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The implication of cryptocurrency volatility on five largest African financial system stability

Tonuchi E. Joseph[1], Atif Jahanger[2,3*], Joshua Chukwuma Onwe[4,8] and Daniel Balsalobre-Lorente[5,6,7]

*Correspondence: atif_jahanger@hotmail.com

[1] Department of Statistics, Central Bank of Nigeria, Abuja, Nigeria
[2] International Business School, Hainan University, Haikou City 570228, Hainan, China
[3] Institute of Open Economy, Hainan University, Haikou City 570228, Hainan, China
[4] School of General studies, Federal Polytechnic Ohodo, Enugu, Enugu State, Nigeria
[5] Department of Applied Economics I, University of Castilla La Mancha, Ciudad Real, Spain
[6] Department of Management and Marketing, Czech University of Life Sciences Prague, Faculty of Economics and Management, Prague, Czech Republic
[7] UNEC Research Methods Application Center, Azerbaijan State University of Economics (UNEC), Istiqlaliyyat Str. 6, Baku 1001, Azerbaijan
[8] Department of Economics, UNZIK Business School, Nnamdi Azikiwe University, Akwa, Nigeria

Abstract

This study examined the interconnectedness and volatility correlation between cryptocurrency and traditional financial markets in the five largest African countries, addressing concerns about potential spillover effects, especially the high volatility and lack of regulation in the cryptocurrency market. The study employed both diagonal BEKK-GARCH and DCC-GARCH to analyze the existence of spillover effects and correlation between both markets. A daily time series dataset from January 1, 2017, to December 31, 2021, was employed to analyze the contagion effect. Our findings reveal a significant spillover effect from cryptocurrency to the African traditional financial market; however, the percentage spillover effect is still low but growing. Specifically, evidence is insufficient to suggest a spillover effect from cryptocurrency to Egypt and Morocco's financial markets, at least in the short run. Evidence in South Africa, Nigeria, and Kenya indicates a moderate but growing spillover effect from cryptocurrency to the financial market. Similarly, we found no evidence of a spillover effect from the African financial market to the cryptocurrency market. The conditional correlation result from the DCC-GARCH revealed a positive low to moderate correlation between cryptocurrency volatility and the African financial market. Specifically, the DCC-GARCH revealed a greater integration in both markets, especially in the long run. The findings have policy implications for financial regulators concerning the dynamics of both markets and for investors interested in portfolio diversification within the two markets.

Keywords: African financial market, BEKK-GARCH, Cryptocurrency, DCC-GARCH, Volatility spillover

Introduction

The emergence of cryptocurrency in the financial sector has arguably revolutionized the conventional system, similar to how social media has revolutionized traditional media space. Cryptocurrencies aim to revolutionize the traditional financial space and provide financial consumers with an alternative, decentralized financial system to support community funding (crowdfunding) and transactions; this system contrasts with the traditional financial system, which is highly centralized and where funding comes with a high cost (Ghorbel and Jeribi 2021). A decentralized financial system means individuals can engage in a monetary transaction through peer-to-peer transactions without relying on the government or banks. This situation implies that monetary transactions can be carried outside the purview of regulatory authorities like the government (Halaburda et al. 2020).

While cryptocurrency has enjoyed wide reception and adoption from financial consumers, particularly in Africa, the technology often used as a financial instrument has become a severe concern for governments and monetary authorities worldwide. Evidence has revealed that cryptocurrency is susceptible to a high level of volatility in its price, facilitates terrorism financing and money laundering, and encourages corruption in developing countries (Halaburda et al. 2020; Joseph et al. 2022; Hasan et al. 2022; Qiao et al. 2023; Xu et al. 2019). Due to their short history, limited regulatory oversight, and lack of established valuation models, these unique challenges from cryptocurrency mirror Knightian uncertainty affecting the region (Mao et al. 2023).

To this end, several efforts have been made to understand the interconnectedness between the cryptocurrency market and the traditional financial system, and two strands of literature focus on the correlation between cryptocurrency volatility and the traditional financial market. The first strand finds no significant correlation between cryptocurrency and traditional financial markets, concluding that cryptocurrency is a diversifier or hedge to volatility in the traditional financial system rather than a threat (Kliber et al. 2019; Shahzad et al. 2020; Majdoub et al. 2021). This finding is consistent with portfolio theory, which argues that investors could reduce investment risks by diversifying their portfolios across multiple asset classes with different risk and return characteristics. The second strand of literature found a moderate and growing correlation between cryptocurrency and the traditional financial market, and researchers have called for more cryptocurrency regulation to prevent the spillover effect (Iyer 2022).

Regarding whether the financial crisis in the cryptocurrency market spills into the traditional financial market, some literature has found little or no evidence of a spillover effect (Zhang et al. 2018; Kumah and Odei-Mensah 2021). Conversely, other strands of literature have found significant evidence to suggest that volatility in the two markets comoves and that financial crisis within the cryptocurrency space could spill into the traditional financial market (Omane-Adjepong and Alagidede 2019). For example, Symitsi and Konstantinos (2018) found a bidirectional spillover effect from the two markets, such that spills from the traditional market could impact the cryptocurrency market similarly, as a financial crisis from the cryptocurrency market could spill into the traditional financial market. This finding is consistent with financial integration theory, which suggests that financial markets are becoming increasingly interconnected and that shocks in one market can quickly spread to other markets.

Other studies, like Shahzad et al. (2021), found evidence of a spillover effect across the cryptocurrency market, especially during the COVID-19 pandemic. Qiao et al. (2023) also argued that the spillover effect between cryptocurrency coins, defi coins, and NFTs indicates integration across the different financial markets. Furthermore, Antonakakis et al. (2020) found evidence of a spillover effect between oil prices and other classes of financial assets, further validating the financial integration theory.

Most of these studies focused on establishing interconnectedness between cryptocurrency and advanced economies financial markets and currencies (Kliber et al. 2019; Shahzad et al. 2020; Zhang et al. 2018); very few studies (Kumah and Odei-Mensah 2021) focused on Africa. Based on the available evidence, no study has been dedicated to

Sub-Saharan Africa (SSA), despite the popularity of cryptocurrency in Africa and SSA. Ndemo (2022) of Brooking Institute, citing China analysis, argued that SSA received about 105.6 billion US dollars (USD) worth of cryptocurrency payments between July 2020 and June 2021, representing a 1200% increase. This growth is consistent with KuCoin's report that cryptocurrency would rise to about 2670% in Africa in 2022 (Hall 2022). Urinalysis also revealed that the African continent ranks above others regarding cryptocurrency adoption (Hall 2022; Joseph et al. 2022). Similarly, the African financial system is integrated mainly with other advanced and emerging market equity markets. This integration means that the financial crisis emanating from cryptocurrency could spill directly into the financial market or indirectly through the advanced and emerging market financial system (Hall 2022; Kumah and Odei-Mensah 2021). Kumah and Odei-Mensah (2021) found moderate and growing integration between the African financial system and cryptocurrency for medium-frequency data and a perfect integration for low-frequency data. This integration between both markets requires additional research to establish its degree and mechanism.

