

VOLATILITY SPILL OVER EFFECT OF CRYPTOCURRENCY PRICES AND FOREIGN EXCHANGE IN NIGERIA

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Abstract

The study analyzes the volatility spillover effects of cryptocurrencies and foreign exchange market in Nigeria, covering a two-year period from September 19th, 2019, to September 19th, 2021. It captures a period where the domestic and foreign economy experienced a series of challenges, reflecting on its financial markets and cryptocurrency. The study adopts the Vector Autoregressive - Multivariate Generalized Conditional Heteroskedastic methodological framework, with the Baba, Engle, Kraft, and Kroner transformation (VAR-MGARCH-BEKK), to determine the volatility spillover effect between Nigeria's Foreign exchange returns and the price returns of four of the largest cryptocurrencies traded in Nigeria. Findings indicate foreign exchange have positive effect on the mean spillovers on cryptocurrencies, and an overall market influence over cryptocurrencies, due to a high GARCH and low ARCH estimate. However, the ARCH parameters show that past errors of foreign exchange market are observed to be vulnerable to external volatilities. Therefore, the study is able to conclude that cryptocurrencies serve as a viable hedging, safe haven and an effective diversification instrument against financial uncertainties, and therefore, recommends optimal diversification strategies and low leverage contracts to avoid the high risks cryptocurrencies present, as they are highly volatile, hence, susceptible to speculative attacks.

Keywords: *Cryptocurrency, Foreign Exchange, Volatility, Spill Over Effect.*

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1. Introduction

According to Polansek (2016), a cryptocurrency is a digital asset designed to work as a medium of exchange such that records are stored in a form of computerized database with the aid of an array of cryptographic algorithms to secure transaction records, to control the creation of additional coins, and to verify the transfer of coin ownership. Although, the idea of embedding digital cryptographic algorithms into daily financial transactions is originally traced

back to Chaum (1982), with 'e-cash' digital currency, based on the 'blind signature cryptosystems', it is Nakamoto (2008) 'Bitcoin', a peer-to-peer electronic payment system based on blockchain cryptography that gained rapid popularity in the financial system, laying the foundation for cryptocurrencies in general, to be recognized as a form of financial asset.

As of September 2021, there are 11,819 cryptocurrencies in circulation, with a market capitalization of over \$2 trillion and \$107.2 billion trade volume on a 24-hour average globally. Bitcoin holds the dominant market share of 41% of market capitalization, followed by Ethereum, Cardano and Binance cryptocurrencies controlling market shares of 18.8%, 3.97%, and 3.29% respectively (CoinMarket Cap, 2021).

Although, Nakamoto's (2008) framework was initially designed to control the gaps that constrains the conventional financial system, such as additional bank charges, hedging inflation, user security and anonymity, however, the decentralized system of cryptocurrencies have raised concerns by government bodies and regulatory institutions, in all parts of the world, especially in Nigeria. The Central Bank of Nigeria have issued warnings and strong notices against cryptocurrency transactions in 2017, citing they possess no legal tender (Sanni, 2019), followed by prohibitive sanctions against commercial banks facilitating cryptocurrency transactions in 2021, citing its direct link to illicit activities, and its volatility structure, making it relatively riskier assets to hold, and more susceptible to speculative buying.

However, the underlying regulatory sanctions have been unable to deter cryptocurrency trading in Nigeria, as there has been a persistent rising trend of cryptocurrency transactions in Nigeria as of recent. As of the fourth quarter of 2020, Nigeria held a total of 60,215 BTC with an approximate trade volume of \$566 million, surpassing China as the second largest bitcoin peer-to-peer market in the world (Williams, 2020). Moreover, peer-to-peer transactions of local cryptocurrency purchase soared over 50% between the last few quarters (Baydakova, 2021); (Zimwara, 2021), where premium prices of bitcoin and other cryptocurrencies in Nigeria, rose between 16% - 40% higher than its corresponding market price (Zimwara, Nigeria Crypto Ban: Bitcoin Sells for \$76K as Deposits on Centralized Exchanges Plummet, 2021), since the prohibitive sanctions issued in February 2021.

One key determinant of cryptocurrency adoption in Nigeria is the urgent need to seek investment alternatives outside the framework of the Nigerian Financial System, specifically to hedge against domestic currency depreciation. As it is common knowledge, the Nigerian foreign exchange market has been experiencing challenges over the past few years. Due to the oil crisis that occurred as a result of the COVID-19 pandemic, the value of the domestic currency has depreciated in value, from \$1 - \$365.00 in 2019 to \$1 - ₦411.5 (Central Bank of

Nigeria, 2021). Unfortunately, the collective efforts made by the regulators and government to maintain stability have been ineffective as of recent, having experienced a series of socio-economic challenges like insecurity, oil price volatilities, inflationary gaps, diminishing Foreign Private Investment, personal remittance of U.S dollar received, etc., giving domestic investors the incentive to hedge their assets by adopting alternative means.

