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Cryptocurrencies and Economic Community of West African States Stock Markets: An Analysis by the DCC-GARCH Model

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Abstract

This article is one of the first to analyze the links between the market of the main cryptocurrencies (bitcoin, ethereum) and the main stock markets of ECOWAS (Note 1) (WAEMU, Ghana, Nigeria). The methodology uses a DCC-GARCH model and a non-linear causality test, over the period 2014-2023. The results highlight the existence of a persistent transmission of volatility going from cryptocurrencies to the WAEMU stock markets and of Ghana and the absence of co-movement between these cryptocurrencies and the Nigerian stock market. This is explained by different portfolio adjustment processes due to different reasons for holding cryptocurrencies. The study recommends that regulators take into account strategies to stabilize cryptocurrency prices with a view to achieving financial stability. Other recommendations concern the strengthening of financial integration between ECOWAS stock markets and the consideration of cryptocurrencies in investors' portfolio allocation strategies.

Keywords: cryptocurrencies, stock market, volatility, DCC-GARCH, ECOWAS

JEL classification: C22, E42, G11, G28.

1. Introduction

Cryptocurrencies are fully decentralized digital currencies that, unlike fiat currencies, are not backed by the government and central bank. Most monetary and financial authorities also adopt mixed positions with regard to these alternative currencies. Some encourage their adoption while others advocate restricting or even banning their use. Cryptocurrencies are accused of promoting tax evasion, capital flight, money laundering and financing terrorism (Tirole, 2017). For Stiglitz (2017), bitcoin only exists and has value because it allows illicit financial activities to be carried out and to escape taxes and regulation. Cryptocurrencies are also accused of increasing financial risks, in particular exchange rate risk, liquidity risk and especially market risk linked to extreme price volatility. Studies have shown that cryptocurrencies can have a destabilizing effect on the monetary system in Indonesia (Narayan et al., 2019), the United Kingdom and Japan (Sarker & Wang, 2022). This negative effect of cryptocurrencies on monetary stability justifies the political position of central banks to restrict or even prohibit their use. The quest for financial stability also justifies the attention of financial authorities to the effect of cryptocurrencies on stock markets.

The limited impact that the May-June 2023 cryptocurrency shocks (Note 2) had on financial markets is linked to the fact that at present, the cryptocurrency ecosystem is not large and interconnected enough to threaten developed stock markets stability. Studies have also highlighted a weak positive or negative correlation of cryptocurrencies with stocks on these markets (Baur et al., 2015, 2016, 2017; Dyhrberg, 2016a; 2016b). The reason is that the price of cryptocurrencies is subject to factors that differ significantly from those affecting conventional assets such as stocks and bonds. Liu and Tsyvinksi (2021) show that cryptocurrency prices and returns are independent of typical asset pricing factors: macroeconomic factors, stock market factors, commodities, foreign exchange market returns. The returns and volatilities of cryptocurrencies depend on external factors such as capital controls (Biais et al., 2019), regulations (Auer & Claessens, 2018; Jakub, 2015; Iyidogan, 2019), unconventional monetary policies (Schilling & Uhlig, 2019), etc. This low correlation between cryptocurrencies and traditional assets (stocks, bonds, etc.) justifies the valuable role of cryptocurrencies as diversification assets and effective hedging of asset portfolios.

But for stock markets in developing countries, which are smaller in size compared to cryptocurrency transactions, cryptocurrencies could compromise the stability of stock markets. Investor behavior aimed at exploiting inefficiencies in cryptocurrency markets could destabilize stock markets. In particular, in African countries, the variability of exchange rates, galloping inflation and the rise in uncertainties lead economic agents to hold cryptocurrencies in their asset portfolios, in addition to traditional assets (shares, bonds, deposits banking, real estate assets, etc.). In the event of cryptocurrency shocks, agents make adjustments in their portfolios by varying their cryptocurrency holdings to the benefit or detriment of stock market assets, affecting returns and volatility on stock markets. This is the substitution effect. In addition, agents receive a variation in their income. Feeling richer or less rich, agents increase or reduce their demand for cryptocurrencies and securities, which tends to cause security prices to vary. This is the wealth effect (or income effect). The total effect results from the comparison between the substitution effect and the income effect.

The cryptocurrency market is also characterized by high liquidity risk, which makes liquidity shocks very likely that lead to excessive portfolio adjustments by investors in other markets (Hafner et al., 2023). Due to imperfect information in the cryptocurrency market, a shock to the cryptocurrency market may be interpreted by investors in other markets as relevant information, leading to a fall in prices, resulting in excessive effects on this second market compared to to its fundamentals. Portfolio adjustments, linked to cryptocurrency shocks, have an effect on the volatility of stock market assets due to the size effect (the value of cryptocurrencies is not negligible compared to that of stock market assets). Thus, theoretically, cryptocurrency shocks could affect stock returns and volatilities in African stock markets. This is all the more compelling given that Africa represents the fastest growing cryptocurrency market among developing economies and the third fastest growing market in the world (Triple, 2023). Africa is also considered the next hub for the development of cryptocurrencies.

The general objective of this article is to empirically analyze the effect of cryptocurrency shocks on African stock markets. The study is restricted to the particular case of ECOWAS, which in 2023 concentrated more than 15 million cryptocurrency users, or approximately half of the users in all of Africa (Triple, 2023). This general objective is broken down into two specific objectives. This involves, firstly, highlighting co-movements between the cryptocurrency markets and the three main ECOWAS stock markets: the WAEMU Stock Exchange (BRVM), the Ghana Stock Exchange (GSE), the Nigerian Stock Exchange (NGSE). Then, we analyze the causal relationships between these cryptocurrency markets and these stock markets. The general hypothesis is that cryptocurrency shocks have a significant effect on the three main ECOWAS stock markets. The specific hypotheses are as follows: H1: an increase in the volatilities of bitcoin and ethereum is accompanied by an increase in the volatilities of the BRVM, GSE and NGSE stock indices; H2: There is a unidirectional and non-linear causal relationship from cryptocurrencies to stock markets. This study is of importance for investors in the area and for financial regulators seeking financial stability. The article is organized as follows: after a brief literature review on the interconnectivity between cryptocurrencies and stock markets (section 2), section 3 formalizes the DCC-GARCH model used for the analysis, describe the data and carry out the preliminary tests. Section 4 is devoted to the estimation of models and the analysis of co-movements and causal relationships. Section 5 concludes the article.