The present study aims to determine whether cryptocurrency and the Five largest African economies financial market are integrated and establish the degree and possible spillover effect between both markets. This study contributes to the extant literature by employing both dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH) and Baba–Engle–Kraft–Kroner (BEKK), which is a modified version of Bollerslev's (1986) GARCH model. This approach allows us to confirm the degree of spillover effects between the cryptocurrency market and the traditional financial market in the five largest African countries.

Our findings indicate a significant but low spillover effect from the cryptocurrency market to the African equity market. Additionally, we observed a weak but increasing positive correlation between these two markets, suggesting that investors can potentially use cryptocurrency as a hedge for traditional equity and consider it a diversification option in the long run. The rest of this paper is structured into four sections. Section "Literature review" will review related literature, and "Methodology" section will discuss the data and method of data analysis. The data will be presented and discussed in "Result and discussion" section, while "Conclusion and policy implication" section provides the conclusion and policy implications.

Literature review

Cryptocurrency as money, commodity, or financial instrument

The existing literature has long debated whether cryptocurrency is money, a commodity, or a financial instrument. If "money" must be issued by a sovereign country, qualifying cryptocurrency as money will not be easy; however, if we consider other attributes of money like a store of value, medium of exchange, unit of account, and standard for deferred payment, we can conjecture that cryptocurrency is not entirely different from conventional fiat currency (Wolla 2018; Levulytė and Šapkauskie 2021; Kinateder and Choudhury 2022). Some literature has argued that cryptocurrency should be categorized as currency and an alternative to fiat currency (Levulytė and Šapkauskie 2021; Fang et al. 2022). Similarly, literature has attributed cryptocurrency to a commodity like gold, given that its value is driven by supply and demand (Bouri et al. 2020).

For any instrument to be qualified as money, it must command general acceptability and be used as a medium of exchange; however, as Carrick (2016) argued, the extent of settlements an instrument must possess to be qualified as money is unclear. Furthermore, Levulytė and Šapkauskie (2021) pointed out that the number of settlement points should be high enough for an instrument to serve as a medium of exchange. For example, Bitcoin is enjoying significant growth in acceptance and usage in El Salvador (Gupta et al. 2020; Joseph et al. 2022).

Research has also suggested that cryptocurrency must gain wider acceptance as a means of global exchange to be qualified as money (Wolla 2018; Jareño et al. 2020). Whether cryptocurrency is money or a financial instrument, Joseph et al. (2022) argued that cryptocurrency is essentially a financial instrument because money is a highly liquid financial asset.

Available evidence has revealed that different countries have varying regulations regarding cryptocurrency. For instance, cryptocurrency is treated as money in countries like El Salvador and Japan (though not in the same context as El Salvador) for regulation. Countries like Australia treat cryptocurrency more like a commodity than a currency, and regulations guiding transactions in cryptocurrency are handled in the capital market. Similarly, countries like the USA, Germany, and Canada—with a high level of cryptocurrency adoption—treat cryptocurrency as financial instruments that can act as money or a commodity depending on the purpose of the transaction and the medium of the transaction (Levulytė and Šapkauskie 2021; Joseph et al. 2022).

Cryptocurrency market interconnectedness with traditional financial market

Several studies have used different methodologies to investigate the interconnectedness and spillover effect between cryptocurrency and traditional financial markets. This present study is interested in two specific strands of literature. The first focuses on determining whether cryptocurrency is a diversifier, hedge, or safe haven for the traditional financial system (Bouri et al. 2020; Okorie and Lin 2020; Kumah and Mensah 2020; Majdoub et al. 2021; Kozak and Gajdek 2021; Lavelle et al. 2021; Iyer 2022).

Several studies revealed that cryptocurrency acts as a diversifier to other stock portfolios and traditional financial instruments, given the low but positive correlation between instruments from the two markets (Okorie and Lin 2020; Majdoub et al. 2021; Kozak and Gajdek 2021; Lavelle et al. 2021). Most of these studies found cryptocurrency to have higher returns with higher risk. In contrast, studies like Iyer (2022) found that although the correlation between cryptocurrency and the traditional financial market was initially low, cryptocurrency correlation with the equity market has grown above 20%, making it difficult for cryptocurrency to function as a diversifier. For instance, Sebastian and Alenka (2020) investigated the correlation strength of cryptocurrency using daily frequency data and the Pearson correlation coefficient. They discovered that cryptocurrency could effectively serve as a tool for diversifying portfolio risk. Similarly, Pho et al. (2021) investigated the relative strength of Bitcoin and gold in diversifying risk associated with portfolio investment, determining that gold significantly lowers the risk of portfolio investment than Bitcoin because of its volatility. The implication is that investors with higher risk aversion would prefer gold to Bitcoin to diversify their portfolio investment.

Other literature has also found that cryptocurrency is a safe haven for the traditional financial market rather than a diversifier (Lavelle et al. 2021; Qarni and Gulzar 2021). For instance, Wang et al. (2020) examined the relationship between the stock market and the cryptocurrency market using the stock of 30 countries concerning cryptocurrency. They discovered that cryptocurrency did not effectively diversify the stock market for 30 countries; however, the study concludes that given the profitability of Bitcoin over the traditional stock in the long run, cryptocurrency (Bitcoin) can be effectively categorized as a haven investment. Conversely, Lavelle et al. (2021) investigated whether the relationship between Bitcoin and the aggregate cryptocurrency market and the "US stocks, bonds, the US dollar, commodities, real estate, and gold" act as a hedge, diversifier, or safe haven. The study concludes that no evidence suggests cryptocurrency is a strong or weak safe haven for the traditional market. In managing investment risk arising from market uncertainty, Lv et al. (2023) found evidence to support the conclusion that price diffusion ambiguity is critical in influencing investor portfolio decisions, especially during rare events, in both markets.

The second strand of literature aims to validate the degree of spillover effect between the cryptocurrency market and the traditional financial market. Most of these studies aim to establish the existence of spillover effects between the cryptocurrency market and the traditional financial market. If a spillover effect exists between the two markets, a financial crisis from the cryptocurrency market could spill into the traditional financial system. Given that cryptocurrency is highly unregulated, regulators may struggle to detect creeping crises within the eco-system, representing a danger to the health of the financial system (Kyriazis 2019; Liang et al. 2019; Shahzad et al. 2020; Frankovic et al. 2022; Lavelle et al. 2021).

Most studies, especially earlier ones, found little or no spillover effect from the cryptocurrency market to the traditional financial market (Zhang et al. 2018; Kumah and Odei-Mensah 2021); however, studies like Hsu et al. (2021) and Umar et al. (2021) found significant but moderate spillover effects of cryptocurrency volatility on the traditional financial market and call for greater market regulation. Other studies, such as Bouri et al. (2020) and Symitsi and Konstantinos (2018), found an asymmetric spillover effect on cryptocurrency. In other words, rather than a financial crisis spilling from cryptocurrency to the traditional financial market, it is a cryptocurrency receiving spillover effects from another financial market. However, Symitsi and Konstantinos (2018) found a bidirectional spillover effect between Bitcoin and the equity market, while the correlation between the two markets is weak, suggesting that the spillover might not be significant.

