VOLATILITY SPILLOVERS ACROSS BITCOIN, STOCK, AND EXCHANGE RATES MARKETS

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Abstract

Globalization of the world economy has ensured flexible exchange rate mechanisms are executed thereby creating interdependence between and within the stock, digital currency and foreign exchange markets. Unfortunately, in emerging African countries, few studies conducted on volatility spillovers failed to adequately establish the significance and pattern of volatility spillover effects between returns on Bitcoin, stock markets and exchange rates. Hence, the need for this study using the diagonal-BEKK approach. While Botswana had an inverse pattern of spillovers, Tunisia had a positive pattern. Bitcoin and stock prices both had volatility spillover effects between each other in South Africa. South Africa and Namibia were the only countries with significant volatility spillovers between stock prices and exchange rates. In countries like Kenya that had significant cross-volatility from the stock market to the exchange rate, news about the stock market stimulated reactions from investors that impacted volatility within the market. This volatility creates a multiplier effect on other economic circles of influence, depending on whether reactions are favourable to the market or unfavourable. When volatility in the Kenyan stock market rises, exchange rates in the next period experience less volatility, against the common theory that investors' actions that cause volatility in the stock market cause withdrawal of investments.

Keywords: Volatility Spillover, Crypto-Currency, Stock Market, Bitcoin, Emerging African Countries, BEKK-GARCH

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1. INTRODUCTION

Investments in the non-real sector of any nation have major holdings in the financial market. As a result, monetary policy becomes essential in the state of such investments within respective geographical boundaries. Exchange rates, stock prices, and digital currencies are characterized by fluctuations (Abanikanda, 2022; Dumitrescu et al., 2023). These fluctuations referred to as volatility do not just occur within each of the variables, the study proposed that volatility of one of the variables could influence the volatility of another since investors try to be aware of the latest news in the market and could make certain decisions regarding their investments as a result of information available to them. The study has its focuses on volatility spillover transmission between exchange rates, and Bitcoin and how these spillovers influence stock prices in twenty emerging countries. Umoru (2013) reported the exchange rate as a highly sensitive variable that predicts the direction and speed of economic activities. An essential part of the global economy of each country is the stock market. Bitcoin is a variant of cryptocurrency, and it is a digital currency.

Bitcoin may be stated to be the most popular and valued cryptocurrency with records of exchange value worth over $60,000 in a period (Wu et al., 2022). As a store of value, its digital characteristic implies that the currency is transferred via encryption mechanisms into personalized wallets. Bitcoin volatility would mean fluctuations in the Bitcoin returns presented as appreciation when the value increases or depreciation when the value falls against the United States (US) dollar. With Bitcoin as a store of wealth and a form of investment, investors may be interested in adding it to their portfolio to diversify unsystematic risks (that is risks that arise from the individual investments that make up a portfolio). Investors may also be interested in Bitcoin investments given the initial exponential growth in value it recorded in past years. Rising or anticipated rising values of Bitcoin are likely to cause investors to pull out some of their investments in the stock market with slower returns to benefit from the abnormal returns that would emanate from a spike in the value of this cryptocurrency. This activity could impact stock prices given the reduced demand for stocks in the market.

Globalization of the world economy has ensured flexible exchange rate mechanisms are executed in both developed and African countries thereby creating interdependence between and within the stock, digital currency and foreign exchange markets (Manasseh et al., 2019; Aydemir & Demirhan, 2009). African countries fall under the developing cadre and it is a combination of oil and non-oil sectors. Stock markets as part of the non-oil sector reportedly have a bearing on economic growth because it helps in the allocation of collected funds to productive sectors of the economy. It serves as a medium to provide capital for financing investment and a device to reflect the well-being of the economy through the price of securities. Stock prices are the prices at which investors buy and sell shares of companies at the stock exchange market to the forex market. The prices of securities as revealed by the efficient market hypothesis fully reflect the information set available to investors although, researchers have shown that the prices of securities do not show the reality of the market as a result of the influence of many other factors on stock prices (Nasiru et al., 2021; Thai Hung, 2020; Nguyen et al., 2019). Unfortunately, the ability of African stock markets to mobilize the desired funds through the issuance of equity and allocation of collected funds to useful sectors for productive activities is however affected by the problem of low liquidity, few listed companies on the stock exchange and low market capitalization. These problems may not be unconnected with the volatility in Bitcoin return and returns from foreign exchange markets as well as some macroeconomic variables that affect stock prices thereby discouraging existing investors and also unable to attract new investors to the market.

Moreover, African countries in their emerging stage of development have largely a lot of weak capital markets. With the infantile capital market, dividend yield which is a component of dividend payout and stock prices could be affected either, by volatility in the exchange rate or Bitcoin thereby hampering investment in the stock market as investors would be discouraged when the yields on investment are not robust as expected. With a fall in investment in the stock market, the efficacy of monetary and fiscal policies as tools for regulating the economy would be questioned. Also, in emerging African countries with underdeveloped capital markets, very few studies have been conducted to establish the one that matters most between own-volatility and cross-volatility spillovers in Africa. These few types of research have not been able to adequately establish the significance and pattern of volatility spillover effects between returns on Bitcoin, stock markets and exchange rates in emerging African countries. The research questions emanating from the problem identified are as follows:

RQ: To what extent does the volatility in exchange rates affect stock prices, and to what extent does the volatility in Bitcoin affect stock prices, to what extent does lag volatility affect stock prices?

Accordingly, our objective is to examine the rate of volatility spillover between returns on exchange rates, Bitcoin and stock prices in Africa.

The study is significant as it contributes empirically to volatility spillover between exchange rates and Bitcoin, Bitcoin and stock prices, and exchange rates and stock prices in Africa. The study will help policymakers to understand better the behaviour of stock prices concerning exchange rates and Bitcoin volatility. In particular, the study contributed to the fact that exchange rate volatilities may spill more to commodity prices, interest rates and treasury bills rather than long-term funding platforms such as the stock market. The sensitivity of exchange rates and their volatile nature in international transactions has made it an essential study. Also, its stability (rise and fall) is stated to influence stock prices. In this regard, the policy findings of the study established that investments involving exchange rates, stocks and Bitcoin will create a good diversification of portfolios. The diversification is evident because they each have independent volatilities, reducing the embedded risk.

Another relevance and contribution of the study is that it quantifies and provides a description of the patterns of volatility spillovers among exchange rates, Bitcoin and stock prices. Specifically, the study demonstrated the presence of cross-volatility between the stock market and exchange rates in Tunisia. By implication, Tunisia's exchange rate is sensitive to Bitcoin news, whereas, in South Africa and Namibia, volatility spillover is significant and negative. This further established that news from stock markets stimulates and influences exchange rate fluctuations. Also, the study established that in South Africa, Bitcoin and stock prices displayed cross-volatility with the finding that South African investors likely find the risk in investments in Bitcoin tolerable causing stock market decisions to be impacted by Bitcoin fluctuations of past periods.

Also, the study found that for countries like Kenya that had significant cross-volatility from the stock market to the exchange rate, news about the stock market stimulated reactions from investors that impacted volatility within the market. This volatility creates a multiplier effect on other economic domains, depending on whether responses are favourable to the market or unfavourable. When volatility in the Kenyan stock market rises, exchange rates in the next period experience less volatility, against the common theory that investors' actions that cause volatility in the stock market will cause the withdrawal of investments and similar fluctuation responses in exchange rates. Moreover, it has been reported that cryptocurrency and stock markets are favourably connected (Bakas et al., 2022; Bao et al., 2022; Wu et al., 2022; Palazzi et al., 2021; López-Cabarcos et al., 2021; Bouri et al., 2021). As a result, volatility in the crypto stock market could influence stock market performance. It is, therefore, imperative that we recently researched the link between returns from exchange rates, Bitcoin and stock markets. Hence, the study found that the returns on stock which are reflected through prices are highly volatile based on the instability of the returns in exchange rate and Bitcoin markets of South Africa and Namibia. The economies of these countries are confronted by macroeconomic instabilities and managed by weaker monetary regulators. Finally, the policy findings benefit policymakers as well as investors in the economy and enhance investment decisions.

The remainder of the paper is structured as follows. Section 2 entails conceptual, theoretical and empirical summaries of past works on volatility spillovers on exchange rates, Bitcoin and stock prices. Section 3 raises a theoretical framework backing up the likely findings of the study and data sources, study models and analytical tools used. Section 4 contains descriptive statistics and other inferential statistics specified in the methodology section. Section 5 discusses the policy implications of analytical outputs for proper evaluation and appropriate management. The last Section 6 presents clearly stated study results, recommendations and conclusions.

2. LITERATURE REVIEW

The conventional economic theory supports that exchange rates significantly affect stock prices because they affect the value of firms on the exchange floor, especially when these values in local currencies are converted to foreign currency bases. In all, this effect becomes aggregated in the stock market influencing overall stock market performance and returns. Javangwe and Takawira (2022) opined that exchange rate policies influence stock market performances and this makes investments and portfolio managers continuously monitor these exchange rates. Economic theory also suggests exchange rates and stock prices share a causal relationship. The volatility of stock prices is central to asset pricing theory (Black & Scholes, 1973). However, there has been no consensus on the nature of the relationship that exists between both variables, given the alterations (usually swift) in foreign currencies and stock prices.

In the theoretical discussions of Adekoya (2020), the traditional and portfolio channels are the channels through which exchange rates and stock prices interact. The traditional channel impacts the overall economy through its effects on the goods market as explained by Dornbusch and Fisher (1980) whereby changes in the exchange rate affect goods and services, and so influence the trade balance as well as real output. The change in real output impacts the cash flows of businesses and results in stock price variation. Also, movements in the exchange rate result in higher debt repayment in foreign currencies. The portfolio channel as explained by Frankel (1992) and Gavin (1989) works through the asset market changes in stock prices that affect exchange rates. In effect, when aggregate demand rises, it escalates stock prices which results in wealth effects and accordingly escalates money demand. The rise in money demand increases the interest rate which invites additional foreign portfolio investments. This in turn stimulates appreciation in the exchange rate of the local currency. According to Kallianiotis (2021), the portfolio balance approach of exchange rate determination provides the basis for volatility spillover between exchange rates and stock prices.

The empirical literature can be reviewed as follows. The results and findings of Prempeh et al. (2023) showed that the era of COVID-19 ushered in short-lived volatility persistence. Javangwe and Takawira (2022) used the autoregressive distributed lag model to analyze South African quarterly data from 1980Q1 to 2020Q4 the study found a long-term association between exchange rate behaviour and the stock market, and this relationship was found to be negative. In short term, the relationship was positive. Uzonwanne (2021) established the presence of volatility spillover among Bitcoin and five stock markets based on the vector autoregressive moving average-asymmetric generalized autoregressive conditional heteroskedasticity (VARMA-AGARCH) model. Aydoğan et al. (2022) found evidence of volatility spillover effects among Bitcoin and Ethereum in the Group of Seven (G7) stock markets. Ah Mand and Thaker (2020) used the VARMA-AGARCH approach to examine the link between the price of the Bitcoin index and equity market indices for Japan, Korea, Singapore, Hong Kong and the Philippines. The results revealed low negative co-movement between Bitcoin and Japan, and also low positive association existed between Bitcoin and Hong Kong. Bhullar and Bhatnagar (2020) using vector error correction model (VECM) reported a long-term link between Bitcoin and the stock exchange of India. Kumah et al. (2022) and Sami and Abdallah (2022) reported a high point of association between cryptocurrency market disorder and African stock returns. Nguyen (2022) obtained results that showed a low time-varying correlation between Bitcoin and the stock market. The authors also established that the stock markets responded more to negative shocks than positive shocks in the Bitcoin market between 2018 and 2021.

Bakas et al. (2022) found Google trends, overall circulation of Bitcoins to US consumers and the S&P 500 Index as principal factors responsible for Bitcoin volatility. Several other studies namely, Wu et al. (2022), Bouri et al. (2021), Bariviera and Merediz-Sola (2021), López-Cabarcos et al. (2021), Blau et al. (2021), Palazzi et al. (2021), Fang et al. (2019), Corbet et al. (2019), Panagiotidis et al. (2018), Benhamed et al. (2023), Mokni et al. (2024), Wu et al. (2021), Bakas et al. (2022), Mai et al. (2018), and Demir et al. (2018) examined the determinants of Bitcoin volatility and the relationship between Bitcoin and other risky financial assets. Google trends, market sentiment, policy uncertainty, finance, and prevailing macroeconomic scenario, were all identified as determinants of the variation in Bitcoin. Alnasaa et al. (2022) the use of cryptocurrency significantly encourages corruption and capital controls. According to Makarov and Schoar (2020), investors who are confronted with ineffective financial organizations and restricted capital controls prefer the acquisition of Bitcoin as a financial asset. According to Bao et al. (2022), with the exemption of Hong Kong and Korea, a positive correlation between Bitcoin variation and Morgan Stanley Capital International World Index (MSCI Index) indices exists in several countries.