2. Brief Literature Review

The study of co-movements and causal relationships between financial markets is part of the general problem of contagion between financial markets based on the mechanisms for transmitting information between these markets. These have been at the center of research since the 1990s (Forbes & Rigobon, 2002; Gande & Parsley, 2005). Defined as the transmission of asset price volatility from one market to another, from one country to another (Pericoli & Sbracia, 2003), contagion takes various forms: fundamental contagion (interdependence) and pure contagion. Fundamental contagion occurs when connectivity between multiple financial markets persists regardless of the nature of the economy. These links create spillover effects, leading to the transmission of shocks. In other words, there is fundamental contagion when the propagation of a shock from one country to another is due to fundamental links (commercial links, financial links, common shocks; macroeconomic or financial similarities, or “wake-up call”). Pure contagion occurs when shocks spread not because of commercial and financial ties, but because of the behavior of investors (withdrawal of investments, rational or irrational behavior, herd behavior, panics, loss of confidence, etc.).

Pure contagion can spread through three transmission channels: multiple equilibria due to sunspots and self-fulfilling prophecies; liquidity shocks that lead to excessive portfolio adjustments by investors in other markets, even if this does not correspond to the fundamental situation of those markets; information asymmetry: rational agents seek to infer information from price volatility in other markets, causing an error in one market to propagate to others. Work analyzes connectivity between financial markets in the form of fundamental contagion and/or pure contagion to understand periods of crisis, including all possible contagion channels linked to financial instruments. Connectivity between financial markets is studied through the asymmetries of volatility in financial markets in the transmission of shocks (Black, 1976; Christie, 1982; Pindyck, 1984; French et al., 1987). In addition to the magnitude, direction and duration of shocks, the sign of this asymmetric response makes it possible to determine the effect on the affected assets. Studies that address the co-movements of financial markets to understand contagion between financial markets use different methods: factorial model, Gaussian copula model, cointegration and error correction model, spillover model, correlation model. These are volatility models.

The factor model allows examining evidence of co-movement, contagion and transmission pathways between multiple asset portfolios spanning different countries and industries during financial crises (See Bekaert et al., 2014; Baur, 2012). Multivariate regime-switching Gaussian copula models allow us to study financial contagion between countries during crises. Volatility spillovers models examine, via a generalized decomposition of the forecast error variance, volatility spillovers between different markets in different countries (Fowowe & Shuaibu, 2016). Fitting into this category, Diebold and Yilmaz (2009, 2012) provided a simple quantitative measure of market connectivity: volatility spillovers, which quickly became popular among researchers. This indicator is obtained by decomposing the variance of forecast errors from VAR models. By combining the framework of Diebold and Yilmaz (2009, 2012) with the observed (realized) semivariance developed by Barndorff-Nielsen et al. (2010), Baruník et al. (2017) proposed a measure of spillover asymmetries (Note 3). Dynamic Conditional Correlation GARCH (DCC-GARCH) models examine signs of contagion, of correlation between markets in different countries. They point to evidence of cross-transmission and dependence between markets in different countries. These models jointly model time-varying conditional volatility and correlations by continuously updating the risk estimate to reflect changing economic conditions. They take heteroskedasticity into account by using standardized residuals to estimate correlation coefficients (Mollah et al., 2016; Fowowe & Shuaibu, 2016).

The first study on the connectivity between traditional assets and cryptocurrencies in terms of volatility spillovers is that of Bouri et al. (2018) in developed and emerging countries. Using an spillover model inspired by Diebold and Yilmaz (2009, 2012), they highlight transmissions of volatility between bitcoin and traditional assets in bearish and bullish markets. Their study also shows that the connectivity between cryptocurrency markets and traditional stock markets exhibits more characteristics of pure contagion. Indeed, the cryptocurrency market is characterized by the herd behavior of traders (Bouri et al., 2019). This partly explains the extreme volatility displayed by cryptocurrencies unrelated to fundamentals. In the context of a cryptocurrency market microstructure characterized by a lack of quality information and a weak legal framework, cryptocurrency traders imitate the investment decisions of others, similar to imperfect learning systems. Corbett et al. (2018c) extend the analysis of volatility spillovers between cryptocurrencies and traditional assets to the time-frequency domain. This allows them to highlight the fundamental elements of the interdependence between cryptocurrencies and traditional assets. The aim here is to understand the interdependence between cryptocurrency markets and traditional financial markets for asset management and for the management of potential financial crises (Note 4).

Kurka (2019) analyzes in depth the mechanisms of asymmetric transmission of shocks between more liquid asset classes (commodities, currencies, stocks) and cryptocurrencies, represented by bitcoin. To do this, Kurka (op. cit.) uses the theoretical framework of volatility spillover developed by Diebold and Yilmaz (2009, 2012). This allows it to highlight a global level of connectivity between cryptocurrencies and traditional assets in developed countries. While unconditional connectivity between cryptocurrencies and traditional assets is negligible, conditional connectivity is not, hinting at periods of substantial shock transmission between bitcoin and traditional assets. It also identifies the timing and particular signals related to shock transmission. The hedging potential of cryptocurrencies vis-à-vis traditional assets is confirmed, but it is called into question by significant idiosyncratic shocks and periods of temporary transmission of shocks by traditional assets.

Chowdhury et al. (2023) use asymmetric multifractal models to analyze the efficiency and asymmetric multifractal characteristics of different financial assets such as traditional assets, cryptocurrencies, NFTs (Non Fungible Tokens) and DeFi (Decentralized Finance) transacted in financial markets developed countries. Their analysis of asymmetric multifractal cross-correlations over the period November 2017-February 2022 shows that the volatility dynamics of cryptocurrencies and traditional assets follow strong non-linear cross-correlations. These findings have significant implications for portfolio diversification when an investor’s portfolio includes traditional assets and cryptocurrencies as well as relatively new blockchain-based assets like NFTs and DeFi. Most studies on connectivity between cryptocurrencies and traditional assets have a geographic framework of developed and emerging countries. The case of developing countries in Africa is, to our knowledge, little or not studied at all. This paper is undertaking such an analysis for the African ECOWAS countries. More precisely, this research uses a DCC-GARCH model to study the transmission of volatility between cryptocurrencies and the stock markets of WAEMU, Nigeria and Ghana, the main ECOWAS countries.

