE_R
LB-Q (10)	105.82***	103.12***	165.71***	251.41***
LB-Q2 (10)	87.458***	79.88***	88.191***	337.59***
ADF	-19.497***	-19.300***	-22.941***	-6.590***
Observations	353	353	375	375
	Bivariate (JSE˙R, BTC˙R) Conditional Heteroscedasticity Test Q (10) = 15.968*		Bivariate (JSE˙R, BTC˙R) Conditional Heteroscedasticity Test Q (10) = 160.402***	

Notes: LB-Q (10) represents Ljung-Box Q-test statistics of returns up to a 10th-order serial autocorrelation and LB-Q2 (10) represents Ljung-Box Q-test statistics of square returns, up to a 10th-order serial autocorrelation. ADF stands for the Augmented Dickey-Fuller test statistic for a unit root. ***, **, and * show 0.01, 0.05, and 0.1 level of significance of the tests, respectively.

4.3 Estimation Results

Table 3 presents the results of the volatility dynamics of bitcoin and stock using the BEKK models considered. It can be seen from results of diagnostic tests that the chosen bivariate models are generally elastic and appropriate to represent the dynamics of the conditional return and volatility of the series. This is based on the values of the standardized residuals and squared standardized residuals. Based on the values of log likelihood ratio, AIC and SIC, the full-BEKK-GARCH model is best-suited for modeling the joint dynamics of bitcoin and stock market returns.

In the period before the pandemic, none of the constants in the mean equations is significant for the models; the one-period lagged stock return is significant at 1 percent level, while that of bitcoin is insignificant at 5 percent level. The implication is that before the pandemic, bitcoin (stock) had effect on the volatility of stock (bitcoin) returns. As for A and B matrices, there is no evidence that shock or volatility of bitcoin and stock are related. This implies that past shock in bitcoin market has no effect on the volatility of stock returns. Also, the volatility coefficients are significant for the models but there is no evidence that past volatility of stock market affects the volatility of bitcoin returns.

During the pandemic, significant past shocks were observed in bitcoin and in stock returns but there is no significant spillover effect. Therefore, past shocks on bitcoin(stock) has zero effect on the volatility of stock(bitcoin) returns. This is also valid for the volatility effect as can be seen on Table 3.

Table 3: AR (1)-Full BEKK-GARCH(1, 1) Results

	Before COVID-19		During COVID-19	
	JSE	Bitcoin	JSE	Bitcoin
Constant	-0.0001	-0.0001	-0.00009	0.0043*
	(0.0006)	(0.0018)	(0.0006)	(0.0023)
Stock (-1)	-0.1768***		-0.3218***	
	(0.0547)		(0.0667)	
Bitcoin (-1)		-0.0164		0.0215
		(0.0127)		(0.0176)
C	0.00185***	0.0030	0.0035***	0.0030
	(0.0004)	(0.0107)	(0.0006)	(0.0024)
		-0.0056		0.0088***
		(0.0049)		(0.0023)
A	0.0326	1.0149	0.1725	0.4183
	(0.1990)	(0.8389)	(0.1317)	(0.2992)
	-0.0075	0.4712*	0.0133	-0.2728***
	(0.0151)	(0.2441)	(0.0193)	(0.0655)
B	0.9617***	0.0362	0.8917***	-0.0871
	(0.0116)	(0.1548)	(0.0313)	(0.0829)
	0.0064	0.7634***	0.0069	0.9068***
	(0.0159)	(0.0586)	(0.0103)	(0.0194)
LogL	1806.2492		1750.5866	
AIC	-10.5121		-9.4543	
SIC	-10.042		-8.9920	
JB	12.5762***	198.3021***	35.37351***	10923***
$LB-Q(10)$	5.289	7.2146	11.833	5.0120
$LB-Q^2(10)$	1.3200	1.0560	26.092***	1.8982

Notes: Stock(-1) represents the one-period lagged returns of South African stock market while Bitcoin (-1) represents that of Bitcoin cryptocurrency. The matrices A, B and C are the model parameter matrices. The numbers in parentheses are the standard errors of the parameters estimates. J-B stands for Jarque-Bera statistic for testing the normality assumption. LogL is the log likelihood ratio, AIC is the Akaike Information Criterion and SIC is the Schwarz Information Criterion. LB-Q(10) represents Ljung-Box Q-test statistics of returns up to a 10th-order serial autocorrelation and LB-Q^2(10) represents Ljung-Box Q-test statistics of square returns, up to a 10th-order serial autocorrelation,. ***, **, and * show 0.01, 0.05, and 0.1 level of significance, respectively.