Gupta and Chaudhary (2022) reported a significant spillover effect between Bitcoin and Ether, with an asymmetric impact in their volatility concerning Litecoin (LTC) and Ripple (XRP). According to Bouri et al. (2021) return on cryptocurrencies increases with volatility. According to Dutta and Bouri (2022), time-varying jumps are considerably present in Bitcoin. According to Özdemir (2022), the volatility of Litecoin, Ethereum, and Bitcoin is extremely high, spillover effects of such high volatility across the three markets were considerably dominant during the COVID-19 lockdown. The three cryptocurrencies were reported by Özdemir (2022), to be jointly reliant throughout the period analysis. The analysis implied that the shockwave in the Bitcoin market, for example, moved investors to act similarly concerning the Litecoin and Ethereum markets. This indeed stimulates volatility spillovers in all markets. In their study, Nasiru et al. (2021) demonstrated that only the exchange rate has a leverage volatility effect in Nigeria. The total portfolio flows into a country, and capital trading between a country and another are all positively correlated with capital control (Fan et al., 2020).

Mechri et al. (2021) found significant stock market fluctuation effects of exchange rate volatility in Tunisia and Türkiye. Uzonwanne (2021) found substantial returns and volatility spillovers through the Bitcoin market and stock markets using the VARMA-AGARCH methodology. Thai Hung et al. (2020) established that irrespective of the volatility regime (low or high), movements in exchange rates do not influence returns of the stock market in Gulf Arab countries. According to Sodiq and Oluwasegun (2020), in Nigeria, the instability of Bitcoin and Ethereum prices substantially influenced stock market prices. The authors also reported evidence of uni-directional interconnection from Bitcoin and Ethereum to all share indexes. Analysis was based on Granger causality and exponential GARCH (EGARCH) techniques respectively. Manasseh et al. (2019) found a bidirectional volatility diffusion between stock prices and exchange rates. Kurka (2019) found evidence of increasing market capitalization of cryptocurrencies, an insignificant unconditional association between traditional assets and cryptocurrencies and traditional assets, with the implication that Bitcoin cannot be relied upon to hedge against traditional assets especially when market disorders can spread from Bitcoin to the domestic economy. The results reported by Lakshmanasamy (2021) established insignificant negative volatility consequences of the euro exchange rate on the S&P Bombay Stock Exchange Sensitive Index (BSE SENSEX) dollar-rupee and British pound-rupee exchange rate. Additional results showed that own lagged values of the stock return affected further volatility in stock returns than innovation.

Guizani and Nafti (2019) applied the ARDL model to establish that the attractiveness indicator and the mining struggle have a significant influence on Bitcoin price variations over time. The study by Manasseh et al. (2019) based on the value-at-risk GARCH (VAR-GARCH) modelling technique found a significant unidirectional mean spillover from the stock market to the foreign exchange. Ofori-Abebrese et al. (2019) established the positive influence of exchange rate instability on the stock prices of financial bodies listed on the Ghana Stock Exchange using the GARCH modelling approach. Aimer (2019) established that the exchange rate was a significant influencer on the performance of the stock market in Middle Eastern countries. Adjasi et al. (2008) explored the link between stock markets and foreign exchange rates affecting the stock market in Ghana. The EGARCH model established a long-run positive association between stock and exchange rate returns.

Korsah and Fosu (2016) investigated the influence of the depreciation of Ghana cedis on stock market capitalization. Quarterly data from 1990 to 2013 were used in the research. Results from the research revealed exchange rate is an indirect predictor of stock market capitalization through periods. Suriani et al. (2015) researched the impact of the exchange rate on the stock market of Pakistan and observed zero relationships between the exchange rate and stock price in Pakistan from January 2004 to December 2009. Rahman and Uddin (2009) stated that exchange rate falls were weak in the prediction of stock market performance after they used Granger causality to analyze monthly data from 2003M1 to 2008M6. The study cut across the stock market in Bangladesh, Pakistan, and India. The results were the same for both long-run and short-run periods.

3. RESEARCH METHODOLOGY

The data for the study were time series for different African economies comprising exchange rates, stock market statistics and global Bitcoin values. A monthly frequency of data was used from

2012M04 and spanned through to 2022M12. The sample period began at 2012M04 because the earliest available data for Bitcoin was 2012M03. In all, the log values of these data were used to mitigate the effects of heteroskedasticity in inferential analysis. Data were described in terms of averages, dispersion and normality. Mean, minimum and maximum values were calculated, the standard deviation was used to measure dispersion between values and kurtosis was used to determine the normality of the dataset. Next, the study analysed data for suitability of time series analysis. The dataset was tested for stationarity and a co-integration test was conducted.

Other methods for assessing dynamics of volatility spillover across financial markets include frequency domain regression method, nonlinear regression framework, dynamic conditional correlation GARCH (DCC-GARCH) and wavelet methods, rolling sample analysis, dynamic Bayesian model averaging approach, machine learning methods, integrated cluster detection, autoregressive distributed lag (ARDL) modelling technique, optimization, and interpretation method, Markov regime-switching VAR estimation method, generalized VAR technique, bankruptcy prediction model estimation technique, multivariate stochastic volatility model. Given that the study sought to determine volatility spillovers across exchange rates, Bitcoin and the stock market returns, we used the asymmetric BEKK-GARCH model which is specified as follows, according to Engle and Kroner (1995):

$$R_t = \alpha + DR_{t-1} + \rho \times EXR + \sigma \times SM + \delta \times BTC \quad (1)$$

where, R_t is the log returns matrix; EXR is exchange rates; SM is the stock market; BTC is Bitcoin; ρ, σ, and δ are measures of volatility transmission in the foreign exchange, stock, and Bitcoin markets respectively.

Eq. (1) is the mean return equation. In matrix representation, Eq. (1) can further be specified as in Eq. (2) below.

$$R_t = \mu + \Gamma_0 R_t + \Gamma_1 R_{t-1} + \varepsilon_t \quad (2)$$

$$G_t = A'A + F'\varepsilon_{t-1}\varepsilon'_{t-1}F + B'G_{t-1}B + D'\xi_{t-1}\xi'_{t-1}D \quad (3)$$

where, μ is 3×1 vector of constants; ε_t is $\mathrm{N} \times 1$ vector of residuals; G_t is restricted variance-covariance matrix; G is 3×3 matrix of constants; F is 3×3 matrix of ARCH effect; B is 3×3 parameter matrix of GARCH effect; D is 3×3 matrix of leverage effects. If ε_t is negative, $\xi_t = \varepsilon_t$; otherwise, $\xi_t = 0$. The $H'H$ as a 3×3 matrix and H_t matrix is defined below.

$$\begin{bmatrix} a_{11} & 0 & 0 \\ a_{12} & a_{22} & 0 \\ a_{13} & a_{23} & a_{33} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} = \begin{bmatrix} a_{11}^2 & a_{11}a_{12} & a_{11}a_{13} \\ a_{11}a_{12} & a_{12}^2 a_{22}^2 & a_{12}a_{13} + a_{22}a_{23} \\ a_{11}a_{13} & a_{12}a_{13} + a_{22}a_{23} & a_{13}^2 a_{23}^2 a_{33} \end{bmatrix} \quad (4)$$

$$H_t = \begin{bmatrix} g_{11,t} & g_{12,t} & g_{13,t} \\ g_{21,t} & g_{22,t} & g_{23,t} \\ g_{31,t} & g_{32,t} & g_{33,t} \end{bmatrix} \quad (5)$$

$$\begin{bmatrix} g_{11,t} & g_{12,t} & 0 \\ g_{21,t} & g_{22,t} & g_{23,t} \\ a_{31,t} & g_{32,t} & a_{33,t} \end{bmatrix} = \begin{bmatrix} \varphi_{11,t} & \varphi_{12,t} & \varphi_{13,t} \\ \varphi_{21,t} & \varphi_{22,t} & \varphi_{23,t} \\ \varphi_{31,t} & \varphi_{32,t} & \varphi_{33,t} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} \begin{vmatrix} u_{1,t-1} \\ u_{2,t-1} \\ u_{3,t-1} \end{vmatrix} \begin{vmatrix} u_{1,t-1} \\ u_{2,t-1} \\ u_{3,t-1} \end{vmatrix} \begin{bmatrix} a_{11} & 0 & 0 \\ 0 & a_{22} & 0 \\ 0 & 0 & a_{33} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \begin{bmatrix} g_{11,t-1} & g_{12,t-1} & g_{13,t-1} \\ g_{21,t-1} & g_{22,t-1} & g_{23,t-1} \\ g_{31,t-1} & g_{32,t-1} & a_{33,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \quad (6)$$

By expansion, the diagonal BEKK-GARCH model becomes:

$$g_{11,t} = \varphi_{11} + \gamma_{11}^2 u_{1,t-1}^2 + b_{11}^2 g_{11,t-1} \quad (7)$$

$$g_{12,t} = \varphi_{12} + \gamma_{11}\gamma_{12} u_{1,t-1} u_{2,t-1} + b_{11} b_{22} g_{12,t-1} \quad (8)$$

$$g_{13,t} = \varphi_{13} + \gamma_{11}\gamma_{33} u_{1,t-1} u_{3,t-1} + b_{11} b_{33} g_{13,t-1} \quad (9)$$

$$g_{22,t} = \varphi_{22} + \gamma_{22}^2 u_{2,t-1}^2 + b_{22}^2 g_{22,t-1} \quad (10)$$

$$g_{23,t} = \varphi_{23} + \gamma_{22}\gamma_{33} u_{2,t-1} u_{3,t-1} + b_{22} b_{33} g_{23,t-1} \quad (11)$$

$$g_{33,t} = \varphi_{33} + \gamma_{33}^2 u_{3,t-1}^2 + b_{33}^2 g_{33,t-1} \quad (12)$$

Specifically, the asymmetric BEKK-GARCH analyses how the volatility of one variable in a lagged period influences the volatility of another variable in a current period. The diagonal BEKK model was used because, unlike the full BEKK, it provides suitable benchmarks from the presence of regularity conditions, underlying stochastic process and asymptotic properties (Allen & McAleer, 2018). Asymptotic properties possessed by the diagonal BEKK-GARCH model aid the validity of standard statistical inferences. The asymmetric BEKK-GARCH model was used because it reduces misspecification errors. Exchange rates were measured by the units of the local currency equivalent to a US dollar on a monthly frequency. Bitcoin monthly returns in United States dollars were utilized as Bitcoin data, stock market index was measured by the all-share index on respective stock exchange floors associated with each sampled country. Data were sourced per country and per stock market from the https://www.investing.com website, a database for different financial data.

4. RESULTS

Descriptive statistics were conducted per variable to take note of individual investment climates (countries) considered in this research. Tunisia had the least local currency units exchanged for the US dollar while Uganda had the most units being exchanged for the US dollar within the period of study. The francophone West African countries, Burkina Faso, Benin, Côte d'Ivoire, Guinea-Bissau, Niger, Togo, Mali and Senegal had the same or almost near rates of exchange given that most of them use Central African franc (CFA). Kurtosis values are less than 3 and show that exchange rate data for each country follow a normal distribution.

Table 1. Exchange rates

Countries	*Mean*	*Minimum*	*Maximum*	*Std. dev.*	*Kurtosis*	*Observations*
Benin	555.22	473.62	622.29	40.94	2.09	117
Botswana	10.06	7.37	12.18	1.17	2.33	117
Burkina Faso	555.22	473.62	622.29	40.94	2.09	117
Côte d'Ivoire	555.22	473.62	622.29	40.94	2.09	117
Egypt	12.31	6.03	18.73	4.83	1.15	117
Guinea-Bissau	548.33	474.56	610.99	36.90	2.13	117
Kenya	98.63	83.22	113.14	8.43	1.90	117
Mali	555.22	473.62	622.29	40.94	2.09	117
Mauritius	34.89	29.03	43.53	3.67	2.59	117
Morocco	9.24	8.11	10.14	0.57	2.01	117
Namibia	13.01	7.74	18.13	2.45	2.35	117
Niger	548.33	474.56	610.99	36.90	2.13	117
Nigeria	260.76	157.26	411.25	85.73	1.60	115
Rwanda	804.01	608.13	1009.62	120.96	1.73	117
Senegal	555.22	473.62	622.29	40.94	2.09	117
South Africa	13.00	7.74	18.06	2.44	2.35	117
Tanzania	2050.44	1567.20	2299.53	293.17	1.72	117
Togo	555.09	474.56	622.18	40.80	2.05	117
Tunisia	2.28	1.53	3.05	0.50	1.50	117
Uganda	3298.42	2472.36	3879.54	481.83	1.73	117

Table 2. Stock market indices

Countries	*Mean*	*Minimum*	*Maximum*	*Std. dev.*	*Kurtosis*	*Observations*
Benin	212.1066	126.25	318.68	56.78245	1.74153	117
Botswana	805.609	749.8	960.26	43.81542	6.818199	117
Burkina Faso	212.1066	126.25	318.68	56.78245	1.74153	117
Côte d'Ivoire	212.1066	126.25	318.68	56.78245	1.74153	117
Egypt	2169.604	1027.81	3396.61	726.3967	1.619731	117
Guinea-Bissau	212.1066	126.25	318.68	56.78245	1.74153	117
Kenya	145.5526	76.91	191.23	24.36812	3.815828	117
Mali	212.1066	126.25	318.68	56.78245	1.74153	117
Mauritius	1959.606	1468.59	2292.27	212.0217	2.041083	117
Morocco	10668.26	8413.72	13555.45	1335.839	1.909189	117
Namibia	1133.132	850.6	1571.7	175.1354	2.192596	117
Niger	212.1066	126.25	318.68	56.78245	1.74153	117
Nigeria	32560.09	21300.47	44343.65	6199.668	1.791677	117
Rwanda	136.9995	124.44	151.19	7.673244	1.814215	106
Senegal	212.1066	126.25	318.68	56.78245	1.74153	117
South Africa	3149.932	2077.61	3837.45	448.9921	2.83498	117
Tanzania	2069.575	1317.22	2743.39	354.6111	2.28407	117
Togo	212.1066	126.25	318.68	56.78245	1.74153	117
Tunisia	5954.521	4381.32	8418.49	1069.59	1.826284	117
Uganda	1619.198	998	2203	263.9506	2.637588	117

Nigeria had the largest all-share index across studied countries with a mean value of 32560, the francophone countries in West Africa have a common exchange, the Bourse Régionale des Valeurs Mobilières (BRVM), and hence the same mean values. Indices for all countries followed normal distribution patterns except for the Botswana Stock Exchange and the Nairobi Securities Exchange (NSE) in Kenya.