Within the context of the African market, Kumah and Odei-Mensah (2021) examined the interrelation between the cryptocurrency market and African stock markets using data from 13 African stock markets. Specifically, the study employed a wavelet-based method and frequency domain spillover index, determining that low integration exists between the market at higher frequencies but grows stronger at medium frequencies and perfectly integrates at low frequencies.

Conceptually, both the cryptocurrency and traditional equity markets are related and integrated; both involve buying and selling financial instruments for profit and raising capital in the form of initial offerings. Both markets experience varying volatility in asset returns, which prompts the use of cryptocurrency as a diversifier to traditional financial instruments (Bouri et al. 2020). Given the tendency of cryptocurrency to be used as an investment diversifier and integrating financial markets (Hassan et al. 2022), a possible spillover effect exists across the two markets.

Methodology

Model and research approach

In time series analysis, particularly one measuring volatility across the board, extra care is taken to prevent data breaks. For instance, most studies using the autoregressive conditional heteroskedasticity (ARCH) technique are driven by the fact that ARCH considers volatility and clustering, in that changes in asset prices follow subsequent changes in the asset price (Gillaizeau et al. 2019). Earlier studies on volatility often relied on the computation of standard deviation within a short time. Several issues accompany this method, including the period the standard deviation will be sampled.

This approach stems from the fact that volatility itself is a measure of future risk and when we take a forecast, we predict future volatility based on today's volatility (Engle 2004). The ARCH model is built assuming that volatility behaves dynamically (heteroskedastic), and ARCH is believed to be most effective when forecast variance differs across time. As Symitsi and Konstantinos (2018) argued, when financial instruments are based on their expected mean of return and variance, changes in the demand for the instrument must be connected to changes in the expected mean of the instrument returns and variance. For instance, in Eq. (1) in the ARCH model, y_t captures the changes in the endogenous variable within time. A typical full ARCH model is presented in Eq. (1).

$$y_t = \beta_0 + \beta_1 x_{1,t} + \beta_2 x_{2,t} + \beta_3 x_{3,t} + \mu_t \quad \mu_t \sim N\left(0, \sigma_t^2\right), \tag{1}$$

$$\sigma_t^2 = \Omega + \alpha_1 \mu_{t-1}^2. \tag{2}$$

From Eqs. (1) and (2), y_t represents the equation of conditional, while σ_t is the conditional variance equation. The ARCH (1,1) model was also modified with the generalized ARCH (GARCH) model. The ARCH model allows the "conditional variance to differ over time as a function of past errors, leaving the unconditional variance constant" (Symitsi and Konstantinos 2018). It also allows the conditional variance to depend on its lag; thus, Eq. (2) can be modified as in Eq. (3) to include conditional variance past value for a univariate GARCH case.

$$\sigma_t^2 = \Omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 \mu_{t-1}^2 \tag{3}$$

The literature has revealed that GARCH performed well in investigating volatility cases.

Dynamic conditional correlation GARCH (DCC-GARCH)

The study employed DCC-GARCH because it allows the examination of variables as their relationship evolves without assuming the relationship remains constant over time. By modeling time-varying correlations, the DCC-GARCH model provides a more accurate and flexible framework for investment optimization and financial risk management. The DCC-GARCH model is computationally efficient, making it possible to estimate large-scale models with many variables (assets). This approach is instrumental in portfolio management, where the number of assets can be large (Antonakakis et al. 2020). Moreover, the DCC-GARCH model allows for the estimation of asymmetric effects of volatility shocks, which is essential in capturing the effects of different market events. It provides a dynamic and sophisticated modeling that captures financial asset volatility and its dynamic correlations.

The DCC-GARCH method has also been used in literature to estimate the relationship or correlation between instruments in one market and those in another or within a specific market. DCC-GARCH was first used by Engle and Shepard (2001) to extend "Bollerslev's (1990) CCC-GARCH model" as a measure of the degree of correlation across market instruments. Gürbüz and Şahbaz (2021) argued that both DCC-GARCH and constant conditional correlation generalized ARCH (CCC-GARCH) are classes of correlation and conditional variance models. The critical difference is that DCC-GARCH is designed with the dynamic interaction of the variables. This study employed DCC-GARCH to examine the degree of correlation between returns in cryptocurrency and SSA stock returns.

We examine the dynamic conditional correlation of return in both cryptocurrencies "$(r_{1,t})$ and the SSA stock market $(r_{2,t})$ using DCC-GARCH (1,1). Let r_t be the vector of the two markets return series such that $r_t = (r_{1,t}, r_{2,t})^T$." Thus, the DCC-GARCH can be given as follows:

$$A(L)r_t = \omega + e_t \tag{4}$$

A(L) in Eq. (4) represents the lag polynomial of the market returns, ω represents the baseline value of the conditional mean of the market return (r_t), and e_t represents the vector of error terms. The underlying assumptions of DCC-GARCH are that the conditional return follows a normal distribution with zero means during the return conditional covariance, $H_t = E[r_t r_t^T]$, given as:

$$H = D_t R_t D_t \tag{5}$$

where D_t is N*N diagonal matrix $[diagonal \cdot (h_t)]^{1/2}$ of the conditional variance (σ_t^2) from the univariate GARCH (1,1). Similarly, R_t in Eq. (5) is an N*N standardized return of conditional correlations, where the error term (e_t) is given as $D_t^{-1} r_t$. The return is therefore given as follows:

$$R_t = \begin{bmatrix} 1 & q_{12t} & \dots & q_{1Nt} \\ q_{21t} & 1 & \dots & q_{2Nt} \\ \vdots & \vdots & \dots & \vdots \\ q_{N1t} & q_{N2t} & \dots & 1 \end{bmatrix} \tag{6}$$

Engle (2002) argued that two requirements are necessary when R_t is specified. The first is that H_t must be positive definite, meaning that R_t must also be positive definite. The second condition is that the elements of the R_t correlation matrix should be the sum of less than unity (1). As Engle (2002) suggested, to ensure the two conditions are fulfilled, R_t must be decomposed as in Eq. (7).