3. Modeling, Descriptive Analysis and Preliminary Tests

This section presents, on the one hand, the DCC-GARCH model, the data used and the descriptive statistics. On the other hand, it carries out preliminary tests (stationarity test, ARCH effect test).

3.1 Model

Let Y_t: stock index return; X_t: vector of explanatory variables (yield of cryptocurrencies, control variables such as inflation rate, economic growth rate, etc.); ε_t: shock on return; h_t: conditional variance of shock; z_t: gaussian white noise; I_{t-1}: information set available until t-1; Θ: vector of parameters; $\alpha_0, \alpha_i, \beta_j$ positive or zero reals to ensure the positivity of h; q: number of delays chosen to express h. The GARCH model (Bollerslev, 1986), which captures three essential elements of volatility (volatility clusters, volatility persistence, volatility asymmetry), is written as:

$$Y_t = \Theta X_t + \varepsilon_t \quad with\ \varepsilon_t = z_t\sqrt{h_t} \text{ and } \varepsilon_t / I_{t-1} \to N(0, h_t)$$
$$h_t = \alpha_0 + \textstyle\sum_{i=1}^{q} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{p} \beta_j h_{t-j} \tag{1}$$

The most widespread specification is GARCH (1,1) allowing a fairly general representation of conditional volatility processes. In its simplest form, GARCH(1,1) is written: $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$ or $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}$; with α_0: minimum conditional variance; α_1: parameter which governs the impact of the past shock, β_1: parameter interpreted as the speed of return to minimum volatility α_0. GARCH models and their univariate variants (EGARCH, TGARCH, etc.) make it possible to model conditional volatility over time for a single financial asset. Other models in the ARCH family make it possible to model the dynamic dependence between several financial assets or several financial markets. Among these multivariate GARCH models, we have the VEC-GARCH model (Bollerslev, Engle, & Wooldridge, 1988) (Note 5), the DCC-GARCH model (Engle, 2002). The latter allows us to capture the dynamic behavior of investors in response to new information by assuming that conditional correlations between assets vary over time. Unlike adjusted volatility across correlated markets, the DCC-GARCH model continuously adjusts the correlation of time-varying volatility, thereby detecting possible changes in conditional correlations. Such dynamic conditional correlations make it possible to establish the existence of a contagion effect resulting from herding behavior observed in financial markets (Corsetti et al., 2005; Boyer et al., 2006; Chaing et al., 2007, Syllignakis & Kouretas, 2011). Another advantage of the DCC-GARCH model is that it estimates the correlation coefficients of the standardized residuals and represents heteroskedasticity directly (Chiang et al., 2007). The DCC-GARCH model is written:

$$Y_{t,k} = \Theta X_{t,k} + \varepsilon_{tk} \quad \text{with } \varepsilon_{tk} = z_{tk}\sqrt{h_{tk}} \text{ and } \varepsilon_{tk}/I_{t-1,k} \to N\left(0, h_{t,k}\right)$$
$$\text{where } h_{t,k} = \alpha_{0,k} + \textstyle\sum_{i=1}^{q} \alpha_{i,k} \varepsilon_{t-1,k}^2 + \sum_{j=1}^{p} \beta_{j,k} h_{t-j,k}$$
$$k = 1,2, \dots, K \text{ index of financial asset} \tag{2}$$

As we have several financial assets, we have several returns and conditional variances, we then form a matrix H_t designating the variance-covariance matrix in t conditional on the set of information in t-1. Considering R_t, the matrix of conditional correlations between the conditional volatilities of the assets, we can write $H_t = D_t R_t D_t$, where D_t is the diagonal matrix of the conditional temporal standard deviations of the return, obtained from the estimation of a GARCH(p,q) model. Limiting itself to the case of a GARCH (1,1), the DCC-GARCH (1,1) model is written in the form:

$$h_{11,t} = \alpha_{01} + \alpha_{11} \varepsilon_{1,t-1}^2 + \beta_{11} h_{11,t-1} \tag{3}$$

$$h_{22,t} = \alpha_{02} + \alpha_{21} \varepsilon_{2,t-1}^2 + \beta_{21} h_{22,t-1} \tag{4}$$

The estimation of a DCC-GARCH model takes place in two steps to estimate the conditional covariance matrix. The first step is to estimate a GARCH model (estimation of asset returns and their conditional variance). The second step concerns the estimation of time-varying conditional correlations. Here, the residuals of the returns are transformed by their standard deviations estimated in the first step, we obtain the standardized residuals as follows: $\delta_{t,k} = \varepsilon_{t,k}/\sqrt{h_{t,k}}$. These are then used to estimate the parameters of the conditional correlation.

Noting Q_t the conditional covariance matrix of the standardized residuals, we establish a relationship between it and R_t, the conditional correlation matrix, as follows: $R_t = (diagQ_t)^{-1/2} Q_t (diagQ_t)^{-1/2}$. Considering two financial assets (or two stock markets) k and k', we note $Q_t = \left|q_{t,kk'}\right|$ with $q_{t,kk'}$ an element of the matrix Q_t where k represents the row and k' represents the column. $\bar{Q}_t$ the conditional covariance matrix of standardized residuals, i.e $\bar{Q}_t = |\bar{q}_{t,kk'}|$ with $\bar{q}_{t,kk'}$ an element of matrix $\bar{Q}_t$. The parameters $\alpha_{0,k}$, $\alpha_{i,k}$ and $\beta_{j,k}$ measure respectively the effects of shocks and dynamic correlations delayed on the current, contemporary level of the latter. The conditional correlations for a pair of assets (or stock markets) k and k' at time t are written as follows:

$$p_{t,kk'} = \frac{q_{t,kk'}}{\sqrt{q_{t,k} \times q_{t,k'}}} = \frac{(1-\alpha-\beta)\bar{q}_{kk'}+\alpha\delta_{t-1}\delta_{t-1}+\beta q_{t-1,kk'}}{\sqrt{(1-\alpha-\beta)\bar{q}_{kk'}+\alpha\delta_{t-1}\delta_{t-1}+\beta q_{t-1,kk'}} \times \sqrt{(1-\alpha-\beta)\bar{q}_{kk'}+\alpha\delta_{t-1}\delta_{t-1}+\beta q_{t-1,kk'}}} \quad (5)$$