Table 3. Bitcoin statistics

Variable	*Mean*	*Minimum*	*Maximum*	*Std. dev.*	*Kurtosis*	*Observations*
BTC	7798.024	4.91	61355.8	13898.16	8.53911	117

Note: BTC — Bitcoin.

Bitcoin was very low when it first became a form of exchange in 2012. It got to an all-time high value in 2019 at 61355 US dollars. Unlike most of the data examined, the Bitcoin rates do not follow the normal distribution (Kurtosis 8.54 > 3). Figures 1, A.1, and A.2 (see Appendix) represent the graphical plots of Bitcoin, exchange rates, and stock market index, respectively. The graphs show volatility in different countries except for Tanzania, Rwanda and Egypt. Figure A.2 shows that the graphs of all countries' stock markets showed volatility though some had more volatility persistence than others. Bitcoin's volatility became evident in 2017 with periods of high volatility between 2020 and 2021.

Figure 1. Graphical plot of Bitcoin

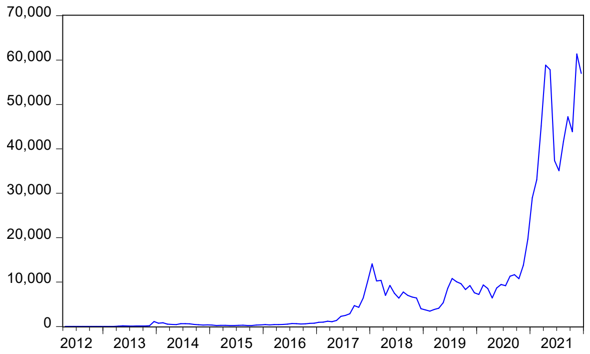

Figure A.1 is the graphical plot of exchange rates. It shows periods of turbulence in different countries with incessant rises and falls in currency exchange rates except for Nigeria, Tanzania, Rwanda and Egypt. The West African francophone countries — Togo, Benin, Guinea-Bissau, Senegal, Mali and Niger — had all periods marked by fairly high volatility. Nigeria seemed to have its rates rise in chunks with the step pattern of its exchange rate graph, such that a rate becomes stable within a period, then rises drastically before having minor fluctuations before spiking drastically again. No downward trend exists within the period revealing that from time to time, the West African francophone countries' naira value keeps falling against the dollar. Tanzania also has the West African francophone countries Tanzanian shilling continuously falling against the dollar with a major dip between 2014 and 2016. The Egyptian pound followed the same pattern but the dip was swift and occurred in 2016. Rwanda seemed to be the most stable currency with exchange rates rising steadily throughout the study. Generally, the study finds that the exchange rates of all studied African countries depreciated against the dollar.

Figure A.2 shows graphs of the stock market index. The graphs showed the volatility of the stock market of all countries, though some countries had more volatility persistence than others. Most of the charts showed that the share index of local stock markets dropped in 2020 and this may be attributable to investors' decisions as a response to the COVID-19 pandemic.

Panel unit root tests revealed stationary variables at first differencing for tests that assumed individual unit root processes (the last three tests). Co-integration test results of Table 5 show that no long-run relationship exists among the variables.

Table 4. Unit root results

Tests	*BTC I(0)*	*BTC I(1)*	*EXR I(0)*	*EXR I(1)*	*SM I(0)*	*SM I(1)*
Levin, Lin & Chu t*	9.98 (1.00)	44.66* (0.00)	1.41 (0.92)	-42.79* (0.00)	-1.92* (0.02)	-53.78* (0.00)
Breitung t-stat	0.64 (0.74)	-12.80* (0.00)	-0.61 (0.27)	-20.86* (0.00)	2.59 (0.99)	-13.49* (0.00)
Im, Pesaran and Shin W-stat	-0.43 (0.33)	-11.87* (0.00)	1.79 (0.96)	-43.52* (0.00)	1.28 (0.90)	-44.62* (0.00)
ADF-Fisher Chi-square	28.59 (0.91)	210.06* (0.00)	20.22 (0.99)	1080.3* (0.00)	23.01 (0.98)	1128.46* (0.00)
PP-Fisher Chi-square	0.78 (1.00)	1012.28* (0.00)	24.05 (0.97)	1113.38* (0.00)	21.59 (0.99)	1195.54* (0.00)

*Note: * Significance at 0.05. BTC — Bitcoin, EXR — Exchange rates, SM — Stock market.*

Table 5. Co-integration results

Hypothesized No. of CE(s)	*Fisher stat.* (Trace test)*	*Fisher stat.* (Max-eigen test)*
None	33.23 (0.68)	35.47 (0.58)
At most 1	15.26 (0.99)	15.15 (0.99)
At most 2	20.07 (0.99)	20.07 (0.99)

*Note: * Significance at 0.05. CE — Co-integrating equation.*

To determine the suitability of GARCH models for volatility testing, the rule of thumb requires that the ARCH effect is present in the dataset. To test for ARCH effects, lag 2 was used. Lag 1 captured ARCH effects in only three countries — Kenya, Uganda and Namibia. To increase the number of countries for which volatility spillovers will be tested, lag 2 was used. Though fluctuations were not very evident in the exchange rates of Egypt, Rwanda and Tanzania, the volatility noticed in stock market indices required that ARCH effects were still tested in exchange rates to determine spillovers. Overall, ARCH effects were found for all variables in the respective panels and confirmed the use of the asymmetric diagonal BEKK model to determine the volatility of variables and volatility spillovers in terms of magnitude and direction of spillovers.

Table 6. ARCH effects (Part 1)

Country	*Exchange rate*		*Stock market index*	
	Obs. R-squared	*p-value*	*Obs. R-squared*	*p-value*
Benin	14.97**	0.0002	8.05**	0.0045
Botswana	12.28**	0.0005	26.56**	0.0000
Burkina Faso	14.97**	0.0002	8.05**	0.0045
Côte d'Ivoire	14.97**	0.0002	8.05**	0.0045
Egypt	27.74**	0.0000	18.49**	0.0000
Guinea-Bissau	28.06**	0.0000	8.05**	0.0045
Kenya	4.46**	0.0347	7.11**	0.0077

Table 6. ARCH effects (Part 2)

Country	Exchange rate		Stock market index	
	Obs. R-squared	p-value	Obs. R-squared	p-value
Mali	14.97**	0.0002	8.05**	0.0045
Mauritius	16.34**	0.0001	25.69**	0.0000
Morocco	15.64**	0.0001	21.31**	0.0000
Namibia	24.42**	0.0000	8.36**	0.0038
Niger	28.06**	0.0000	8.05**	0.0045
Nigeria	19.91**	0.0000	19.84**	0.0000
Rwanda	8.59**	0.0034	22.99**	0.0000
Senegal	14.97**	0.0002	8.05**	0.0045
South Africa	25.66**	0.0000	4.14**	0.0418
Tanzania	36.19**	0.0000	8.86**	0.0029
Togo	43.53**	0.0000	8.05**	0.0045
Tunisia	5.67**	0.0173	22.71**	0.0000
Uganda	5.13**	0.0236	11.83**	0.0006
Bitcoin	49.99**	0.0000		

*Note: ** Significance at 0.05.*

The results of volatility spillovers are shown in Table A.1 (see Appendix). The mean equation values for the three variables under each panel show that returns of exchange rates, stock market prices and Bitcoin are significantly dependent on their returns in the last period. Own mean spillovers are positive across panels revealing that an upward drift is prevalent in each of these markets.

5. DISCUSSION

Own-volatility spillovers. Own-volatility spillovers show the volatility persistence of each variable owing to its errors in previous periods. For Benin, Côte d'Ivoire, Mali, Guinea-Bissau, Senegal, Niger, Togo, Burkina Faso, and Tunisia own volatility spillover for exchange rates was negative and significant (-0.08; $p < 0.05$). Stock market prices also had positive and significant internal volatility spillovers (0.01; $p < 0.05$). Bitcoin spillovers within itself were positive and significant (0.09; $p < 0.05$). Examining the three variables, Bitcoin is viewed as the least responsive to volatility shocks from the environment with a coefficient of 0.09. Nevertheless, persistence was only found in Tunisia's stock market and exchange rate as given by the GARCH term (contained in B-matrix) which measures the impact of lagged conditional variance (0.104; $p < 0.05$).

For Botswana, internal volatility spillovers of exchange rates and stock market prices were individually found to be significant and positive with the coefficient of 0.007 and 0.001, respectively, at 0.00 probability. Botswana stock prices also showed volatility persistence (0.204, $p < 0.05$). By implication, future stock prices can be forecasted correctly from past values to a significant level of accuracy. Bitcoin within the volatility relationship in Botswana did not show significance ($p = 0.47 > 0.05$). Own-volatility spillovers showed that the exchange rate is least affected by volatility external to its volatility of the three variables. Kenya also had positive own-volatility spillovers of exchange rates and stock market prices though by a larger magnitude (0.879 and 5.773, respectively). Conditional covariance (GARCH term) was significant but negative for the country's stock prices and exchange rate on the NSE, taking out persistence from the time series. Bitcoin spillovers within Kenya were positive and significant (55.4; $p = 0.00 < 0.05$).

Egypt as a country in North Africa had a slightly different pattern. The volatility of stock prices from lagged periods spills over to current stock market prices significantly and negatively. Volatility was also found to be persistent ($B = 0.294$; $p < 0.05$). Therefore, increased volatility in the stock market in a previous period would cause reduced volatility in the present period and vice versa. Exchange rates had a negative and significant internal volatility spillover (-0.0005; $p = 0.03 < 0.05$) also found to be persistent and Bitcoin followed with a positive and significant own spillover (0.1046; $p = 0.00 < 0.05$). Rwanda had no significant internal volatility spillovers in each of the three variables. Namibia had all variables have own-volatility spillovers persistent, significant and positive, with Bitcoin having the major resistance against external volatility with the largest coefficient (0.109). Mauritius and Morocco also had positive internal volatility spillovers for exchange rates and stock market prices. Stock prices in both countries also showed volatility persistence (GARCH $p < 0.05$). For exchange rate volatility persistence, only Morocco's rates showed persistence. However, Bitcoin's internal volatility spillover was significant but this was in a negative direction. Bitcoin within Nigeria's volatility relationship was also significant but negative. Exchange rates in the same vein had similar own-volatility spillover cross-periods of a negative magnitude with significant persistence in the series. The Nigerian stock market also had significant internal volatility spillovers but in a positive direction, and this was also found to be persistent.

Cross-volatility spillovers. Referring to cross-volatility effects, past innovations of each of exchange rates, stock market and Bitcoin were not found to be significant in influencing volatility in another given that p-values were above 0.05. However, the directional analysis showed that the cross-volatility of exchange rates and stock prices, as well as the cross-volatility of stock prices and Bitcoin, had inverse movements. In other words, when fluctuations intensity rises in stock prices, Bitcoin becomes more stable, and exchange rates do too. However, cross-volatility across the three variables was not significant in Benin, Togo, Kenya and Rwanda. Nigeria, Guinea-Bissau and Niger had no significant cross-volatility among exchange rates, Bitcoin and their respective stock markets, although coefficients were positive revealing that the volatility of the three variables goes in the same direction. In Benin, Togo, Senegal, Guinea-Bissau, Burkina Faso, and Niger operate on the same stock exchange and use the West African CFA currency, volatility spillovers from exchange rates to the stock market and Bitcoin are insignificant given that p-values were above 0.05, although they had positive coefficient values based on directional analysis. Volatility from the Bitcoin market in a past period did not influence the volatility of the CFA or the volatility of the BRVM in the present period. In other words, when fluctuations intensity rises in stock prices, Bitcoin and exchange rates become more stable. Côte d'Ivoire, Mali, Namibia, Senegal, Tanzania, Mauritius, Uganda, Morocco, and Egypt also had no volatility spillovers among the three variables. Directions of volatility spillovers however varied across variables pair. Côte d'Ivoire, Mali, Namibia, and Senegal had Bitcoin volatility spillover to exchange rate volatility in a direct but insignificant pattern. The same pattern of volatility spillover was observed between Bitcoin and stock prices in Tanzania, Mauritius, Uganda, Morocco, and Egypt. For these countries, volatility spillovers between other variables were negative and insignificant.