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{7}$$

Here Q_t represents the positive definite matrix of conditional covariance and variance of the white noise (e_t), and Q_t^{*-1} represents an inverted diagonal matrix. The Qt diagonal element square root is given in Eq. (8).

$$Q_t^{*-1} = \begin{bmatrix} 1/\sqrt{q_{11t}} & 0 & \cdots & 0 \\ 0 & 1/\sqrt{q_{22t}} & \cdots & 0 \\ \vdots & \vdots & \cdots & \vdots \\ 0 & 0 & \cdots & 1/\sqrt{q_{NNt}} \end{bmatrix} \tag{8}$$

Thus, the DCC-GARCH (1,1) is given as:

$$Q_t = \omega + \alpha e_{t-1} e_{t-1} e_{t-1}^T + \beta Q_{t-j} \tag{9}$$

where "α" and "β" are non-negative scalars to ensure positive definiteness in Q_t, and $(1-\alpha-\beta)\overline{Q}$ represents the weighted average of the unconditional covariance matrix $\overline{Q}$. Similarly, $\overline{Q}$ represents the unconditional covariance matrix of e_t. The interactive modification of Eq. (9) yields the DCC-GARCH correlation shown in Eq. (10).

$$Q_t = \left(1 - \sum_{i=1}^{P} \alpha_i - \sum_{j=1}^{Q} \beta_j\right)\overline{Q} + \sum_{i=1}^{P} \alpha_i e_{t-i} e_{t-i}^T + \sum_{j=1}^{Q} \beta_j Q_{t-j} \tag{10}$$

Our DCC-GARCH equation is therefore given as:

$$p_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} \tag{11}$$

The BEKK model for estimating the spillover effect from cryptocurrency to the traditional market

Engle and Kroner (1995) introduced the BEKK model, the modified version of Bollerslev's (1986) GARCH model. BEKK is a multivariate GARCH model that permits examining spillover among two or more variables. The aim is to parameterize the multivariate variable, allowing positive definiteness in the process and facilitating "complicated interaction" within the series (Engle and Sheppard 2001). This approach allows us to examine how shocks in one market spill over to another.

We select BEKK because it can capture more complex patterns of volatility clustering and spillovers than the standard GARCH model. This ability is crucial in the financial market, where volatility in one instrument impacts the volatility in another, and understanding these interdependencies is crucial for risk management and investment optimization. The BEKK-GARCH model provides a more flexible, efficient, and accurate measure for modeling the volatility of financial assets, which is instrumental in understanding spillover effects across financial markets. Therefore, we can specify the estimated multivariate conditional variance of GARCH (1,1) in Eq. (12),

$$H_t = C^T C + D^T e_{t-1}^2 D + C^T H_{t-1} B \tag{12}$$

where H_t is the multivariate conditional variance of BEKK-GARCH, and C represents a N*N upper triangular matrix of constants. D and B represent an N*N matrix parameter, and e_{t-1} represents the matrix of the error terms with a $t-1$ time dimension. Equation (12) can be rewritten as follows:

$$H_t = M_t + A_t^T e_{t-1} * e_{t-1}^T A_t + B_t^T H_{t-1} B_t \tag{13}$$

where A_t, M_t, and B_t are the coefficients of the estimated BEKK-GARCH models in Eqs. (14)–(17):

$$H_t = \left(h_{i,t}\right) \quad where \quad i = 1, 2, 3, \ldots\ldots, N \tag{14}$$

$$M_t = \left(C_{i,j,t}\right) \quad where \quad i, j = 1, 2, 3, \ldots\ldots, N \tag{15}$$

$$A_t = \left(\propto_{ij,t}\right) \quad where \quad i, j = 1, 23, \ldots\ldots, N \tag{16}$$

$$B_t = \left(\beta_{ij,t}\right) \quad where \quad i, j = 1, 2, 3, \ldots\ldots, N \tag{17}$$

Thus, $\propto_{ij,t}$ and $\beta_{ij,t}$ are vital in determining the spillover effect from the cryptocurrency market to other traditional markets.

Data and sources

The study employed time series data on the daily price movement of the three most traded cryptocurrencies (Bitcoin, Ethereum, and Tether) and the five largest economies in African stock market indices (Nigeria, South Africa, Egypt, Morocco, and Kenya). The data are sourced from Investing.com[1] and Yahoo Finance,[2] covering January 1, 2017, to December 31, 2021. The chosen period encompasses the time of increased cryptocurrency market participation, significant price fluctuations, notable regulatory changes, and major global events like COVID-19. The daily data spans 5 days a week (Monday to Friday), accounting for weekends when stocks are not traded. The closing price return is calculated as the first difference in the log prices defined as follows:

$$R_t = \ln\left[\frac{P_t}{P_{t-1}}\right]100 \tag{18}$$

where P_t and P_{t-1} represent the daily closing stock at time t and $t-1$.

Result and discussion

Descriptive and preliminary

In the result, "d" represents returns in the data series. For instance, DBTC implies a return on BTC, as calculated in Eq. (18). Table 1 summarizes the descriptive statistics, stationarity, and diagnostic tests, revealing that the cryptocurrency market has the highest return between the two financial markets, with Ethereum (eth = 0.00298) topping the chat. Within the African stock markets, South African stocks yield the highest return (dS_Africa = 0.00038), closely followed by the Nigerian stock market. Regarding the

[1] https://ng.investing.com/.

[2] https://finance.yahoo.com/.

Table 1 Descriptive statistics, unit root, and residual diagnostic test

	DBTC	DETH	DXRP	DNIGERIA	DSAFRICA	DEGYPT	DKENYA	DMOROCCO
Mean	0.00192	0.00298	0.00083	0.00030	0.00038	0.00023	0.00018	0.00007
Median	0.00147	0.00194	0.00045	0.00064	−0.00004	0.00023	0.00031	0.00011
Maximum	0.17742	0.23077	0.44899	0.09057	0.06048	0.03812	0.23653	0.05305
Minimum	−0.49728	−0.58964	−0.54102	−0.10450	−0.05033	−0.05672	−0.09477	−0.09232
Std. Dev	0.03958	0.05250	0.06205	0.01139	0.00941	0.00944	0.01433	0.00843
Skewness	−1.57430	−1.40810	0.05559	−0.57754	0.44405	−0.61122	2.87691	−2.24234
Kurtosis	24.8660	18.6102	17.3183	14.3870	7.8922	7.4029	65.7159	35.4757
Jarque–Bera	25,174.5	12,978.8	10,575.9	6757.3	1275.2	1077.1	204,599.3	55,441.0
Probability	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**	0.000**
ADF @Level	−15.94**	−13.99**	−13.22**	−13.75**	−16.07**	−15.67**	−18.12**	−13.86**
PP @ Level	−15.96**	−14.08**	−13.21**	−13.80**	−16.09**	−15.54**	−18.09**	−12.74**
ARCH effect	457.4** (0.000)	132.9** (0.000)	82.7** (0.000)	234.3** (0.000)	820.4** (0.000)	47.8** (0.000)	931.4** (0.000)	42.3** (0.000)
ARCH-LM (5)	25.3** (0.000)	91.4** (0.000)	62.4** (0.000)	83.3** (0.000)	304.4** (0.000)	47.8** (0.000)	5.4** (0.000)	42.4** (0.000)
Observations	1238	1238	1238	1238	1238	1238	1238	1238

NB: ** and * equal 1% * = 5% significance levels, respectively; p values are in parentheses

riskiness of the financial instrument, as expected, the cryptocurrency market is riskier than the African market, as revealed by the standard deviation. Ripple (XRP = 0.062) appears to be the riskiest financial instrument in the cryptocurrency market, while Nigeria stock (dNigeria = 0.011) is the riskiest among African stocks.