We estimate the parameters of this DCC-GARCH model by the maximum log-likelihood method where, noting n: number of equations and Φ: vector of parameters to be estimated, the log-likelihood function is written:

$$L(\Phi) = nlog(2\pi) + log|D_t|^2 + \varepsilon_t{}' D_t^{-1} \varepsilon_t + (log|R_t| + \delta'_t R_t^{-1} \delta_t - \delta'_t \delta_t) \quad (6)$$

The first part of the likelihood function ($nlog(2\pi) + log|D_t|^2 + \varepsilon_t{}' D_t^{-1} \varepsilon_t$) represents the volatility (sum of the individual probabilities of the GARCH model). Given the parameters estimated in the first step, the likelihood function in the second step (which contains the correlation parameters) can be maximized to estimate the correlation coefficients

3.2 Database and Descriptive Statistics of Return Series

This study uses daily data on the closing prices of the main cryptocurrencies (bitcoin and ethereum) and the main ECOWAS stock indices (BRVMC, NGSE, GSE). These data come from the sites african-markets.com (2023) and coinmarketcap.com (2023) (Note 6). The sampling period is from January 3, 2014 to December 20, 2023, depending on data availability. All series are log transformed by applying the following formula $R_t = (logS_t - logS_{t-1}) \times 100$ with R_t: return of financial asset at period t, S_t: price of the financial asset at t. The table presents the descriptive statistics of the transformed data series. Jarque-Bera statistics (J.B.) reject the null hypothesis of normality.

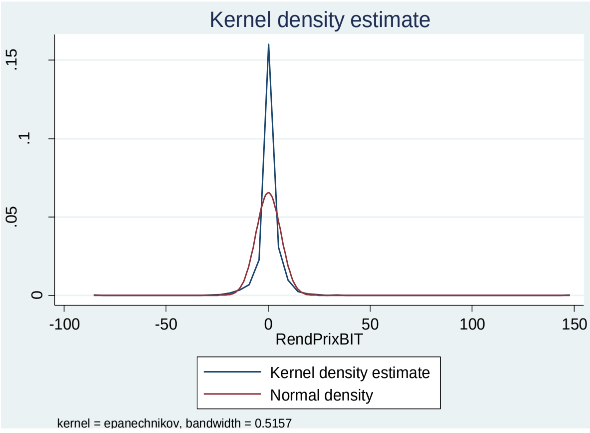
Table 1. Descriptive statistics of return series

	BIT	**ETH**	**BRVMC**	**NGSE**	**GSE**
Observation	2349	1825	2349	2349	2349
Mean	0.167	0.287	0.004	0.024	0.016
Std deviation	6.090	9.040	0.740	1.023	0.876
Minimum	-84.882	-93.711	-4.404	-5.032	-12.423
Maximum	147.418	88.961	3.620	7.972	12.671
Variance	37.086	81.730	0.548	1.047	0.767
Jacques-Bera	2722253	140799.1	1456.430	3486.502	215058.3
Skewness	4.466	-0.126	0.087	0.404	0.250
Kurtosis	169.535	46.029	6.853	8.913	49.872
Probability	0.000	0.000	0.000	0.000	0.000

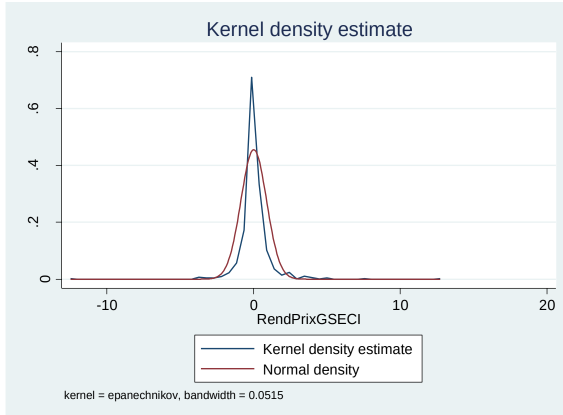
Source: Author, based on data on african-markets.com (2023) and coinmarketcap.com (2023).

Bitcoin, Ethereum, the BRVMC, NGSE and GSE indices respectively have an average return of 0.167; 0.287; 0.004; 0.024 and 0.016, for respective maximums 147.418; 88.961; 3.620; 7.972 and 12.671 and for respective minimums -84.882; -93.711; -4.404; -5.032; and -12.423. The gap between the averages and the extremes is quite significant, highlighting the highly volatile nature of the assets. This is confirmed by standard deviations higher than the means. In addition, the skewness (asymmetry coefficient) of bitcoin, BRVMC and NGSE are positive and greater than 0: their distributions are skewed to the right (long tail on the right), in other words, the majority of their data is concentrated to the right of the average. On the other hand, the skewness of Ethereum and GSE are negative and greater than 0 in absolute value: their distributions are asymmetric to the left (long tail on the left), the majority of the data is concentrated to the left of the average. Furthermore, all kurtosis (kurtosis coefficient) are well above 3, showing that the return distributions of all financial assets studied have thicker tails than normal and a sharper peak than normal. They are called leptokurtic. The return series are therefore not distributed according to a normal distribution. The p-value associated with the Jarque-Bera statistic is less than 0.05 for all the series, which confirms that the distribution of the series is not normal. Graphical representations of the empirical distributions indicate sharper than normal return series. They are therefore leptokurtic and have a thick tail compared to the ends of the normal distribution.