Significant volatility spillovers were recorded in a few countries — Tunisia had a significant positive pattern of volatility spillover between Bitcoin and exchange rates (0.02; $p = 0.04 < 0.05$). Bitcoin and exchange rates follow the same direction. Botswana had a significant negative pattern of volatility spillover between Bitcoin and exchange rates (-0.06; $p = 0.04 < 0.05$). As volatility rises or falls in Bitcoin, exchange rates fall or rise, respectively. Negative significant volatility spillover was also found between stock prices and exchange rates in Namibia and South Africa. South Africa also had a negative and significant volatility spillover between Bitcoin and stock prices. Like Kenya, Botswana had a significant positive pattern of volatility spillover between Bitcoin and exchange rates (0.065; $p = 0.04 < 0.05$). As volatility increases in Bitcoin, investors begin to make more buy decisions especially when volatility leads to a reduction in value, with the hope that they make returns from rising prices in the future. As a result, more dollars are demanded, causing the values of local currencies to fluctuate in tandem with Bitcoin. The comparison of the 0.06 Bitcoin-exchange rate spillover value is very close to the Bitcoin-Bitcoin own-volatility spillover value of 0.064 and thus implies that the spillover of Bitcoin to the exchange rate is rather small, even though it is significant. Kenya had a significant negative pattern of volatility spillover between the NSE and its local currency exchange rates (-2.084; $p = 0.02 < 0.05$). Volatility in the NSE in a lagged period will have exchange rates experience volatility in the opposite direction in the next period. The spillover of the stock market shocks on the Kenyan shilling is large, being about half of the own volatility of the stock market shocks, which is 5.772 ($p = 0.00 < 0.05$). By implication, unexpected news on the floor of the NSE will largely affect the volatility of the local currency.

Asymmetric effects were absent in variables of all countries except for Togo, Tunisia, Rwanda, and Tanzania. Tunisia stock prices, Rwanda's exchange rates-Bitcoin (-0.26, 0.00; -0.27, 0.00), Tanzania's exchange rates-Bitcoin (-0.13, 0.00; -0.09, 0.01), were found in exchange rates revealing that the market responds by a higher degree to bad news than it does to good news. Investors would take more action against a local currency falling against the dollar than they would when domestic currencies are increasing in value. Post-diagnostic tests involved pacing restrictions on coefficients using the Wald test. All tests had chis square statistics with p-values that rejected the null hypothesis of the insignificance of the coefficient in the models. Therefore, results from the employed GARCH models are reliable. Conditional covariance graphs for each country are contained in the appendices section and these are used to graphically reveal volatility transmission across variables of interest. Figure A.3 (see Appendix) depicts the conditional covariance graphs between Botswana and Egypt.

In Egypt, the covariance between the stock market and exchange rate maintained low values until 2016 when it sharply rose and showed volatility clustering with varied spikes across the rest of the period. Its stock market had high volatility with high turbulence found in the earlier and latter parts of the study period. The covariance of the market with Bitcoin declined largely from 2012 to 2013, remained fairly constant and began to rise in 2016 showing cross-volatility between both variables till 2021. Bitcoin and exchange rates like the covariance between the stock and exchange rate markets were low and rose in 2016, recording an all-high in 2021. The covariances of study variables in Botswana did not show as much turbulence relative to most countries examined. The volatility of both the stock market and exchange rate at the introduction of Bitcoin globally, moved in the same direction before its covariance began to decline in the same year 2012 and maintained a relatively stable level before 2020. In 2020, covariance rose slightly and declined swiftly in 2021 before recording the highest value in the period. The covariance between Bitcoin and stock prices was similar in behaviour to that of the stock market and exchange rate. Bitcoin and exchange rate also had a high covariance in 2012 with falls in covariance recorded that same year, reaching zero the next year and moving to be negative such that rather than volatility of both Bitcoin and exchange rate following the same direction of volatility, they began to go in opposite directions. Figure A.4 (see Appendix) demonstrates the conditional covariance graphs between Namibia and Mauritius.

Mauritius had a sharp downfall in the covariance of its exchange rates and stock market series in 2020. Before 2020, covariance had been steadily falling from 2012 and became constant from mid-2017 till 2020 when the plunge occurred. The covariance between Bitcoin and the exchange rate was highest when Bitcoin was introduced into the global market in 2012 and declined till 2015 before remaining fairly constant and rising slowly from 2020. Between Bitcoin and the stock market, covariance has been downward sloping from left to right with relatively unstable movements through the period. For Namibia, Covariance between Bitcoin and exchange rates dipped largely from 2012 to mid-2013 and maintained relative stability before plunging further in 2018 and returning to its initial state till 2021. For Bitcoin and the stock market, covariance was relatively low from 2013 to mid-2017 before it began to rise. The covariance had a fall in 2020, likely due to the COVID-19 pandemic, before reaching an all-time high in 2021. Figure A.5 (see Appendix) shows the conditional covariance graphs between Tunisia and Uganda.

The covariance of Tunisia had its stock markets display high volatility with varied spikes across the period. The plots reveal that co-movements of Bitcoin and stock returns in Tunisia had a very volatile trend in the period. A similar volatility intensity was also noticed between the stock market and exchange rate, though at different periods. Uganda has covariances move in similar directions dwindling from 2012 through to 2016 and maintaining a fairly low co-volatility of each pair of variables. Figure A.6 also shows the conditional covariance graphs between Nigeria and Morocco.

The variance of the stock market shows high volatility clustering in the Nigerian stock market with large spikes following each other in the chart. Covariance between Bitcoin and the stock market on one hand and Bitcoin and exchange rates is each negative in most of the studied years showing the volatility in Bitcoin was accompanied by less volatility in exchange rates and stock markets. Morocco had similar covariance findings as the covariance between the three pairs of variables was initially positive, then declined till it became negative. This revealed that the volatility of variables in each pair was in tandem before 2015 (2017 in case of the stock market and Bitcoin).

The covariance of Tanzania had its stock markets display high volatility with varied spikes across the period (see Figure A.7 in Appendix). Covariances followed similar patterns falling at the beginning of the study period and maintaining relative stability towards the end of the study period. Like Uganda, South Africa had its covariances for each pair of variables followed the same direction, falling swiftly to 2015 and 2016, and then steadily maintaining fair stability around zero. Figure A.8 shows all the conditional covariance graphs between Senegal, Benin, Burkina Faso, Togo, Guinea-Bissau, Mali, Côte d'Ivoire, Niger, and Rwanda.

The covariance of these West African francophone countries shows the co-volatility clustering of Bitcoin and exchange rate, on one hand, and the stock market and exchange rate, on the other. Covariance is also found to be positive though falling in earlier periods before turning negative in subsequent periods. For Rwanda, the covariance between the exchange rate and Bitcoin plunged into negative values and then began to rise steadily. For covariance between the stock market and Bitcoin; as well as the stock market and exchange rate, co-movements of the pairs dwindled before sharply rising between 2020 and 2021.

Own volatility spillovers which describe the volatility of past periods affecting the volatility of the current period's volatility were found within each of the variables for all countries. For example, volatility occurring in exchange rates for this period has a significant influence on how much the exchange rates will fluctuate in the next period. Insignificant cross volatilities in most of the countries show that there is no integration among stock prices, exchange rates and Bitcoin. Rather, the three monetary variables operate independently. The fluctuations in the value of Bitcoin against the US dollar do not cause stock prices to move. The Bitcoin fluctuations do not influence stock market participants to pull out investments or acquire more investments. African countries may as well have stock market participants that take up more investments in stock markets given its more tangible nature than digital coins, causing changes in Bitcoin values to leave them unbothered.

For countries like Kenya that had significant cross-volatility from the stock market to the exchange rate, occurrences and information on the stock market elicit responses from investors that impact volatility within the market. This volatility creates a multiplier effect on other economic spheres, depending on whether responses are favourable to the market or unfavourable. When volatility in the Kenyan stock market rises, exchange rates in the next period experience less volatility, against the common theory that investors' actions that cause volatility in the stock market will cause the withdrawal of investments and similar fluctuation responses in exchange rates. Thus, by the next period after turbulent volatility in the stock markets, exchange rates are most likely to experience more tranquillity. Namibia and South Africa with negative spillovers between stock markets to exchange rates reveal that volatility in exchange rates for a period is influenced by the past volatility in stock markets such that fluctuations in the stock market in a period elicit lower volatility in exchange rates in the next period. The same also applies to exchange rate volatility spilling to stock markets. Thus, the government may be able to use exchange rate devaluation or revaluation as a monetary instrument to elicit a level of tranquillity in the stock market, promoting investors' confidence. Like Kenya, Botswana had a significant positive pattern of volatility spillover between Bitcoin and exchange rates. The spillover between Bitcoin and exchange rates shows that exchange rates in Botswana are impacted by Bitcoin fluctuations. Thus, Bitcoin investors make decisions based on the volatility of Bitcoin, causing higher or lower demand in local currencies and overall fluctuations in rates.

Exchange rate volatility in Africa would not also influence Bitcoin values. The study assumes that the volatility of Bitcoin as a crypto-currency is undisturbed by exchange rates because Bitcoin values and investments extend beyond the borders of African countries. Major players in the crypto-currency market such as Western banks and big business tycoons are domiciled outside the shores of Africa. The independence of volatility of exchange rates and stock prices may be a bit more subtle as *apriori* expectation negated this finding. The result reveals that stock market fluctuations more likely arise from local and international economic news, regulations and policies such as the banks' reconsolidation exercise of 2005 that saw share values plummeting and the 2008 global meltdown affecting stock markets. More recently the distress from COVID-19 in 2020 had investors make decisions that probably influenced investor decisions. Exchange rate volatilities may spill more to commodity prices, interest rates and treasury bills rather than long-term funding platforms such as the stock market.

For policymakers, volatility can be forecasted for exchange rates and stock markets from past volatility within each, thereby improving the suitability of policies for future periods. For investors, the insignificant volatility spillovers in most countries show that investments involving exchange rates, stocks and Bitcoin will create a good diversification of portfolios. The diversification is evident because they each have independent volatilities, reducing the embedded risk. The results quantify and describe patterns of volatility spillovers among exchange rates, Bitcoin and stock prices. For only a few African countries, there is a connection between stock prices and exchange rates. For Tunisia, the presence of cross-volatility between the stock market and exchange rates reveals that Tunisia's exchange rate is sensitive to Bitcoin news. For South Africa and Namibia, which had a significant, negative volatility spillover, information from stock markets influences exchange rate fluctuations. South Africa had Bitcoin and stock prices possess cross-volatility. This implied that South African investors likely find the risk in investments in Bitcoin tolerable causing stock market decisions to be impacted by Bitcoin fluctuations of past periods. At the same time, the South African economy does not fully embrace cryptocurrency as special licences are to be obtained for listings. However, the activities of independent digital wallet holders influence its capital market as confirmed by South Africa as one of the top three African countries engaged in crypto trading besides Nigeria and Kenya.

6. CONCLUSION

The study specifically examined the dynamics of volatility spillover among stock, exchange rates and Bitcoin market returns using a diagonal BEKK-GARCH approach. Amongst others, the study established that exchange rate volatility in Africa would not also influence Bitcoin values. Monthly data from 2012M04 through 2021M12 were utilized in the study. Only Botswana and Tunisia recorded volatility spillovers in at least two of the variables. For every other country in the study, volatility spillovers occurred between periods for every single variable. In effect, Botswana had an inverse pattern of spillovers, and Tunisia had a positive pattern. Bitcoin and stock prices both had volatility spillover effects between each other in South Africa alone. South Africa and Namibia were the only countries with significant volatility transmission between exchange rate returns and stock returns. For these two countries, exchange rates are sensitive to news in their respective stock markets. The insignificance of volatility spillovers in sixteen out of the twenty countries examined reveals a level of homogeneity in the magnitude of spillovers that occur in these variables due to fluctuations within macroeconomic environments. In particular, investments involving exchange rates, stocks and Bitcoin will create a good diversification of portfolios.

Own superseded cross-volatility spillovers for all the countries except Rwanda. This implied that past volatility shocks in other periods influence future volatility for each variable more than volatility shocks from other variables of concern. The volatility of Bitcoin only spills over to stock markets in South Africa. On a general note, occurrences that weaken investor confidence in stocks cause volatility and this volatility lingers in its effects in the market across periods. Exchange rates also had independent volatility across most countries. Bitcoin as a cryptocurrency did not have the volatility within exchange rates and stock markets of African countries to influence its volatility. Policymakers would need to focus on the individual trends of each variable to formulate relevant policies. For countries that have variables that are sensitive to information from other variables, expertise and experience would be required on the part of regulatory agencies to map out directives to forestall occurrences that could cripple the economy. Our modelling techniques indeed provided evidence about asset returns at a given time, however, the paper is limited by not capturing information across different frequencies based on the time horizon. We, therefore, suggest that further research adopt the wavelength approach in evaluating the dynamics of volatility spillover across major financial markets and cryptocurrency returns.