Therefore, the principal objective of the research study is to assess the volatility spillovers between cryptocurrencies and foreign exchange in Nigeria, in order to determine a causal effect between the centralized and decentralized market, so as to verify whether domestic currency depreciation in Nigeria is as a result of cryptocurrency purchases, and/ or vice versa, while capturing the most recent time periods where market uncertainties as indicated determined the prices of both cryptocurrencies and naira value.

The rest of the paper is organised as follows. The literature review will be categorized into the theoretical and empirical framework, where the former looks at prior theories relating to asset pricing, optimal portfolio selection and diversification, while the later centrally focuses on prior analyses regarding the causal relationship and volatility spillover effect between cryptocurrencies, foreign exchange, and centralized financial assets in general. Next, the methodological framework describes the empirical approach that is to be adopted to addressing the underlying objective, where further data analyses and interpretation will be made subsequently. The final section draws conclusions and derives recommendations based on research findings.

2. Literature Review

A rational risk averse investor prefers to adopt optimization strategies in terms of portfolio selection and diversification, such that value returns are maximized, and simultaneously minimizing the risks associated with acquiring such securities. However, the principal challenge that is accompanied with employing such strategies with cryptocurrencies lies with the disparities in volatility between cryptocurrencies and more centralized assets. Hence, cryptocurrencies may be less applicable to a risk averse investor, relative to other securities. Therefore, this session investigates prior theoretical analyses pertaining to optimal portfolio selection and diversification strategies, from the perspective of a risk averse investor, alongside the incorporation of cryptocurrencies in the underlying theoretical framework to determine its empirical validity. This would be followed by exploring prior empirical studies that assessed the volatility dynamics of cryptocurrencies, its spillover effect, and causal relationship with fiat currencies, and other traditional financial assets.

The fundamental notion behind the implementation of optimal portfolio selection and diversification strategies originates from the Modern Portfolio Selection Theory (MPT), suggested by Harry Markowitz (1952), applying the Hicksian decomposition, and mean variance analysis to estimate the correlation and covariance between a set of return assets/securities, so as to allow for investors to efficiently allocate their portfolio based of each asset's risk return potential. It defines a portfolio return as the proportion weighted combination of returns on securities, where the expected value and variance of weighted sum of securities are calculated, popularly known as the ($E - V$) rule. The Brian M. Rom and Kathleen Ferguson (1993) Post-Modern Portfolio Selection Theory (PMPT) extension adopts the downside risk formula or the mean semi-variance approach, which is a financial risk model associated with losses, using the standard deviation of negative returns to regress against the Minimum Acceptable Ratio (MAR), defined as the minimum rate of return that must be earned in order to achieve core financial objectives (Rom & Ferguson, 1993), taking control of some of the limitations of the MPT model (Kenton, Downside Risk Definition, 2019); (Hussain, 2021).

Because of the volatility structure of cryptocurrencies, the empirical validation of prior literatures relating to MPT, and its applicability to the cryptocurrency market, stretches further into the PMPT extension. For instance, Selmi, et al (2018) used the downside risk formula to determine the implication of using Bitcoin as a diversifier against oil and gold. Findings indicate a high explanatory power statistically significant optimal weighted portfolio found in Bitcoin – Oil, and Gold – Oil, implying the high effectiveness of Bitcoin and Gold on risk mitigation, outperforming gold as a diversifier against oil prices. Dyhrberg (2016) found hedging and diversification capabilities of Bitcoin against the US dollar and the FTSE index, hence, qualifying Bitcoin as a risk minimizer. Veldmeijer (2018) observed a more efficient portfolio frontier with the inclusion of cryptocurrencies by 17%, alongside evidence of strong volatility returns, and low correlation with other traditional assets, verifying the empirical application of the MPT framework. Although, Petukhina et al (2020) could neither empirically validate the Markowitz (1952) model nor the downside risk formula but found that cryptocurrencies have a likelihood of improving the risk-return profile of portfolios, however, have a more significant impact for risk premium investors than the risk averse.

The Capital Asset Pricing Model (CAPM), initially proposed by Sharpe (1964) and Lintner (1965) adopts a closely similar analytical construct to the MPT model, however, it considers the systematic risk premium of an additional asset into a portfolio mix. This is attributed to the expectation of compensated risk taken by the investor, and time value of money of a particular stock (Sharpe, 1964); (Kenton, Capital Asset Pricing Model, 2021). Therefore,

the model is generated by estimating the differential covariance between the expected return on the market value and the time value of money (i.e., risk free rate), in turn, obtaining the coefficient of the risk premium an additional security. Overall, CAPM gives an investor the required information to determine the potential risk associated with the returns on capital stock (Lintner, 1965); (Kenton, Capital Asset Pricing Model, 2021). Although, the conceptual analysis of the model has been applied over the years and continue to play an intricate role in the financial market, the challenge of the underlying model partly fails to merit empirical justification (Dempsey, 2013). These challenges are classified into three anomalies, which include the beta (premium) anomaly, value anomaly, and momentum anomaly (Basu, 1977); (Banz, 1981). These challenges make it somewhat unrealistic for the CAPM framework to be applied in the real world (Schmidt, 2020) for either conventional assets or cryptocurrencies, hence, encouraging subsequent scholars to modify the framework to suit empirical justification.