The extent of volatility in both markets shows that the considerable difference between the minimum and maximum values indicates volatility in returns from the two markets, which the large leptokurtic distribution of the series confirms. The significant Jarque–Bera statistics reaffirm that none of the series is normally distributed. The ARCH effect test confirms the presence of heteroskedasticity, which is significant at a 1% level, indicating the time-varying properties of the return variance. We use the augmented Dickey–Fuller (ADF) and Philip Perron tests to determine the presence of unit roots in the series. The result in Table 1 revealed that all the series returns are stationary at a 1% significance level.

Figures 1 (series trend) and 2 (series returns) further reveal the volatility in the series. The trend data in Fig. 1 revealed clear-cut volatility in the two markets, with volatility in cryptocurrency most significant during the COVID-19 pandemic. Morocco and Kenya stocks appear to be the most volatile within the five largest African countries, while South Africa stocks look the most stable and predictable. Figure 2 captured the returns in both markets, clearly revealing evidence of volatility and volatility clustering. The figure revealed that volatility persistence is most prominent in Nigeria's and Kenya's stock markets compared to regional stocks. The finding is consistent with the findings of Dahiru and Taro (2017), who noted significant volatility in Nigeria's stock market above other stocks in the region. This result in Table 1 and Fig. 1 is consistent with the finding of Joseph et al. (2022), who found the cryptocurrency market to be the most volatile financial asset class. This result surpasses the volatility witnessed in the traditional equity market. Most retail investors within the space rarely understand the magnitude of risk involved in cryptocurrency.

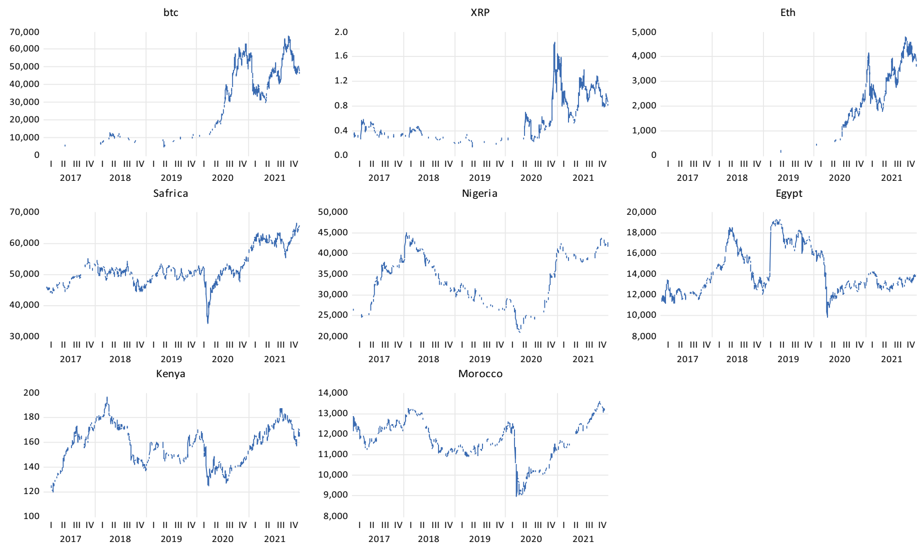

Fig. 1 Trends in cryptocurrency and African stock indices

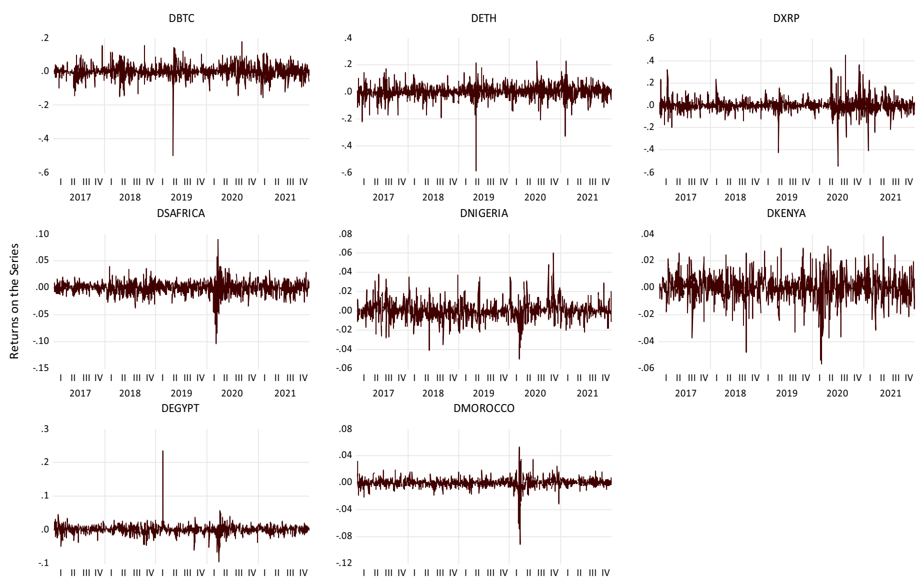

Fig. 2 Cryptocurrency and African stocks returns

Table 2 captures the correlation between the series returns to establish the absence of multicollinearity. The correlation matrix revealed a positive but weak correlation between the returns in the cryptocurrency market and the African stocks. Specifically, South Africa is most correlated with the cryptocurrency market, followed by Nigeria and Kenya. Given the positive correlation, volatility in cryptocurrency market returns moves with volatility in the African market.

Table 2 Correlation matrix of cryptocurrency and African stocks

	DBTC	DETH	DXRP	DSAFRICA	DNIGERIA	DKENYA	DEGYPT	DMOROCCO
DBTC	1							
DETH	0.683	1						
DXRP	0.475	0.525	1					
DSAFRICA	0.274	0.331	0.201	1				
DNIGERIA	0.263	0.276	0.190	0.170	1			
DKENYA	0.274	0.261	0.010	0.233	0.295	1		
DEGYPT	0.093	0.081	−0.041	0.058	0.139	0.216	1	
DMOROCCO	0.111	0.112	0.096	0.296	0.278	0.070	0.068	1

Estimation of BEKK-GARCH

Having satisfied the primary conditions for applying the BEKK-GARCH model and the DCC-GARCH model, we estimated the BEKK-GARCH model shown in Table 3. To estimate the spillover effect, we first estimated the bivariate BEKK to capture its shocks and volatility as in A(11), A(22), B(11), and B(22). Furthermore, the study estimated the cross-volatility spillover effect as in A(12), A(21), B(12), and B(21). The A matrix (A11–A22) represents the ARCH, while the B matrix (B11–B22) represents the GARCH effect.