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APPENDIX

Figure A.1. Graphical plot of exchange rates

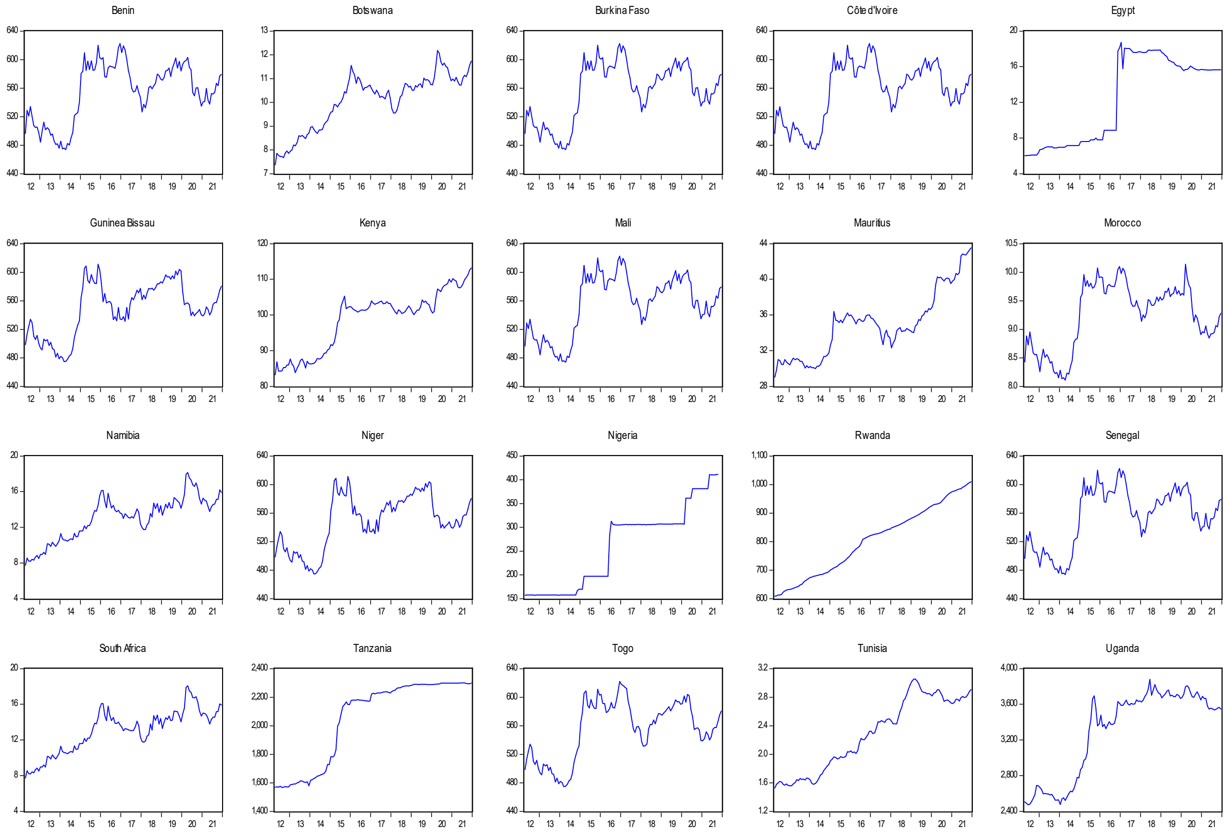


Figure A.2. Graphs of the stock market index

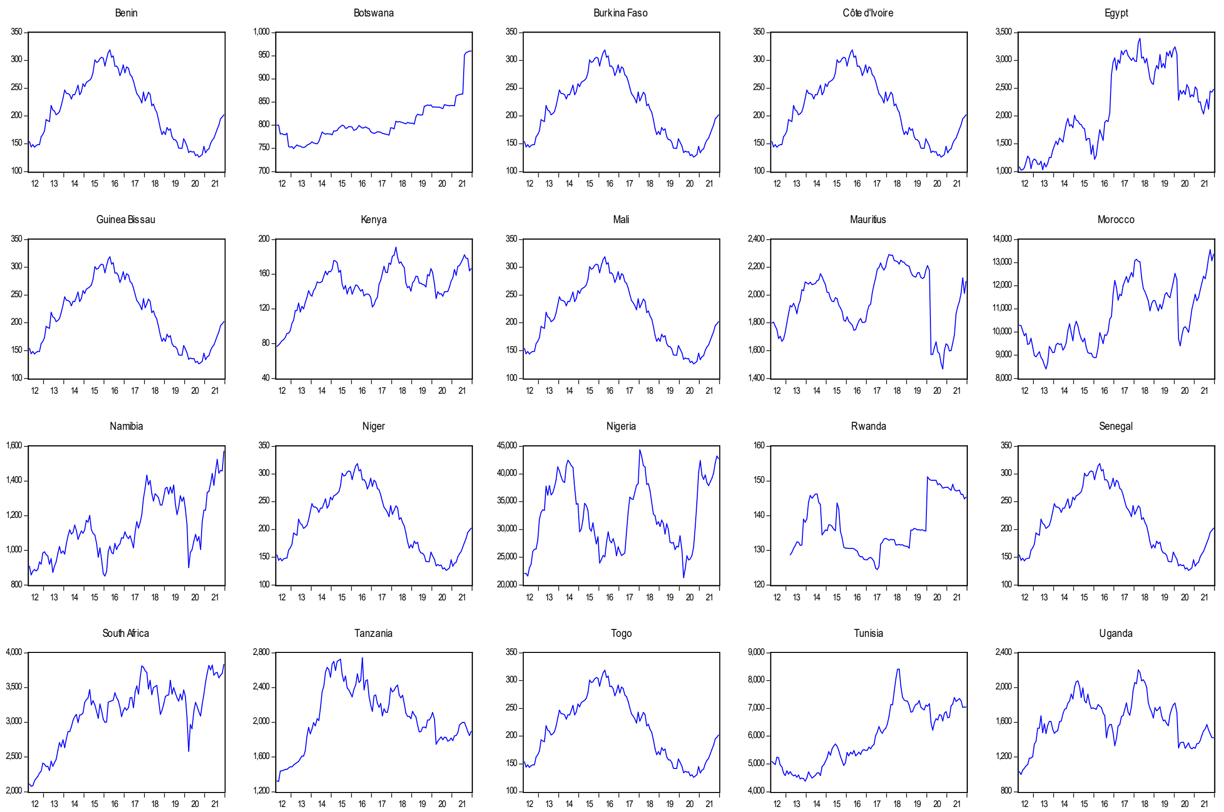
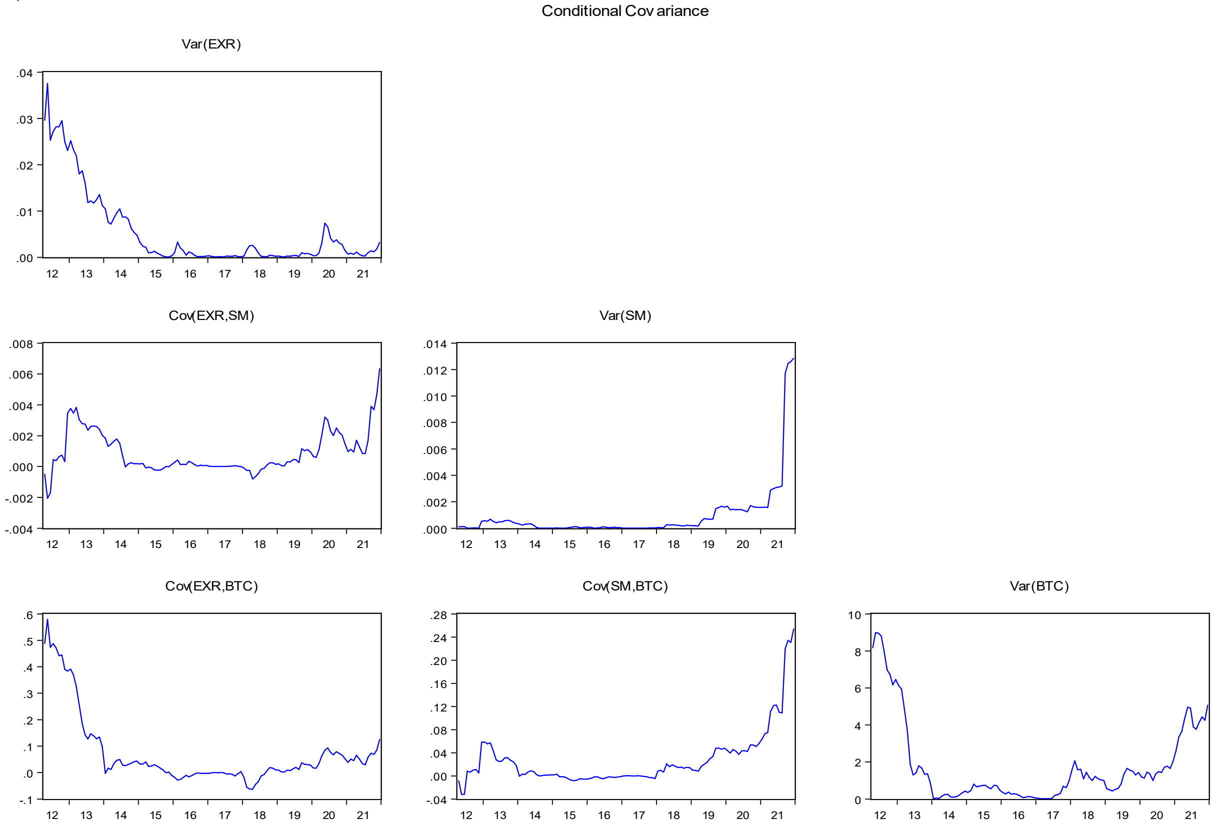