Table 4 presents the descriptive statistics of the conditional correlation coefficients estimated using the BEKK-GARCH models. We can observe that on average, bitcoin is uncorrelated with stock before the pandemic with a coefficient of 0.026. During the pandemic, the correlation between stock and bitcoin on average was 0.2786. This signifies that bitcoin is weakly correlated with stock during the pandemic. According to Bouri *et al.,* (2017a), since bitcoin is weakly correlated with stock during the pandemic, it is therefore not a safe haven asset for stock markets in South Africa.

Table 4: Descriptive statistics of the Dynamic Conditional correlations

	Before COVID-19	During COVID-19
Mean	0.0260	0.2786
Median	0.0215	0.2961
Variance	0.0067	0.0049
Kurtosis	1.1813	1.941
Skewness	-0.1515	-1.077
Minimum	-0.3192	0.0002
Maximum	0.3116	0.5469

Notes: This table reports the descriptive statistics of the dynamic correlations between JSE and BTC before and during covid-19 pandemic from a full BEKK-GARCH model.

4.4 Optimal holding weight

Portfolio weight is the proportion of crypto in a crypto-stock portfolio. The most basic way to determine the weight of an asset is by dividing the dollar value of the security by the total dollar value of the portfolio. This article considers a hedged portfolio composed of bitcoin and Johannesburg stock market index where an investor tries to guard himself against exposure to adverse stock price activities by investing in bitcoin. Practically, the aim of the investor is to bring to the minimum the risk of the bitcoin-stock portfolio while maintaining the optimal expected returns.

Optimal holding weight values for bitcoin are presented on Table 5 for both periods. Before COVID-19, the coefficients show that the optimal weight for bitcoin assets represented by w^{sb} in the hedged portfolios is 0.0730. During the pandemic, the optimal holding weight decreased, implying that less of bitcoin should be held in times of economic turmoil. This supports the finding that bitcoin is not a safe-haven asset for stocks in SA during COVID-19 pandemic. This result concurs with the result of Omane-Adjepong and Alagidede (2021) that bitcoin could not be used as safe haven asset in Africa's emerging markets. Overall, the results show that the minimum risk of bitcoin-stock portfolio can be achieved without lowering the optimal return if investors operating in SA stock markets should hold more stock than bitcoin.

Table 5: Optimal weight for the portfolio of bitcoin and stock in South Africa

	Prior to COVID-19	During COVID-19
w^{sb}	0.0730	0.0183

Notes: This table reports the average optimal holding weight of bitcoin (w^{sb}) in a bitcoin-stock portfolio before and during covid-19 pandemic from the full -BEKK-GARCH model.

4.5 Robustness Test

To test the robustness of our results, we conducted structural breakpoint test on our stock data and test the safe haven property of bitcoin during the subperiods determined by the break points. According to our results, two breaks were identified which split our data into three periods. Period one is from August 1, 2018, to March 16, 2020, a total of 406 observations; period two from March 17, 2020, to August 26, 2020, 112 observations; and period three from August 27, 2020 to June 30, 2021 with 210 observations.

Table 6 contains the shock and volatility dynamics of stock and bitcoin for the three periods and is similar to the results in Table 3. The full-BEKK-GARCH model maintained dominance as the best-suited model for explaining the volatility dynamics of the SA stocks and bitcoin. Cases of spillover effects were identified in periods one and two. In period one, past bitcoin shocks have no role in explaining changes in the conditional volatility of SA stock returns but past volatility of bitcoin returns has significant effect on the market volatility of SA stocks and vice versa. The same pattern was observed in period two which recorded the peak of COVID-19 effects. Finally, there are no interactions in past shocks and volatility of bitcoin and SA stock in period three. It is worthy to note that our results here are only restricted to short periods of COVID-19 pandemic and cannot be generalized except when considering a longer time period.

Table 6: AR (1)-BEKK-GARCH (1,1) model estimates for stock and bitcoin for the three periods