The data in Table 3 for the case of Bitcoin/South Africa stock (A11 = 0.426(0.000)) revealed that the shocks primarily influence Bitcoin's past shocks in its current price. Specifically, the estimate of A11 of 0.426 in BTC/Africa implies that 43% of the structural breaks in Bitcoin persist until the next day. Similarly, the BTC/Africa (A22 = 0.467(0.000)) implies that South Africa's current price shocks are primarily influenced by its past price volatility, accounting for about 47%. The GARCH effects (B11–B22) revealed, among others, for the case of BTC/S-Africa that BTC volatility is influenced by its past volatility (B11 = 0.29(0.003)), and African stock is influenced by its past volatility (B22 = 0.629(0.04)). As revealed in Table 3, most of the series revealed that their current shocks and volatility are influenced mainly by their past shocks and volatility.

Like A11 and A22, A21 and A12 consider the effect of the structural break across the markets, while B21 and B12 also examine the volatility ability between cryptocurrency and the African stock market. Most of the cross-sectional results reveal a unidirectional relationship between cryptocurrency and the African stock market, consistent with Frankovic et al. (2022) for Australia. Table 3 reveals that cross-market volatility spillover originates from the cryptocurrency market rather than the African stock markets. This result implies that structural breaks originating from the cryptocurrency market (Bitcoin, in the first case) will affect volatility in the equity market. B21 has a significant impact in all cases, meaning that none of the African stock markets is strong enough to spillover volatility to the cryptocurrency market. Kenya stock appears significant at 10%, with as small as spilling 1% of its volatility to BTC; however, Table 3 shows that the cryptocurrency market (B12) is significant in some cases, like South Africa, Nigeria, and Kenya. These results indicate the tendencies of volatility in the cryptocurrency market to spill to the equity market in these countries, although in most cases, the percentage influence is negligible and below 10%.

Table 3 BEKK-GARCH model

	BTC					ETH					XRP				
	S-Africa	**Nigeria**	**Kenya**	**Egypt**	**Morocco**	**S-Africa**	**Nigeria**	**Kenya**	**Egypt**	**Morocco**	**S-Africa**	**Nigeria**	**Kenya**	**Egypt**	**Morocco**
C11	0.432 (0.000)**	64.76 (0.000)**	0.250 (0.003)**	0.357 (0.055)*	0.432 (0.046)*	0.539 (0.000)**	0.452 (0.000)**	0.6472 (0.000)**	0.452 (0.027)*	0.532 (0.038)*	0.439 (0.030)*	0.067 (0.000)**	0.545 (0.042)*	0.967 (0.023)*	0.283 (0.080)*
C12	0.042 (0.081)*	0.002 (0.102)	0.001 (0.052)	0.046 (0.056)*	0.011 (0.010)**	0.042 (0.051)*	0.004 (0.054)*	0.018 (0.021)*	0.001 (0.065)	0.063 (0.551)	0.012 (0.031)*	0.040 (0.022)*	0.041 (0.138)	0.082 (0.022)*	0.013 (0.217)
C22	0.087 (0.000)**	0.012 (0.000)**	0.003 (0.180)	0.034 (0.00))**	0.092 (0.008)**	0.042 (0.083)	0.442 (0.001)**	0.042 (0.021)*	0.042 (0.03)*	0.436 (0.021)*	0.044 (0.022)*	0.027 (0.016)*	0.045(0.042)*	0.049 (0.022)*	0.052 (0.028)*
A11	0.426 (0.000)**	0.422 (0.000)*	0.346 (0.000)**	0.222 (0.000)**	0.435 (0.001)**	0.396 (0.030)**	0.178 (0.030)*	0.256 (0.003)**	0.378 (0.000)*	0.356 (0.003)*	0.183 (0.021)*	0.285 (0.031)*	0.258 (0.040)**	0.285 (0.031)*	0.258 (0.018)*
A21	0.083 (0.523)	0.005 (0.734)	0.002 (0.724)	0.042 (0.567)	0.038 (0.537)	0.056 (0.723)	0.052 (0.632)	0.042 (0.562)	0.052 (0.500)	0.042 (0.652)	0.042 (0.174)	0.005 (0.385)	0.021 (0.378)	0.065 (0.293)	0.034 (0.533)
A12	0.051 (0.020)*	0.054 (0.040)*	0.042 (0.064)*	0.004 (0.840)	0.008 (0.346)	0.069 (0.034)*	0.071 (0.028)*	0.046(0.054)*	0.001 (0.284)	0.046 (0.547)	0.068 (0.232)	0.053 (0.098)	0.064 (0.029)	0.053 (0.533)	0.064 (0.828)
A22	0.467 (0.020)**	0.487 (0.040)**	0.576 (0.003)*	0.510 (0.095)	0.376 (0.430)	0.541 (0.040)**	0.781 (0.038)*	0.561 (0.050)**	0.571 (0.040)*	0.494 (0.030)*	0.751 (0.031)*	0.671 (0.054)*	0.722 (0.025)	0.633 (0.086)	0.661 (0.134)
B11	0.292 (0.003)**	0.117 (0.010)**	0.534 (0.030)*	0.165 (0.007)**	0.432(0.002)**	0.539(0.000)**	0.402 (0.000)*	0.438(0.000)**	0.182(0.000)**	0.532 (0.030)*	0.354 (0.040)*	0.087 (0.00)*	0.545 (0.083)	0.067 (0.042)	0.511 (0.043)
B21	0.003 (0.678)	0.001 (0.190)	0.001 (0.089)*	−0.272 (0.090)	0.003 (0.491)	0.032 (0.761)	0.048 (0.451)	0.025 (0.551)	0.009 (0.674)	0.046 (0.971)	0.021 (0.431)	0.028 (0.792)	0.089 (0.138)	0.047 (0.752)	0.033 (0.138)
B12	−0.120 (0.039)*	0.068 (0.045)*	0.098 (0.021)**	0.008 (0.458)	−0.098 (0.871)**	0.028 (0.023)**	0.022 (0.050)*	0.122 (0.082)	0.154 (0.509)	0.004 (0.622)	0.053 (0.134)	0.008 (0.231)	0.154 (0.043)*	0.008 (0.531)	0.005 (0.743)
B22	0.629 (0.040)**	0.5928 (0.050)*	0.153 (0.034)**	0.468 (0.060)*	0.338 (0.080)	3.266 (0.000)*	0.518 (0.050)*	0.351 (0.041)*	0.428 (0.024)*	0.323 (0.000)*	0.443 (0.040)*	0.144 (0.022)*	0.282 (0.030)*	0.138 (0.120)	0.278 (0.250)

Significant at: **1 and *5 percent levels; p values given in parentheses; the results of the estimated mean equation and constants of each variance are not reported for the sake of brevity, while A's and B's are the ARCH and GARCH co-efficient of the BEKK

The finding is consistent with Hsu et al. (2021) and Umar et al. (2021), who found a moderate spillover effect. The finding is also partially consistent with the findings of Bouri et al. (2020) and Symitsi and Konstantinos (2018), who found a bidirectional spillover effect between cryptocurrency and the capital market in the advance market; however, this present study did not find evidence of spillover from African market to cryptocurrency. The finding is also consistent with the financial integration theory and contagion theory that financial markets are becoming more integrated and contagious, such that shocks in one market easily transmit to another.