Figure A.3. Conditional covariance graphs between Botswana and Egypt

a) Botswana



b) Egypt

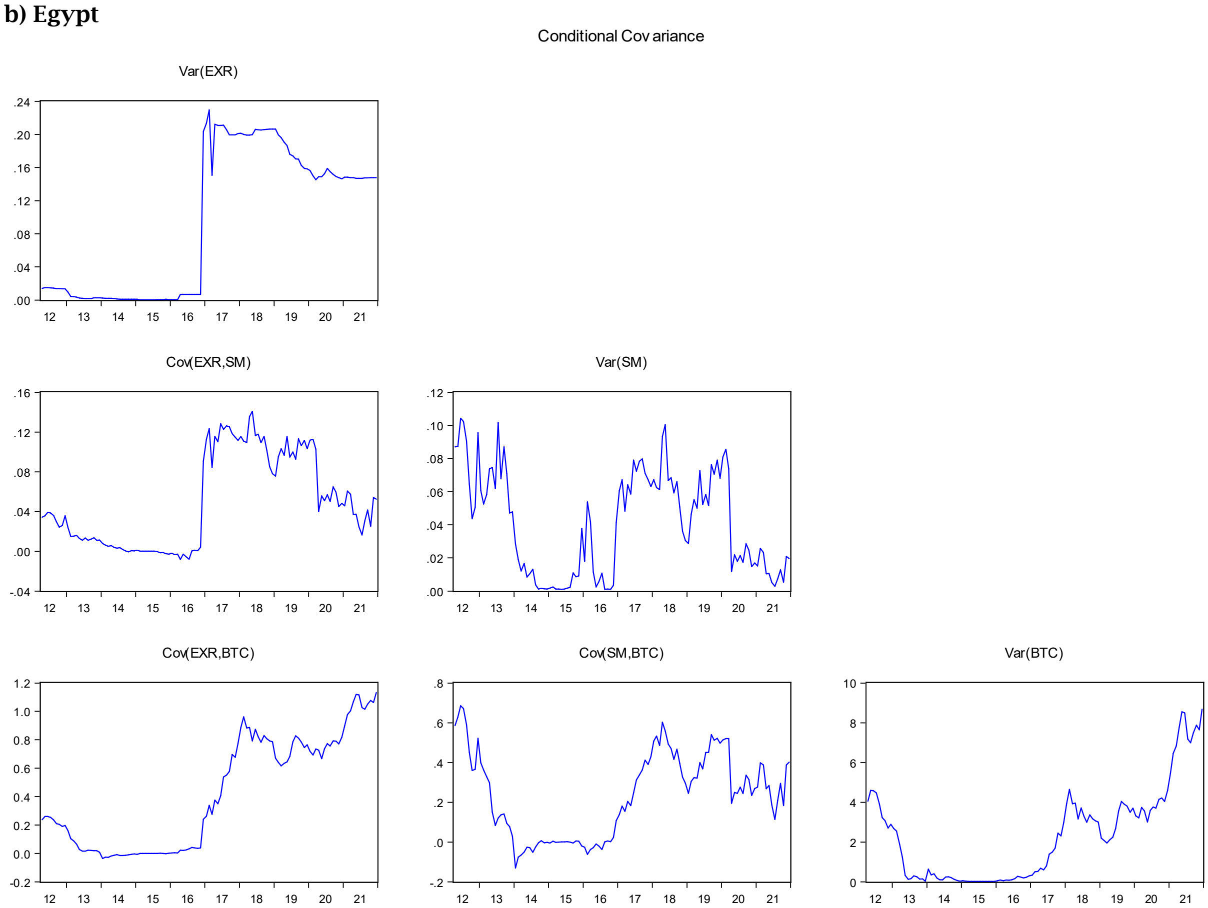
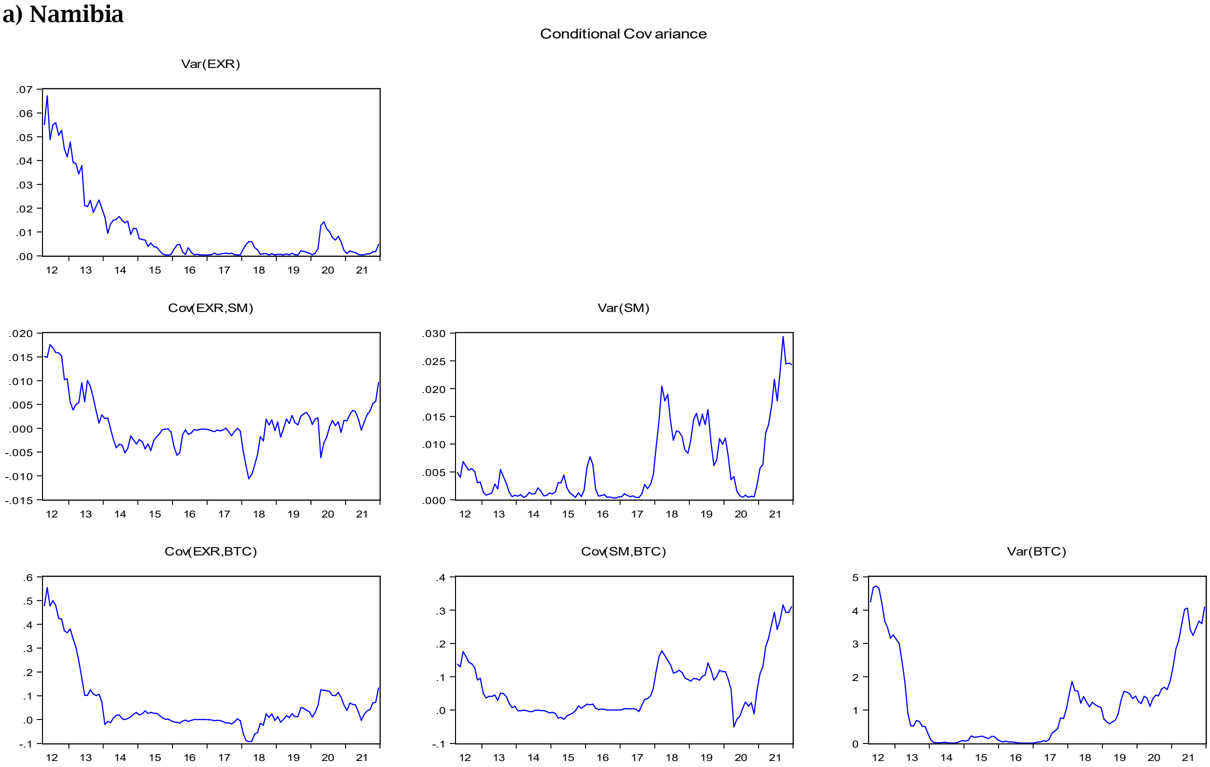


Figure A.4. Conditional covariance graphs between Namibia and Mauritius

a) Namibia



b) Mauritius

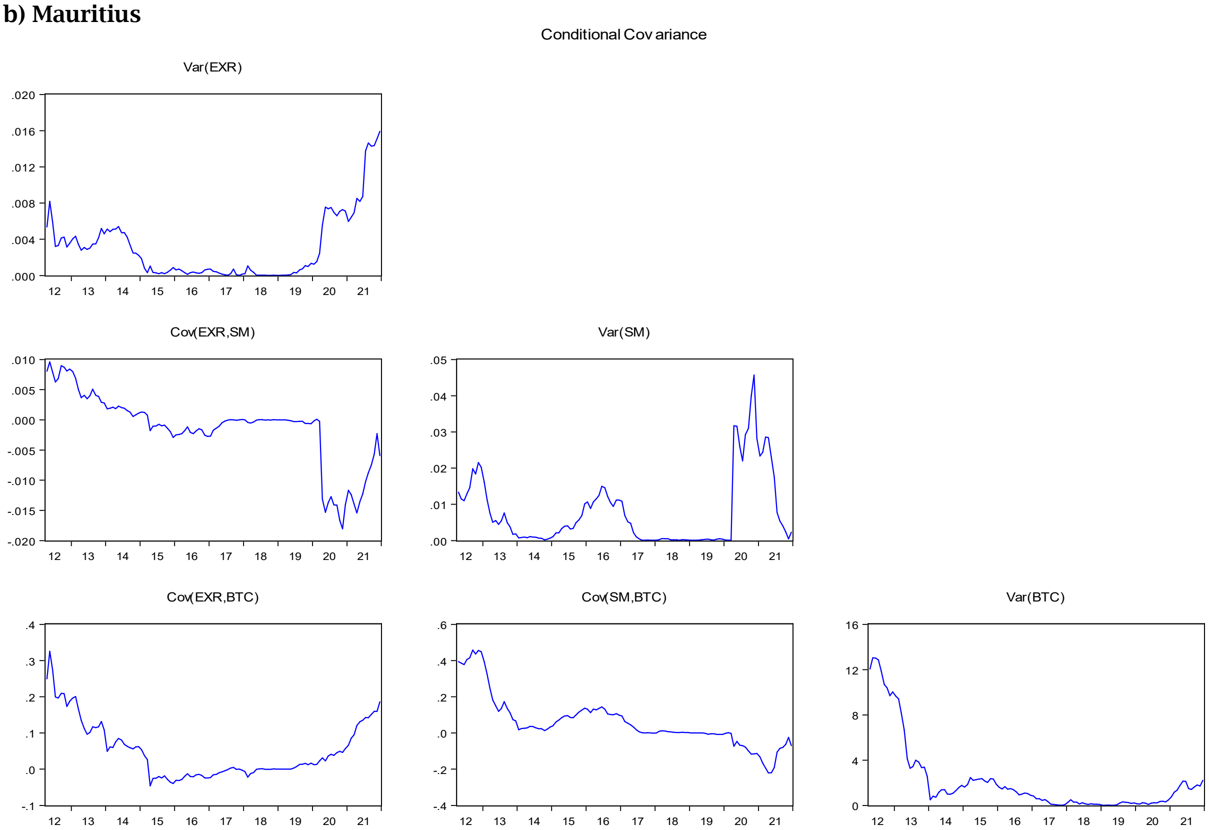
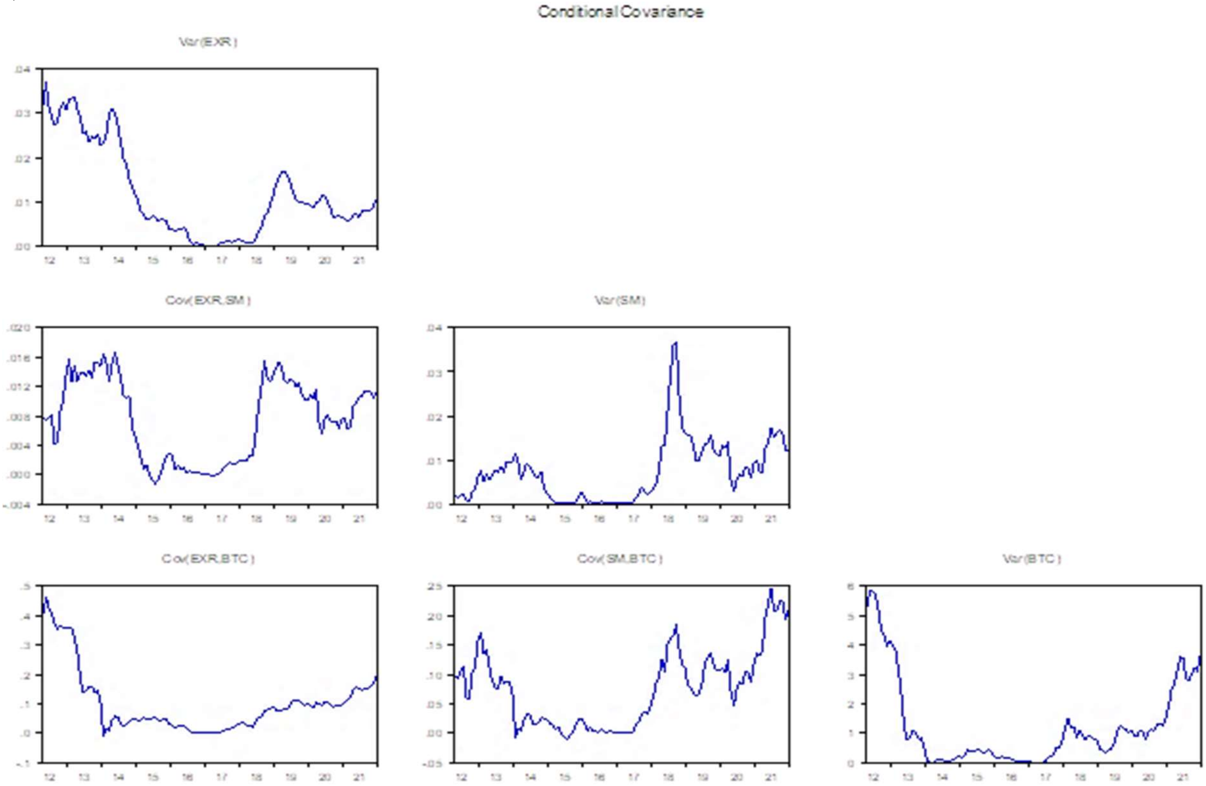