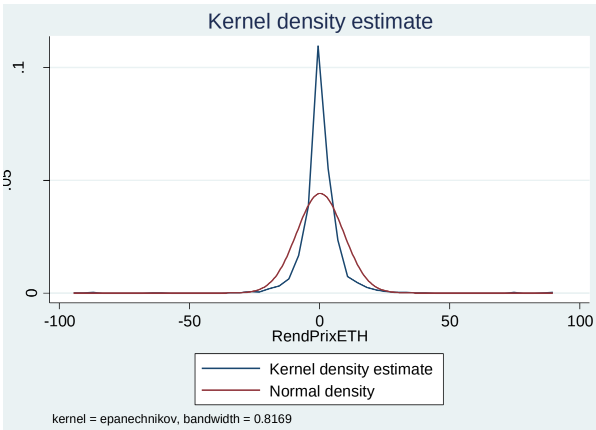
Bitcoin



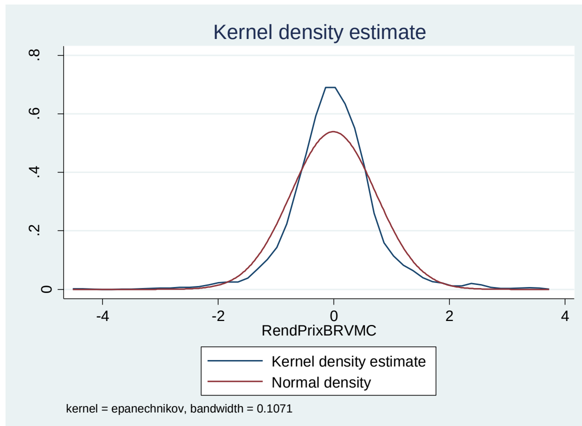
Ethereum



BRVMC



NGSE



GSE

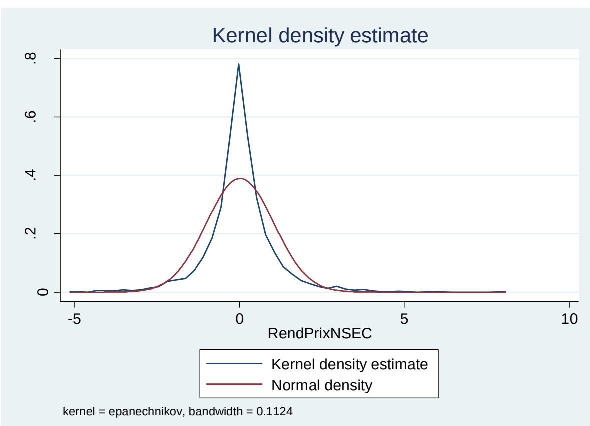


Figure 1. Density functions of daily yield distributions (in blue) versus density of a normal distribution (in red)

Source: Author, based on data on african-markets.com (2023) and coinmarketcap.com (2023).

3.3 Stationarity Tests and ARCH Tests of Return Series

This sub-section implements the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) stationarity tests aimed at detecting the possible presence of unit root in our series. The results are presented in Table 2.

Table 2. Results of the Augmented Dickey-Fuller test and the Phillips-Perron test

	ADF test	PP test	Decision
BIT	-50.886***	-51.935***	Stationary at level
	(0.000)	(0.000)	(I0)
ETH	-48.941***	-51.193***	Stationary at level
	(0.000)	(0.000)	(I0)
BRVMC	-45.959***	-46.016***	Stationary at level
	(0.000)	(0.000)	(I0)
NGSE	-32.514***	-32.515***	Stationary at level
	(0.000)	(0.000)	(I0)
GSE	-44.825***	-44.853***	Stationary at level
	(0.000)	(0.000)	(I0)

Source: Author based on data from african-markets.com (2023) and coinmarketcap.com (2023).

Note. significance threshold: *** significant at the threshold of 1%, ** significant at the threshold of 5%, * significant at the threshold of 10%.

The results of the statistical tests and the p-values of the ADF and PP tests reveal that all the series are stationary at the 1% threshold. We also perform the ARCH heteroskedasticity test, the results of which, revealing the presence of an ARCH effect, are presented in Table 3.

Table 3. Results of the ARCH heteroskedasticity test

Series	TR^2	p-value	F-statistic	p-value	Conclusion
NGSE	66.735	0.000	68.629	0.000	ARCH effect
GSE	427.971	0.000	522.969	0.000	ARCH effect
BRVMC	130.707	0.000	138.298	0.000	ARCH effect
BIT	23.036	0.000	11.617	0.000	ARCH effect
ETH	24.604	0.000	24.913	0.000	ARCH effect

Source: Author, based on data on african-markets.com (2023) and coinmarketcap.com (2023).

4. Estimates of the GARCH and DCC-GARCH Models

This section is dedicated to presenting the results and interpretations of the GARCH and DCC-GARCH models, making it possible to analyze the co-movements between the returns of the ECOWAS stock indices and those of the main cryptocurrencies. Next, it analyzes the causal relationships between cryptocurrency markets and stock markets.

4.1 Estimates of GARCH (1,1) Models

The GARCH (1,1) model is the most commonly used specification in empirical applications, with Bollerslev (1986) having shown that any arbitrary ARCH model can be well approximated by the GARCH (1,1) specification. We present the results of the estimation of the GARCH (1,1) model in Table 4.

Table 4. Estimation results of the GARCH (1,1) model

	BIT	ETH	BRVMC	NGSE	GSE
$\boldsymbol{\alpha_0}$	4.5903	4.630	0.117	0.142	206.480
$\boldsymbol{\alpha_1}$	0.591*	0.271**	0.230***	0.574***	1353.807
$\boldsymbol{\beta_1}$	0.759***	0.821***	0.567***	0.603***	0.444***
$\boldsymbol{\alpha_1+\beta_1}$	1.350	1.092	0.797	1.177	1354.251

Source: Author based on data from african-markets.com (2023) and coinmarketcap.com (2023).

Note. significance threshold: *** significant at the threshold of 1%, ** significant at the threshold of 5%, * significant at the threshold of 10%.

All coefficients α_1 are positive and significant, for all financial assets, except that of the GSE stock index. Thus, on the bitcoin and ethereum markets and on the WAEMU and Nigerian stock markets, the conditional variance h_t (or σ_t^2) is explained by the square of the lagged residuals (ε_{t-1}^2) and by the lagged variance σ_{t-1}^2 while on the Ghana stock market, the conditional variance h_t (or σ_t^2) is explained only by the lagged variance σ_{t-1}^2. In addition, the parameter β_1 presents a fairly high coefficient (0.759 and 0.821) for the two cryptocurrencies and a lower value for the stock indices of WAEMU, Nigeria and Ghana (respectively 0.567; 0.603; 0.444). Thus, the two cryptocurrencies are characterized by a speed of return to minimum volatility greater than that of stock indices. The persistence of conditional volatilities is measured by the sum $\alpha_1 + \beta_1$. We note a persistence of volatility ($\alpha_1 + \beta_1 < 1$) only for the BRVMC stock index. For bitcoin, ethereum and other stock indices, the GARCH (1,1) model is not suitable for capturing the dynamics of volatility, which requires turning to alternative models.