This spillover effect can be attributed to several plausible factors. First, global financial integration significantly transmits fluctuations and shocks from the global cryptocurrency market to regional African markets. Additionally, the increasing adoption of cryptocurrency in Africa, as highlighted by Kumah and Odei-Mensah (2021), contributes to this spillover effect. Furthermore, the rapid growth of Fintech in the region adds to the influence of cryptocurrencies on traditional markets. Finally, macroeconomic crises in Africa have driven many small investors to cryptocurrencies to safeguard against exchange rate crises and escalating regional inflation.

DCC-MGARCH correlation

This study supports the evidence from the BEKK-GARCH with DCC-GARCH, which is popular in the literature, to explore the degree of correlation between volatility and shocks across the markets. DCC-GARCH is driven by its intuitive ability to capture the correlation between volatility across markets and demonstrate whether volatility in one market accompanies volatility in another. Table 4 presents the DCC-GARCH results. The intercept (constant) in the model is represented by "δ," where we captured the impact of previous structural shock (the ARCH effect) by the term "α" (alpha); the previous volatility effect (the GARCH effect) is captured by the "β" (beta). While the ARCH effect incorporates the short-run volatility spillover from the cryptocurrency market, the GACRH effect (β) captures the long-run volatility spillover effects from the cryptocurrency market to the African equity market. Similarly, Dcc(θ_1) and Dcc(θ_2) represent the DCC conditional correlation estimates.

Our result revealed that all the parameter estimates are significant at a 1% significance level. Second, volatility spillover from the cryptocurrency market to the SSA equity market is lower in the short-run, though significant. In most cases, the high value of GARCH effects indicates the persistence of spillover effects from the cryptocurrency market to the African equity market. Again, the sum of the estimates of ARCH and GARCH effect ($\alpha + \beta < 1$) is less than one in all cases. Adding both is usually lower than 0.7, indicating lower volatility persistence.

Similarly, the Dcc($\boldsymbol{\theta}_1$) and Dcc($\boldsymbol{\theta}_2$t) that captures the conditional correlation between cryptocurrency and the African stock market is significant at a 1% significance level. This result implies short- and long-run volatility spillover from cryptocurrency (Bitcoin, Ethereum, and Ripple) to African stocks. For instance, in the case of Bitcoin, $\boldsymbol{\theta}_1 = 0.0361$, implies that short-run volatility spillover from the cryptocurrency market to the African market is very low and less than 4%. Furthermore, $\boldsymbol{\theta}_2 = 0.6038$, indicates significant volatility spillover from Bitcoin to the African market in the long run, suggesting the existence of both markets' integration, especially in the long run, which is consistent with

Table 4 Dynamic conditional correlation GARCH (DCC-MGARCH)

	Bitcoin (BTC)	Ethereum (ETH)	Ripple (XRP)
S_Africa			
δ	0.0023 (0.0125**)	0.0024(0.1672)	0.0054(0.0291**)
α	0.1697 (0.0032***)	0.1659(0.0092***)	0.1655(0.0017***)
β	0.5521 (0.0003***)	0.5521(0.0381**)	0.5682(0.0017***)
Nigeria			
δ	0.0002 (0.0021***)	0.0001(0.0379**)	0.0004(0.0753*)
α	0.2836 (0.0266**)	0.2836(0.0481**)	0.2888(0.0371**)
β	0.5234 (0.0000***)	0.5234(0.0000***)	0.4634(0.0000***)
Kenya			
δ	0.0002 (0.0026***)	0.0002(0.0023***)	0.0001(0.0093***)
α	0.2616(0.0038***)	0.2617(0.0072***)	0.2737(0.0002***)
β	0.5473 (0.0000***)	0.5482(0.0000***)	0.4459(0.0000***)
Egypt			
δ	0.0003(0.0052***)	0.0053(0.0282**)	0.0053(0.0282**)
α	0.2634(0.0427**)	0.35884(0.0227**)	0.3684(0.0458**)
β	0.3567(0.0281**)	0.3367(0.0241**)	0.2667(0.0541**)
Morocco			
δ	0.0015(0.0497**)	0.0005(0.0477**)	0.0001(0.1954**)
α	0.1286(0.0156***)	0.2286(0.0156***)	0.1886(0.0131***)
β	0.6762(0.0000***)	0.5592(0.0000***)	0.6442(0.0000***)
DCC_BTC			
Dcc($\boldsymbol{\theta}_1$)	0.0361 (0.0092***)	0.0138(0.0624*)	0.00329(0.0692*)
Dcc($\boldsymbol{\theta}_2$)	0.6038(0.0001***)	0.6893(0.0000***)	0.6668(0.0008***)

Kumah and Odei-Mensah (2021). The moderate correlation between volatility in the two markets is consistent with the works of Iyer (2022), Ghorbel et al. (2021), and Pho et al. (2021) in advance markets. This finding has significant implications for African countries, as greater integration between both markets amplifies the risks associated with cryptocurrency on the region's financial system, especially without appropriate protection policies. Additionally, increased volatility and shocks from the cryptocurrency market can affect investor confidence and overall financial market stability in the region. While cryptocurrency can serve as a hedge in the short run and a diversifier in the long run, the volatile nature of the asset class can threaten the region's financial stability as the integration between the two markets deepens. Similarly, adding both is less than unity (i.e., $\alpha + \beta < 1$). Figures 3, 4 and 5 further capture the DCC conditional correlation between cryptocurrency markets and African stocks.

The conditional correlation of cryptocurrency and the African stock market revealed, among other things that there is high volatility across the two markets, indicating that investment portfolios change with different periods. Figure 3 reveals that the conditional correlation between Bitcoin and the African market is the most volatile and correlated with African stocks. The high correlation and volatility in the conditional correlation graph of Figs. 3, 4 and 5 indicate contagion between markets. Another key feature is the clustering in the volatility, which signifies that contagion is relatively nonexistent in the short run but persists in the long run between the two markets.