Figure A.5. Conditional covariance graphs between Tunisia and Uganda

a) Tunisia



b) Uganda

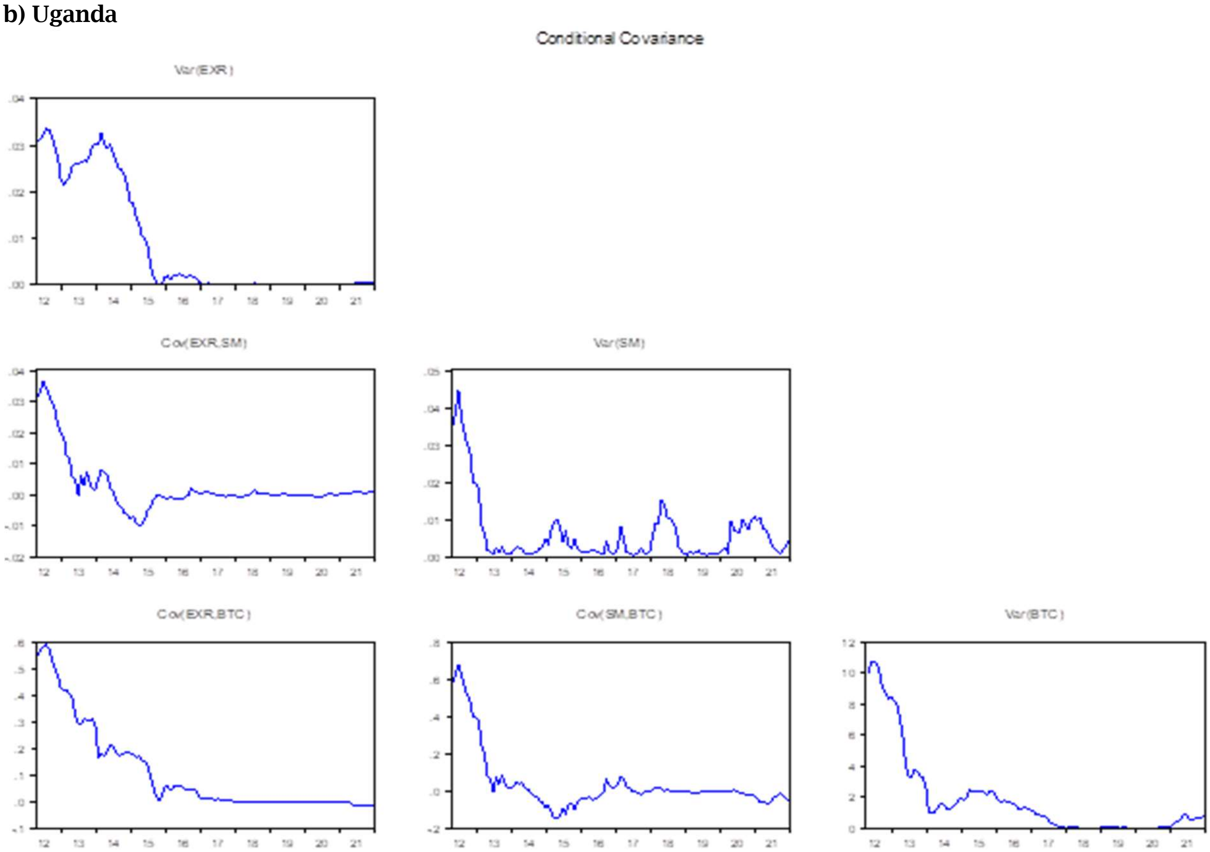
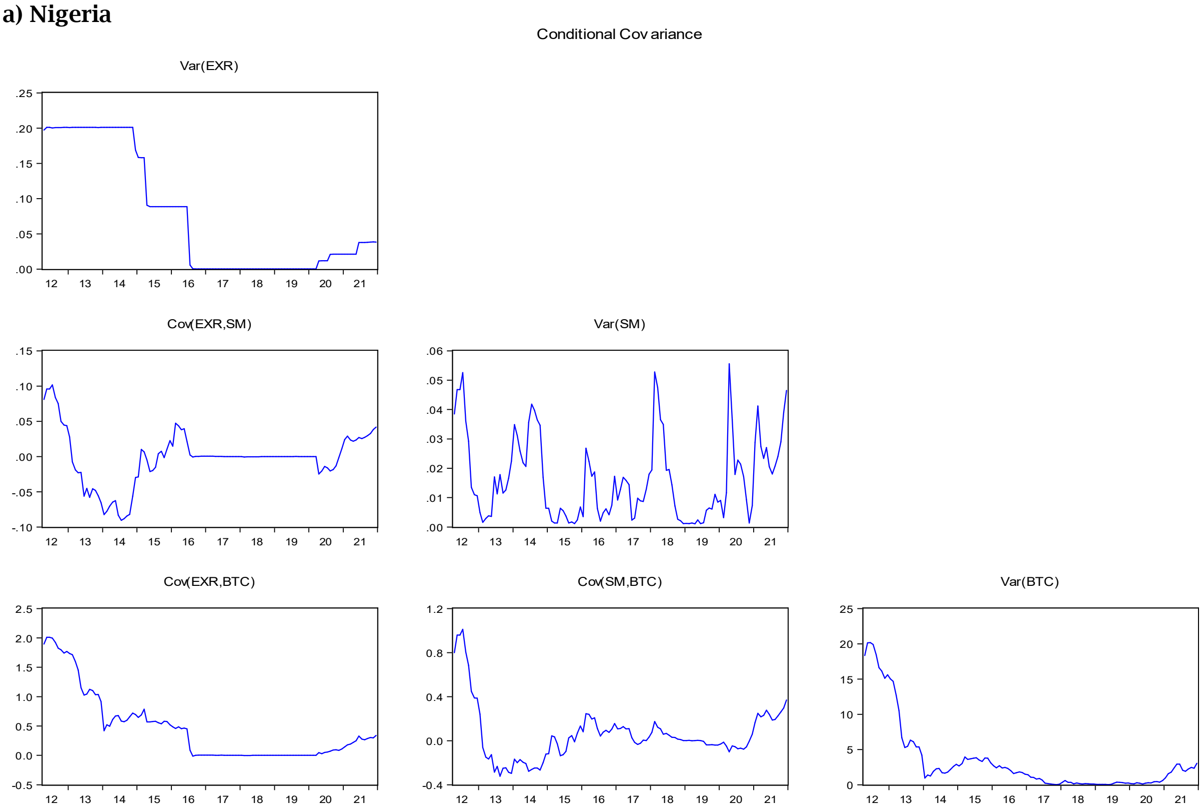


Figure A.6. Conditional covariance graphs between Nigeria and Morocco

a) Nigeria



b) Morocco

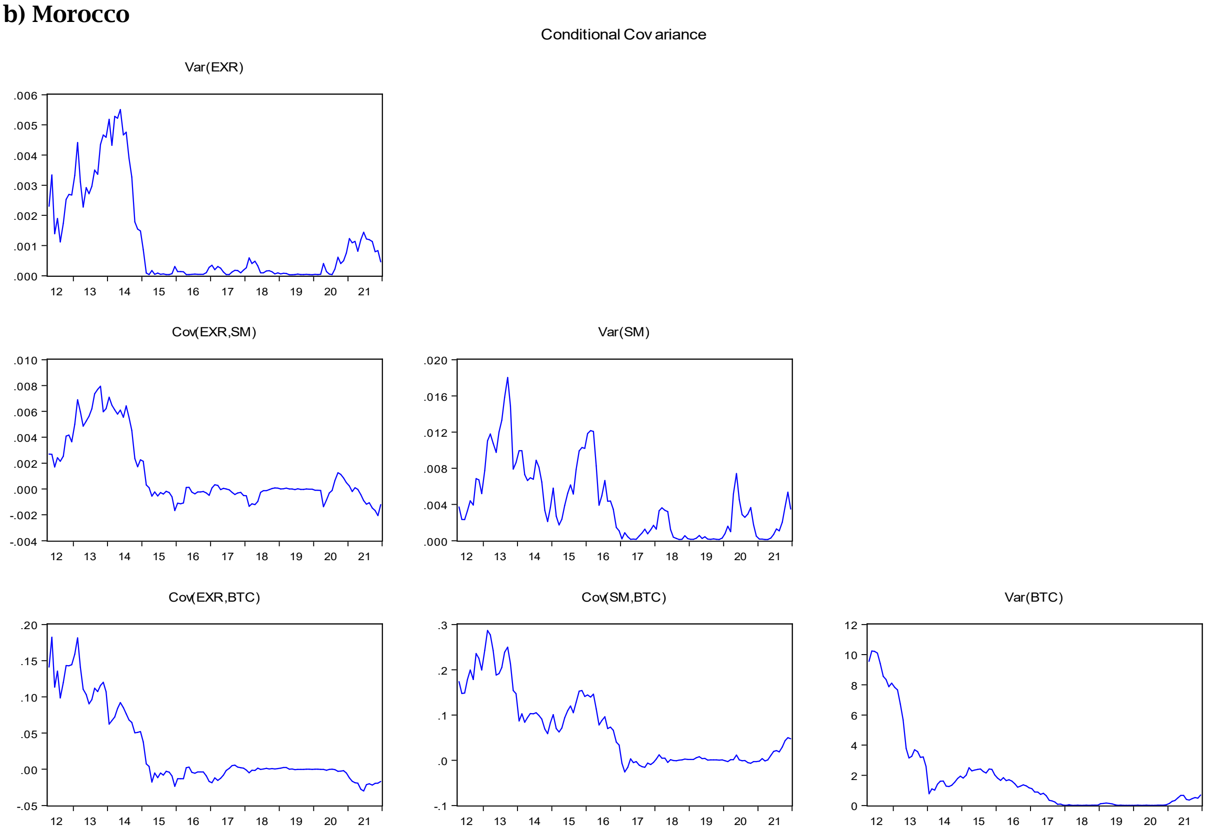
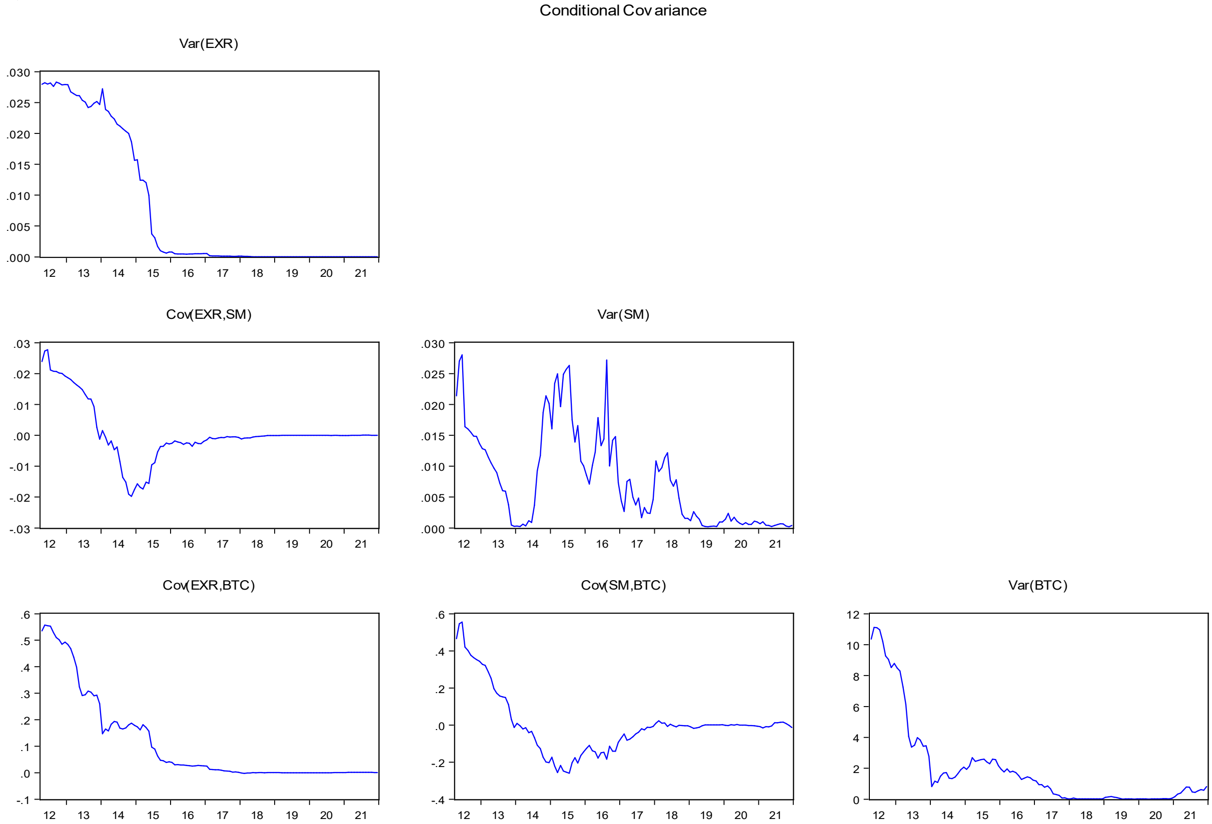