	Period one		Period two		Period three	
	JSE	Bitcoin	JSE	Bitcoin	JSE	Bitcoin
Constant	-0.0003	0.0013	0.0004	0.0061**	0.0002	0.0052*
	(0.0005)	(0.0018)	(0.0013)	(0.0027)	(0.0007)	(0.0028)
Stock (-1)	-0.2812***		-0.2369**		-0.0472	
	(0.0673)		(0.0940)		(0.0815)	
Bitcoin (-1)		-0.0302**		0.1712***		0.0013
		(0.0144)		(0.0512)		(0.0255)
C	0.00311***	0.0059**	0.0042***	-0.0047	0.0066***	0.0094
	(0.0009)	(0.0026)	(0.0013)	(0.0038)	(0.0022)	(0.0067)
		-0.0033		0.0018		0.0000
		(0.0055)		(0.0050)		(0.0100)
A	0.1780	-0.2306	0.2802**	-0.0079	0.3259*	0.7719**
	(0.1098)	(0.5250)	(0.1338)	(0.3256)	(0.1713)	(0.3203)
	-0.0180	-0.2671***	0.0464	-0.0773	0.0252	-0.2064**
	(0.0171)	(0.0660)	(0.0578)	(0.1322)	(0.0212)	(0.0996)
B	0.7719***	1.9639***	0.7900***	1.3660***	0.6779***	-0.7194
	(0.0359)	(0.1324)	(0.0574)	(0.1527)	(0.2178)	(0.4776)
	-0.1584***	0.6636***	-0.2144***	0.4553***	0.0120	0.9509***
	(0.0105)	(0.0345)	(0.0423)	(0.0980)	(0.0157)	(0.0382)
LogL	2014.9168		535.5431		1028.259	
AIC	-9.6231		-9.3930		-9.7192	
SIC	-9.4301		-8.9011		-9.4030	
JB	103.78***	24091***	4.0715	29.500***	0.3675	15.9747**
$Q(10)$	8.6111	1.0910	11.1010	18.9991*	12.8819	7.7333
$Q^2(10)$	17.0029*	0.9547	5.3907	5.2200	14.6301	5.1927

Notes: Stock (-1) represents the one-period lagged returns of South African stock market while Bitcoin(-1) represents that of Bitcoin cryptocurrency. Matrix C is estimated as $C = \begin{bmatrix} c_s & c_{sc} \\ 0 & c_c \end{bmatrix}$ for all the models. For the full-BEKK–GARCH model, $A = \begin{bmatrix} a_s & a_{sc} \\ a_{cs} & a_c \end{bmatrix}$ and $= \begin{bmatrix} b_s & b_{sc} \\ b_{cs} & b_c \end{bmatrix}$; The numbers in parentheses are the standard errors of the paprameter estimates. *, **, ***, JB, Q(10) and $Q^2(10)$ are same as defined in Tables 2 and 3.

The descriptive statistics of the dynamic conditional correlations for the three periods displayed on Table 7 support our initial results that stock were more correlated to bitcoin during the Pandemic than before the Pandemic. To explain the safe haven features of bitcoin, we focus on period two and three which are covid-19 periods. In periods two and three, stock and bitcoin are weakly correlated supporting our findings that bitcoin is not a safe haven asset for SA stock during COVID-19 pandemic..

Table 7: Descriptive statistics of the Dynamic Conditional correlation

Statistic	Period one	Period two	Period three
Mean	0.107	0.2091	0.2326
Median	0.1044	0.2281	0.2408
Variance	0.0089	0.0186	0.0021
Kurtosis	6.796	0.3629	-0.698
Skewness	0.8687	-0.647	-0.339
Minimum	-0.2218	-0.183	0.1296
Maximum	0.7759	0.4416	0.3204

Notes: This table reports the descriptive statistics of the dynamic correlations between Bitcoin and the South Africa stock for the three periods determined by the structural break test using a full and a diagonal-BEKK-GARCH model.

Finally, the mean values of realized optimum weights for the three periods are presented in Table 8. Period two, which reflects the peak of COVID-19 recorded higher optimal weight for bitcoin than other periods. Optimal weight for bitcoin, w^{sb} for period two is 0.134. This implies that investors can include only 13.4% of bitcoin into their portfolio so as to attain minimum risk on optimal return. Overall, investors operating in SA stock markets should hold more stocks than bitcoin during extreme market condition which again clearly supports our pervious results that bitcoin is not a safe haven for stocks in SA.

Table 8: Optimal weight for the portfolio of bitcoin and stock in South Africa

	Period one	Period two	Period three
w^{sb}	0.044	0.134	0.004

Notes: This table reports the average optimal holding weight of bitcoin (w^{sb}) in a bitcoin-stock portfolio before and during covid-19 pandemic from the full -BEKK-GARCH model.

5. Conclusion and Policy Recommendations

This paper tests the safe-haven hypothesis of bitcoin on SA Stock market before and during COVID-19 pandemic. The significance of the study is that it provides evidence for policy makers and investors to determine whether or not bitcoin can be used as safe-haven during period of economic turmoil.

Overall, the results show that during the Pandemic, bitcoin yielded higher returns and higher volatility than South African stock market but cannot be considered as safe haven since it is weakly correlated with the stock. The full-BEKK-GARCH model explained the shock and volatility dynamics of bitcoin and stock better than diagonal-BEKK-GARCH model; there was no evidence of cross volatility effects during COVID-19 pandemic. In the breakpoint periods, past volatility effects of bitcoin return significantly affected SA stock market and vice versa in periods one and two. The optimum holding weight suggests that 13 percent of bitcoin can be held during market uproar to attain minimum risk. Based on the findings of this study, it is recommended that investors and policy makers in South African stock market should not use bitcoin as a safe haven asset, since it lacks the ability to store value during the period of COVID-19 pandemic.

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