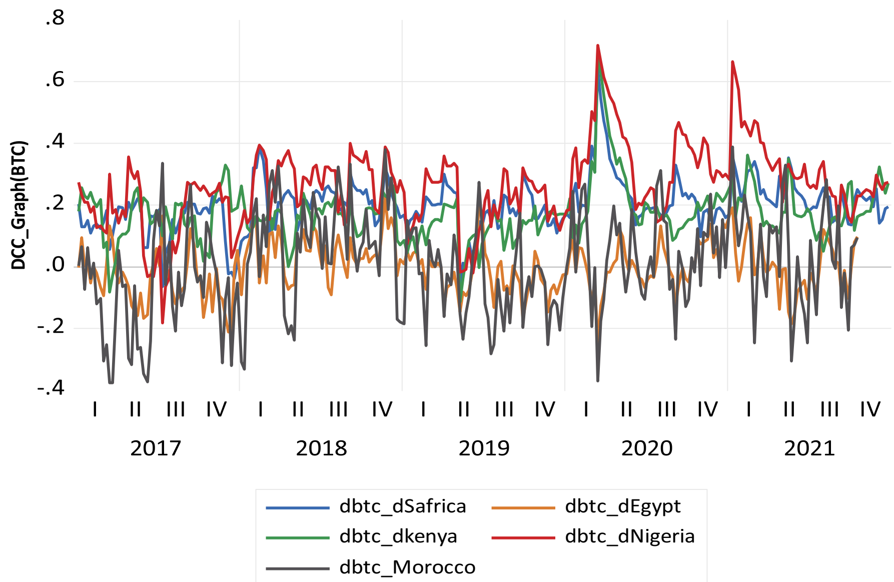

Fig. 3 DCC Graph Bitcoin to African stock

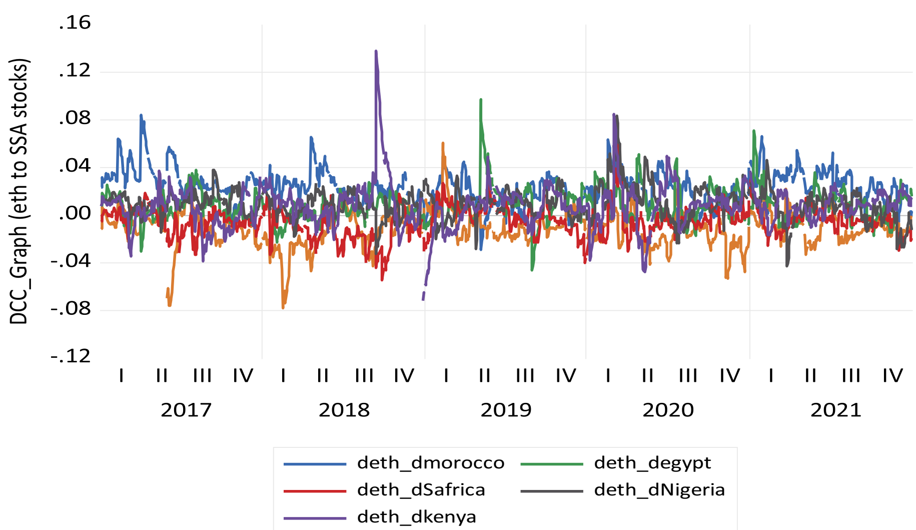

Fig. 4 DCC Graph Ethereum to African stock

Conclusion and policy implication

This study examined the policy implication of cryptocurrency on the largest five African financial markets. In particular, we employed BEKK-GARCH and DCC-GARCH to investigate possible volatility spillover effects from the cryptocurrency market to the African financial market. This study used daily time series data from January 1, 2017, to December 31, 2021, where the returns of each series were only used for the analysis.

Our study revealed, among other things that significant volatility and shock spillover effects exist from the cryptocurrency market to the African financial markets; however, the evidence is insufficient to suggest a spillover effect from cryptocurrency to Egypt and Morocco equity markets, at least in the short run. We found evidence of

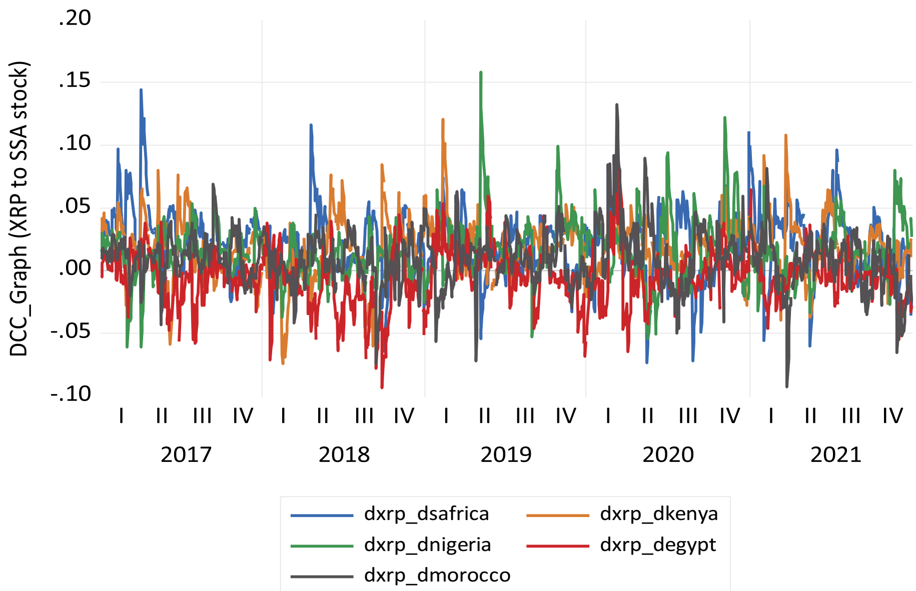

Fig. 5 DCC Graph Ripple (XRP) to African stock

a minimal but growing spillover effect from cryptocurrency to the equity market in South Africa, Nigeria, and Kenya. In contrast, our results show no evidence to support the spillover effect from any African equity markets to cryptocurrency, indicating a unidirectional spillover effect between the two markets. We found a moderate to weak conditional correlation between both markets' volatility. The conditional correlation between both markets is stronger in the case of Bitcoin than in any other cryptocurrencies. Our finding also supports the notion that positive shocks and volatility are more contagious than adverse shocks.

For financial investors, our findings imply that the weak positive spillover and correlation between cryptocurrency and African stocks in the short run indicates that cryptocurrency can be used as a hedge to traditional equity. In contrast, considering the high positive correlation between the two financial asset classes, it could be used as a diversifier in the long run.

To the public and regulatory authorities in Africa, our study first revealed evidence of cryptocurrency's spillover effect on the traditional equity market in Africa. The implication is that regulatory authorities in Africa must partner with other international bodies to develop a regulatory framework to monitor the activities in the cryptocurrency space. Given the moderate to high correlation and integration in both markets' volatility in the long run, consistent with contagion and financial integration theories, more research and attention should be directed at understanding the growing integration between both markets. Furthermore, future studies could focus on comparing emerging and developing markets while maintaining similar objectives.

Abbreviations

BEKK	Baba–Engle–Kraft–Kroner
DCC	Dynamic conditional correlation
ARCH	Autoregressive conditional heteroskedasticity
SSA	Sub-Saharan Africa

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TEJ; AJ; JCO; DBL: Conceptualization, Methodology, Software, Validation, Formal analysis, Data Curation, Writing—Original Draft, Writing—Review & Editing, AJ: Supervision. AJ; TEJ; JCO; DBL, Validation, Writing—Review & Editing. All authors read and approved the final manuscript.

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