4.2 Estimates of DCC-GARCH (1,1) Models

The DCC-GARCH (1,1) model allows to explore the contagion effect between financial markets. The results of the co-movement analysis are given in Table 5.

Table 5. Estimation of parameters of DCC-GARCH models

		BRVMC	**NGSE**	**GSE**
	α_{DCC}	0.248***	0.161***	0.120***
BIT	β_{DCC}	0.591***	-0.057***	0.460**
	$\alpha_{DCC} + \beta_{DCC}$	0.839	0.104	0.580
	α_{DCC}	0.245***	0.162***	0.110***
ETH	β_{DCC}	0.624***	-0.044***	0.342
	$\alpha_{DCC} + \beta_{DCC}$	0.869	0.118	0.452
	α_{DCC}	--	0.580***	0.116***
BRVMC	β_{DCC}	--	0.219***	0.469***
	$\alpha_{DCC} + \beta_{DCC}$	--	0.799	0.585
	α_{DCC}	--	--	--
NGSE	β_{DCC}	--	--	--
	$\alpha_{DCC} + \beta_{DCC}$	--	--	--
	α_{DCC}	--	0.587***	--
GSE	β_{DCC}	--	0.212***	--
	$\alpha_{DCC} + \beta_{DCC}$	--	0.799	--

Source: Author based on data from african-markets.com (2023) and coinmarketcap.com (2023).

Note. significance threshold: *** significant at the threshold of 1%, ** significant at the threshold of 5%, * significant at the threshold of 10%.

The coefficients α_{DCC} and β_{DCC}, representing the parameters of conditional correlations, measure co-movements between financial markets. The β_{DCC} coefficient shows the degree of conditional correlation between the two assets. Furthermore, the persistence of the conditional correlation is calculated from the sum of $\alpha_{DCC} + \beta_{DCC}$. We analyze the results to draw conclusions on the transmission of volatility between ECOWAS stock markets, on the one hand, and between cryptocurrencies and these stock markets, on the other hand.

First, we observe significant, positive but relatively weak dynamic conditional correlations between the BRVMC and NGSE (0.219), BRVMC and GSE (0.469), NGSE and GSE (0.212) indices. Such results can be explained by the weak financial integration between the main ECOWAS stock markets. This corroborates previous results (WAMU, 2011). However, the conditional correlation is less weak between the WAEMU and Ghanaian stock markets between the WAEMU and Nigeria. This could explain the relative proximity of the economic structures of Côte d'Ivoire, the driving force of WAEMU, and Ghana.

Furthermore, the results highlight significant dynamic conditional correlations, positive but low between bitcoin and BRVMC (0.591), low between bitcoin and GSE (0.460), high between ethereum and BRVMC (0.624); on the other hand, the conditional correlation between ethereum and GSE is not significant. The dynamic conditional correlations are significant, negative but very weak between bitcoin and NGSE (-0.057) and between ethereum and NGSE (-0.044).

We interpret these results as follows:

- an increase in the volatility of bitcoin is accompanied by an increase in the volatilities of the BRVMC and GSE stock indices, and a very slight drop in the volatility of the NGSE index: these markets tend to move together, and there is positive transmission of volatility between bitcoin and the WAEMU stock market, between bitcoin and the Ghana stock market. There is very little negative volatility transmission between bitcoin and the Nigerian stock market.

- an increase in the volatility of ethereum is accompanied by an increase in the volatility of the BRVMC index, no significant effect on the GSE index and a very slight drop in the volatility of the NGSE index: there is positive transmission of volatility between ethereum and the BRVM, negative transmission of volatility between ethereum and the Nigerian stock market. On the other hand, there is no transmission of volatility between Ethereum and the Ghana stock market.
- Furthermore, all the sums $\alpha_{DCC} + \beta_{DCC} < 1$, which reflects a persistence of these co-movements and transmission of volatilities.

The persistent transmission of volatility between bitcoin and the WAEMU and Ghana stock markets shows the link between this cryptocurrency and these stock markets. This co-movement is non-existent between ethereum and the Ghana stock market. On the other hand, there is almost no transmission of volatility between these cryptocurrencies and the Nigerian stock market.

A descriptive and graphical analysis of the dynamic conditional correlations between cryptocurrencies and stock markets (see Table 6 and Figure 2) allows us to see how these conditional correlations evolve over time. Examination of the descriptive statistics shows that, for all conditional correlations, the standard deviations are greater than the means, highlighting very volatile conditional correlations over the entire period studied. This means that the conditional correlations are not uniform over time. They vary considerably from one period to another. There are periods when the correlations are stronger and others when they are weak, times when they are positive, others when they become negative. Examination of Figure 2 shows, in the case of correlation between cryptocurrencies and the WAEMU stock market, strong variabilities of conditional correlations during the following years: 2014 (year of greatest media coverage of bitcoin), 2016 (year of Ethereum's breakthrough), 2018 (year of the official position taken by the BCEAO to discourage the use of cryptocurrencies in the WAEMU zone), 2020-2021 (years of global covid-19), 2022-2023 (international cryptocurrency crisis with the collapse of Terra-Luna and the FTX conglomerate, and the difficulties of Binance).

Table 6. Descriptive statistics of dynamic conditional correlations between stock indices and cryptocurrencies

	Mean	Maximum	Minimum	Std Deviation	Obs.
$\boldsymbol{\beta_{DCC}\ (BTC - BRVMC}$	0.0000215	0.264	-0.197	0.013	2349
$\boldsymbol{\beta_{DCC}\ (ETH - BRVMC)}$	0.0004782	0.341	-0.363	0.034	1824
$\boldsymbol{\beta_{DCC}\ (BTC - NGSE)}$	0.0002225	0.157	-0.147	0.011	2349
$\boldsymbol{\beta_{DCC}\ (ETH - NGSE)}$	0.000904	0.306	-0.318	0.032	1824
$\boldsymbol{\beta_{DCC}\ (BTC - GSE)}$	-0.000868	0.434	-0.747	0.031	2349
$\boldsymbol{\beta_{DCC}\ (ETH - GSE)}$	0.000352	0.156	-0.170	0.019	1824

Source: author, based on data from the sites african-markets.com (2023) and coinmarketcap.com (2023).