Figure A.7. Conditional covariance graphs between Tanzania and South Africa

a) Tanzania



b) South Africa

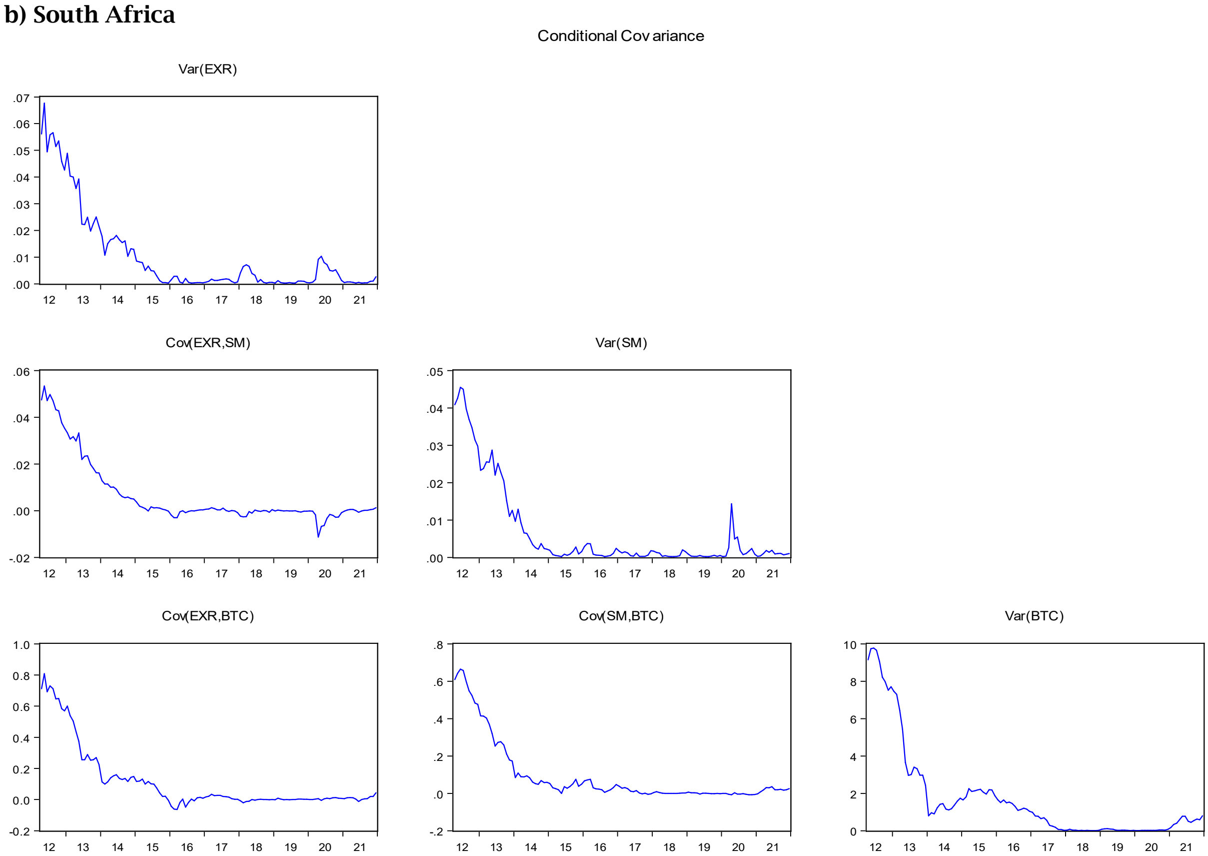
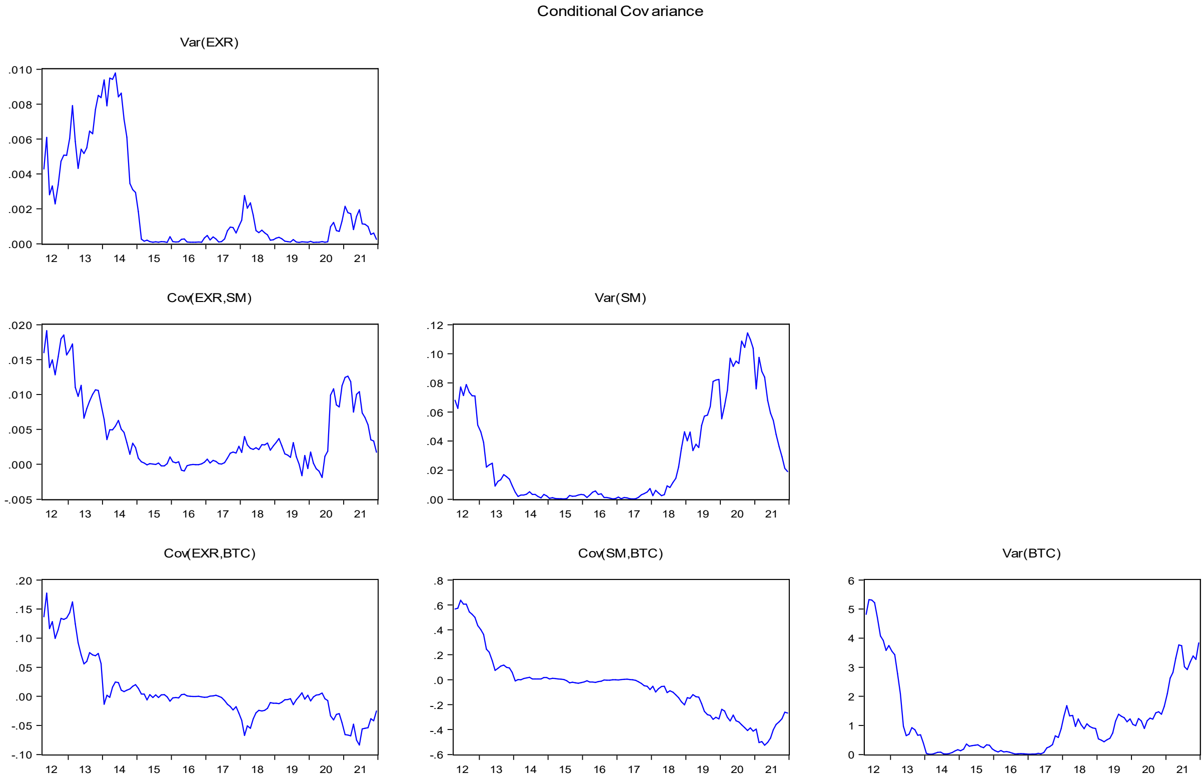


Figure A.8. Conditional covariance graphs between Senegal/Benin/Burkina Faso/Togo/Guinea-Bissau/Mali/Côte d'Ivoire/Niger and Rwanda

a) Senegal/Benin/Burkina Faso/Togo/Guinea-Bissau/Mali/Côte d'Ivoire/Niger



b) Rwanda

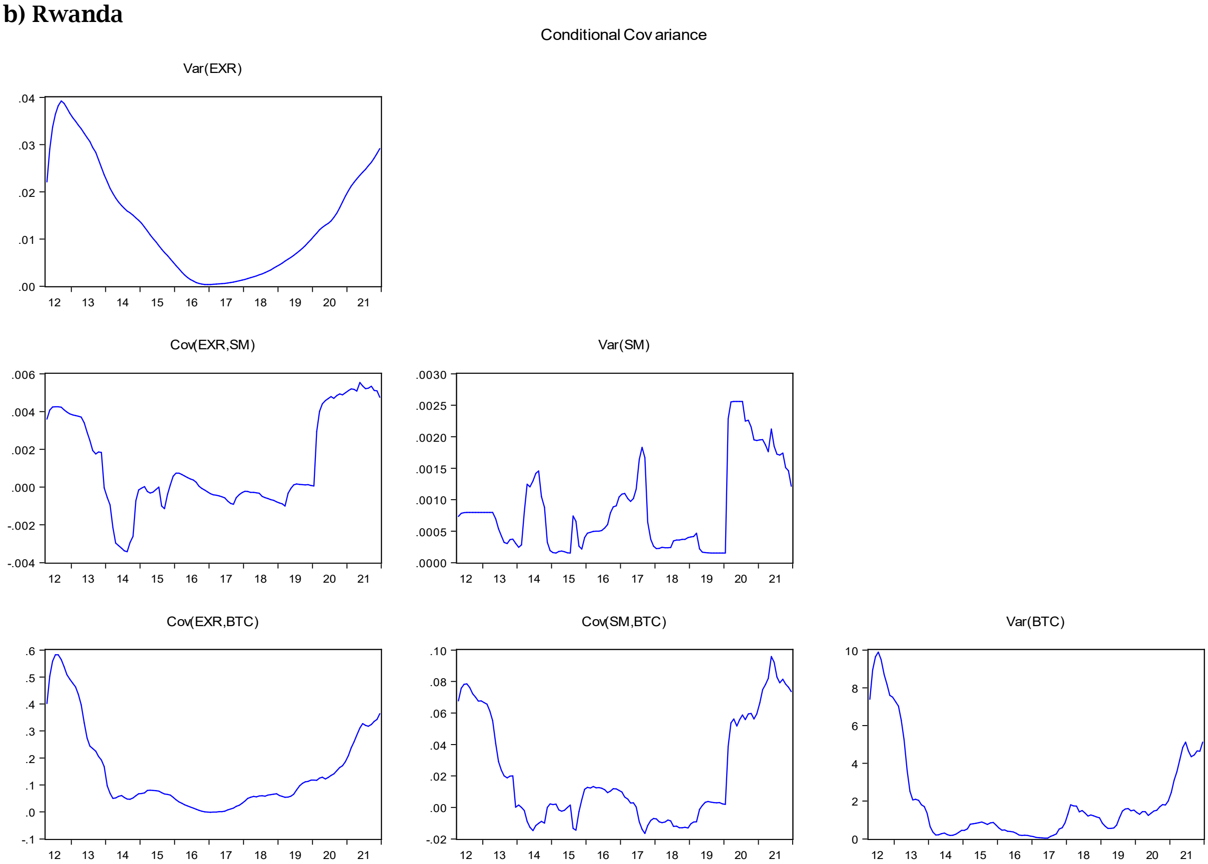


Table A.1. Results of volatility spillovers

Part A											
Variable	***Effect***	***Benin***	***Botswana***	***Burkina Faso***	***Côte d'Ivoire***	***Egypt***	***Guinea-Bissau***	***Niger***	***Togo***	***Kenya***	***Tunisia***
EXR	ARCH term	0.999*	1.253*	1.005*	1.005*	1.107*	1.040*	1.040*	1.023*	1.141*	1.059*
	GARCH term	0.026	0.133	-0.012	-0.012	0.284*	0.040	0.040	0.040	-0.234*	0.104*
	Leverage	0.18*	0.409*	0.177*	0.177*	0.249*	0.052	0.052	0.121	-0.002	0.185
	Mean equation	2.747*	1.014*	2.742*	2.742*	1.194*	2.732*	2.732*	2.747*	102.36*	0.363*
SM	ARCH term	1.02	1.268*	1.027*	1.027*	1.074*	1.041*	1.041*	1.030*	1.076*	1.031*
	GARCH term	0.01	0.204*	0.011	0.011	0.294*	-0.048	-0.048	-0.047	-0.229*	0.044
	Leverage	0.088	0.403*	-0.092	-0.092	0.312*	-0.067	-0.067	-0.101*	-0.001	0.271
	Mean equation	2.355*	2.895*	2.361*	2.361*	3.415*	2.448*	2.448*	2.344*	145.86*	3.747*
BTC	ARCH term	1.044	1.269*	1.047*	1.047*	1.090*	1.045*	1.045*	1.039*	1.255*	1.043*
	GARCH term	-0.024	0.133	0.043	0.043	0.315*	-0.081	-0.081	-0.076	-0.001	0.139
	Leverage	0.00	0.363*	0.009	0.009	0.242*	-0.037	-0.037	-0.001	-0.001	0.118
	Mean equation	3.697*	3.199*	3.852*	3.852*	3.95*	2.874*	2.874*	3.717*	291.29*	3.011*
Spillovers	EXR & EXR	-0.008*	0.007*	-0.008*	-0.008*	-0.0005*	0.007*	0.007*	-0.006*	0.879*	0.008
	SM & EXR	-0.002	-0.0002	-0.002	-0.002	0.0006	0.001	0.001	-0.001	-2.084*	0.004
	SM & SM	0.016*	0.002*	0.015*	0.015*	-0.027*	-0.014*	-0.014*	0.016*	5.772*	0.012
	BTC & EXR	0.025	0.065*	0.026	0.026	-0.033	0.002	0.002	0.026*	-36.01	0.066
	BTC & SM	-0.03	-0.044	-0.027	-0.027	0.021	0.022	0.022	-0.029	-21.75	0.064
	BTC & BTC	0.098*	0.064	0.091*	0.091*	0.104*	0.105*	0.105*	0.092*	55.41*	-0.084
Shape		83.71	5.16*	362774	362774	7,57*	21.77	21.77	169389	7.73*	16.62
Log-likehood		509.4	726.81	511.77	511.77	424.26	525.40	525.40	527.39	-1666	541.19
Coefficient test: prob. value of Wald test		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Part B											
Variable	***Effect***	***Mali***	***Mauritius***	***Morocco***	***Namibia***	***Nigeria***	***Rwanda***	***Senegal***	***South Africa***	***Tanzania***	***Uganda***
EXR	ARCH term	1.005*	1.280*	0.991*	1.005*	1.545*	1.626*	1.005*	0.963*	1.041*	1.115*
	GARCH term	0.043	-0.134	0.329*	0.278*	0.170*	0.069	-0.012	0.220*	-0.02	0.333*
	Leverage	0.177*	0.189*	0.054	-0.000	-0.009	-0.263*	0.177*	0.338*	-0.13*	-0.000
	Mean equation	2.742*	1.535*	0.982*	1.127*	2.487*	2.917*	2.74*	1.154*	3.35*	3.559*
SM	ARCH term	1.027*	1.262*	1.029*	0.962*	1.467*	1.565*	1.027*	0.954*	1.061*	1.017*
	GARCH term	0.011	-0.218*	0.365*	0.399*	0.153*	0.043	0.011	0.225*	0.043	0.373*
	Leverage	-0.09	0.099	0.011	-0.000	-0.078	1.355*	-0.092	0.331*	-0.06	-0.000
	Mean equation	2.361*	3.342*	4.050*	3.031*	4.489*	2.107*	2.36*	3.538*	3.28*	3.211*
BTC	ARCH term	1.047*	1.286*	1.031*	0.978*	1.518*	1.600*	1.047*	0.958*	1.057*	1.075*
	GARCH term	0.043	-0.157*	0.221*	0.336*	0.181*	0.069	0.043	0.264*	0.063	0.385*
	Leverage	0.009	0.055	-0.027	-0.000	-0.020	-0.267*	0.009	0.342*	-0.09*	-0.000
	Mean equation	3.852*	3.580	3.824*	2.968*	3.638*	3.011*	3.85*	3.878*	3.92*	3.034*
Spillovers	EXR & EXR	-0.008*	0.004*	0.005*	0.016*	-.0002*	0.0009	-0.008*	0.015*	0.0002*	0.0035*
	SM & EXR	-0.002	-0.002	-0.002	-0.009*	0.012	-0.001	-0.002	-0.005*	0.005	-0.003
	SM & SM	0.014*	0.007*	0.009*	0.013*	0.030*	0.0004	-0.014*	0.011*	0.012*	-0.018*
	BTC & EXR	0.026	-0.001	-0.019	0.009	0.009					
	BTC & SM	-0.027	0.014	0.010	-0.009	0.032					
	BTC & BTC	0.091*	-0.101*	-0.094*	0.109	-0.153*					
Shape		362774	4.76*	16.44	27.44	3.307*					
Log-likehood		511.77	627.59	603.70	442.24	535.56					
Coefficient test: prob. value of Wald test		0.00		0.00	0.00	0.00	0.00				

*Note: * Significance at 0.05. BTC — Bitcoin, EXR — Exchange rates, SM — Stock market.*