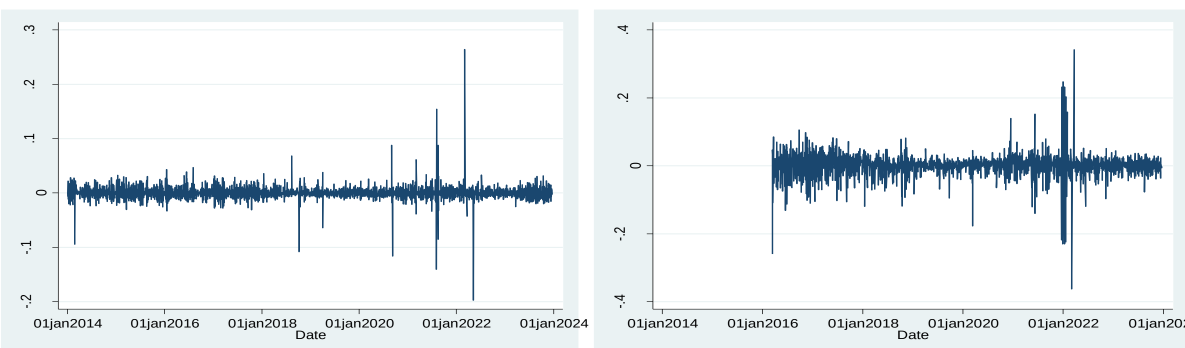


Figure 2. The evolution of dynamic correlations between BRVMC and cryptocurrencies

Source: author, based on data from the sites african-markets.com (2023) and coinmarketcap.com (2023).

To complete our study, it now remains to know the direction of causality between cryptocurrency markets and ECOWAS stock markets.

4.3 Co-Movement and Causal Relationships

According to Granger (1980), a variable X causes Y if the only knowledge of the past of X improves predictions about Y than past of Y would. Since the series are integrated in the same order, we could have used the Granger causality test. But this test is only a test of linear causality which does not take into account the non-linear dependence between the series (Brock et al., 1991). Consequently, we first test the presence of non-linear dependence on the VAR residuals in the series via a BDS test (Brock-Dechert-Scheinkma). When running the test, we select the dimension m from 2 to 6 and a distance $\varepsilon = 0.7$. Table 7 presents the results of this test for all series and their associated p-value.

Table 7. BDS test results

	Dim.2		**Dim.3**		**Dim.4**		**Dim.5**		**Dim.6**	
	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.	Stat.	Prob.
BIT	0.016	0.000	0.034	0.000	0.045	0.000	0.054	0.000	0.058	0.000
ETH	0.016	0.000	0.032	0.000	0.043	0.000	0.049	0.000	0.051	0.000
BRVMC	0.020	0.000	0.038	0.000	0.048	0.000	0.053	0.000	0.053	0.000
NGSE	0.035	0.000	0.062	0.000	0.078	0.000	0.084	0.000	0.085	0.000
GSE	0.022	0.000	0.046	0.000	0.061	0.000	0.069	0.000	0.070	0.000

Source: author, based on data from the sites african-markets.com (2023) and coinmarketcap.com (2023).

The test results show BDS statistics far from unity and probabilities equal to 0.000 for all markets. There is a non-linear dependence in the return series. Although this dependence is low, it is nevertheless present with a very high level of confidence. Consequently, we use the nonlinear Granger causality test, following the example of Hiemstra and Jones (1994). To validate the robustness of the models used for the Granger causality tests, we carry out diagnostic tests: heteroscedasticity, serial correlation and normality tests on the VAR residuals. The ARCH test statistics show that the residuals have equal linear and nonlinear mean-variant (homoscedastic) series. The Lagrange Multiplier (L.M.) test results show no serial correlation in the residuals. The results of the Jarque-Bera (J.B.) tests show that the residuals are normally distributed.

The results of the nonlinear Granger causality test (table) are presented in the table 8.

Table 8. Results of the Granger-causality test of Hiemstra and Jones (1994) between stock indices and cryptocurrencies

Null Hypothesis	Statistic tests	p-value	Decision
BIT does not cause BRVMC in the sense of Granger	-26.944	0.000	Reject
BRVMC does not cause BIT in the sense of Granger	12.14	0.235	Acceptance
BIT does not cause NGSE in the sense of Granger	-26.841	0.000	Reject
NGSE does not cause BIT in the sense of Granger	9.125	0.152	Acceptance
BIT does not cause GSE in the sense of Granger	-26.856	0.000	Reject
GSE does not cause BIT in the sense of Granger	7.565	0.136	Acceptance
ETH does not cause BRVMC in the sense of Granger	-27.241	0.000	Reject
BRVMC does not cause ETH in the sense of Granger	6.564	0.256	Acceptance
ETH does not cause NGSE in the sense of Granger	-26.900	0.000	Reject
NGSE does not cause ETH in the sense of Granger	3.125	0.168	Acceptance
ETH does not cause GSE in the sense of Granger	-26.900	0.000	Reject
GSE does not cause ETH in the sense of Granger	4.253	0.189	Acceptance

Source: author, based on data from the sites african-markets.com (2023) and coinmarketcap.com (2023).

The results of the non-linear Granger causality test show that the returns of cryptocurrencies (bitcoin and ethereum) have a unidirectional causal effect on the three main ECOWAS stock markets. More precisely:

- the transmission of volatility goes from bitcoin to the WAEMU and Ghana stock markets, from ethereum to the WAEMU stock market.
- Very low volatility transmission goes from bitcoin and ethereum to the Nigerian stock market.

4.4 Interpretation and Discussion of Results

The transmission of volatility from cryptocurrencies to the WAEMU and Ghanaian stock markets can be explained by portfolio adjustments. Indeed, the cryptocurrency market is characterized by both high liquidity risk and imperfect information. Therefore, liquidity shocks in the cryptocurrency market lead to excessive portfolio adjustments by investors in financial markets, including stock markets (Hafner et al., 2023). Furthermore, due to imperfect information in the cryptocurrency market, a shock in the cryptocurrency market is interpreted by stock market investors as relevant information, leading to excessive effects on these stock markets compared to their fundamentals.

Thus, in the event of positive shocks in the volatility of cryptocurrencies, economic agents in WAEMU and Ghana adjust their asset portfolios according to two essential motives: the speculation motive aimed at short-term speculative gains, the precautionary motive aimed at protecting themselves in the medium and long term, against exchange risk, inflation and other macroeconomic uncertainties. In the WAEMU, it seems that the speculation motive outweighs the precautionary motive, so that individuals buy cryptocurrencies at the expense of traditional stocks listed on the respective stock markets, with the main aim of making speculative gains. This short-term strategy has the effect of increasing the frequency of stock sales, causing their returns to vary considerably compared to the average return (equal to zero), and therefore their volatility. These results concerning a transmission of volatility between cryptocurrencies and traditional stocks are consistent with those of Bouri et al. (2018), Corbett et al. (2018c), Kurka (2019) and Qezelbash et al. (2023) who use methods (volatility spillover model, GARCH model, time-frequency model) different from that used in this study.

The virtual absence of transmission of volatility from cryptocurrencies to the Nigerian stock market can be explained as follows: shocks on cryptocurrency markets are also interpreted by economic agents in Nigeria as relevant information inducing portfolio adjustments. But in Nigeria, it seems that the precautionary motive prevails over the speculation motive. Indeed, the Nigerian currency, the Naira, is subject to high inflation and speculative attacks which lead individuals to protect themselves against these risks by holding cryptocurrencies, in the medium and long term. This medium and long term strategy tends to stabilize the frequency of stock sales, which tends to make the volatility in the Nigerian stock market independent of the volatility of cryptocurrencies. We could have had an indirect effect of cryptocurrencies on the Nigerian stock market via the WAEMU and Ghana markets. But the weak connectivity between these two stock markets and that of Nigeria makes such an indirect effect unlikely.

5. Concluding Remarks

This study sought to analyze the links between the market of the main cryptocurrencies (bitcoin, ethereum) and the main stock markets of ECOWAS (WAEMU, Ghana, Nigeria) over the period from January 3, 2014 to December 20, 2023. The empirical methodology is based on a DCC-GARCH model useful for studying the transmission of volatilities between financial markets. Estimates from this model showed the existence of a persistent transmission of volatility between the bitcoin market and the WAEMU and Ghana stock markets. Such co-movement is non-existent between ethereum and the Ghana stock market. On the other hand, the results also showed the almost non-existence of transmission of volatility between these cryptocurrencies and the Nigerian stock market. Nonlinear Granger causality studies, following the approach of Hiemstra and Jones (1994), have shown the existence of unidirectional causalities running from cryptocurrencies to stock markets. This is explained by different portfolio adjustment processes due to different reasons for holding cryptocurrencies. While in WAEMU and Ghana, agents primarily hold cryptocurrencies for speculative reasons, individuals in Nigeria hold them primarily for precautionary reasons, leading to a disconnect between these markets.

This study is of scientific interest because it constitutes, to our knowledge, the first study analyzing the links between cryptocurrencies and the ECOWAS stock markets. It is also of practical interest for the regulation of financial stability in the stock markets of WAEMU, Ghana and Nigeria. We have seen that the extreme volatilities observed in the cryptocurrency markets are partly transmitted to the stock markets of the WAEMU and Ghana, which is likely to destabilize them. Therefore, the study recommends that financial market regulators take into account the volatilities on cryptocurrency markets in their financial stability policy. This must include strategies aimed at the stability of cryptocurrency prices: the promotion of stablecoins, the promotion of central bank digital currencies (CBDC), the promotion of cryptocurrencies based on the proof of combustion protocol or concrete utility values, and whose volatility is very low (Saleh, 2020; Pignel, 2019).

Other recommendations concern the promotion of financial integration between the WAEMU stock markets and those of Ghana and Nigeria. For the moment, the weak correlation between them could be an obstacle to the establishment of the monetary union extended to all of ECOWAS. Other recommendations are aimed at investors in ECOWAS stock markets. They should pay attention to cryptocurrencies when managing their asset portfolio. This should affect their asset allocation strategy. A limitation of this study is the failure to take into account other contagion models such as multi-fractal models or BEKK-GARCH models which would have made it possible to study the robustness of our results. We are considering the use of such models for future research which could also focus on empirical studies of the reasons for holding cryptocurrencies in ECOWAS. This would allow a more detailed analysis of the adjustment processes of asset portfolios in the event of cryptocurrency shocks.

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Authors Contributions

Dr. KOUAKOU Thiédjé Gaudens-Omer led the entire study.

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Notes

Note 1. Economic Community of West African States.

Note 2. Collapse of Terra-Luna and the FTX conglomerate, difficulties of Binance.

Note 3. The spillover measures (total spillover index S^H, spillovers of asset i, and spillovers to asset i) are obtained from a decomposition of the variance of the h-step forecast errors from a VAR model of order p:

$$RV_t = \sum_{i=1}^{p} \rho_i V_{t-i} + \varepsilon_t$$

Where RV: realized variance (non-parametric measure of variance obtained from high frequency returns); V: variance.

Note 4. For now, the cryptocurrency ecosystem is far from being large enough to threaten the dominant role of traditional finance. However, this could change in the future, if we look beyond the current difficulties of the sector. It is therefore important to remain vigilant.

Note 5. Each conditional variance h_t depends not only on its own squared errors from previous periods, but also those of the other variable in the system as well as the cross product of the past errors of the two series. The VEC-GARCH model is written:

$$Y_{t,k} = \theta X_{t,k} + \varepsilon_{tk} \quad \text{with } \varepsilon_{tk} = z_{tk}\sqrt{h_{tk}} \text{ et } \varepsilon_{tk}/I_{t-1,k} \rightarrow N(0, h_{t,k}) \text{ and}$$
$$h_{t,k} = \alpha_{0,k} + \sum_{i=1}^{q} \alpha_{i,k}\varepsilon_{t-1,k}^2 + \sum_{j=1}^{p} \beta_{j,k} h_{t-j,k} \qquad k = 1,2,\ldots,K \text{ index of financial asset}$$

Note 6. This data is collected every day of the week except Saturdays, Sundays and public holidays (depending on the calendar of each country) for the stock markets and is collected every day without exception for the cryptocurrency markets. For clarification purposes we have arranged our data so that all markets have the same trading days to obtain the same number of observations.