The Fama-French (1992) three-factor pricing model is an extension to the Sharpe (1964) and Lintner (1965) framework that include both the Size Market Premium, which is the difference between the Market Capitalization of the returns of small and large stocks, and the Value Premium, which is the difference between high and low book market equity (BE/ME) ratios. These variables take control of the value and momentum anomaly respectively and relaxing the statistical significance of the risk premium in the process. It, therefore, goes to imply that asset pricing and portfolio selection strategies go beyond the confines of the risk premium associated with a particular security and is subject to external factors (Fama & French, 1992).

As such, most empirical literatures sought to validate the asset pricing theory, through the application of the factor pricing model, as it has proven to empirically outperform the standard CAPM framework. By developing the three-factor asset pricing model, including market size and the factor of transaction volume relative to the market capitalization of 15 cryptocurrencies, Stoffels (2017) was able to define a high explanatory power of stronger momentum for smaller markets (i.e., recent winners/ losers) about with 35% variation of weekly returns, hence, taking control of the momentum anomaly in the CAPM framework. Not only the three-factor model is empirically valid for cryptocurrency assets, but it also strongly outperforms the initial CAPM framework. Similar findings are uncovered with Shen, Urquhart & Wang (2020) as smaller cryptocurrencies (losers) tend to have a likelihood of higher returns than its larger counterparts. Pontoh & Riakianto (2019) also found high explanatory powers in the empirical application of cryptocurrency returns into the three-factor pricing model. They were able to uncover statistically significant exposure of 17 out of 18 cryptocurrencies in at

least, one of the proposed additional factors, where cryptocurrencies with small market capitalization tend to have higher returns than those with larger market capitalization.

Aside from the Fama (1970), Fama & French (1992), among several other CAPM extension, the Arbitrage Price Theory (APT) is a crucial extension to the CAPM framework, as it empirically presents market conditions for acquiring the same asset in different markets. Initially proposed by Stephen Ross (1976), the APT framework is an analytical tool in investment that explains the trend behaviour of a risky asset, in different markets, providing an opportunity for an investor to select and diversify portfolios in a relatively risk-free market environment. Like the factor model, it is modelled as a linear function of systematic factor inputs, where its sensitivity towards trend fluctuations or volatilities are parameterized as the coefficient of each factor input. The underlying difference lies with each factor input, as it could be investment or macroeconomic related. However, it is presumed that an arbitrageur could be less risk averse than the conventional risk averse stockholders, as their portfolios are mostly leveraged (Ross, 1976).

Because of the premiums attached to cryptocurrency transactions at different markets, as previously the underlying theoretical framework tend to be more appealing to the volatility dynamics of cryptocurrencies seeing that decentralized markets trade at flexible rates. Hayes (2017) was able to identify more arbitrage opportunities between bitcoin and other cryptocurrencies than amongst a variety of altcoins, based on empirical findings of at least, 84% explanatory power on relative value formation of cryptocurrencies, including computational power, mining rate, and complexity of algorithms. Makarov & Schoar (2019) observed price deviations across cryptocurrency trading platforms based on regional diversities, specifically, U.S, Europe, Latin America, and Asia. Likewise, the findings of Czapliński & Nazmutdinova (2019) identified strong arbitrage opportunities in cryptocurrency trading, across three different exchange platforms, within 70% of examined moments with an estimate of 0.62% to 8.79% riskless profit per transaction. The disparities between premium prices across different cryptocurrency trading platforms in Nigeria since the prohibitive circular issued in February 2021 could also indicate arbitrage opportunities for an investor, especially if he/ she has access to foreign markets.

The literatures of Krauss et al. (2017), followed by Fischer, Krauss & Deinert (2019) confirmed arbitrage opportunities among 40 cryptocurrencies with over 100,000 transactions, however, recommended slight delays or premature actions for each transaction could have an adverse effect on the risk return ratio (Fischer, Krauss, & Deinert, 2019). Contrary to the findings of Czapliński & Nazmutdinova (2019), Wang (2018) rejected joint hypothesis on

differences in bitcoin returns between different cryptocurrency trading platforms, except for an investor having to strategically place a short position on one market against the other.

For many stakeholders, the most challenging aspect of cryptocurrencies has been its volatility structure compared to other forms of financial assets. The underpinning theories of asset pricing and portfolio diversification discussed in this study have shown core similarities between cryptocurrencies and traditional financial assets based on the empirical justification of each theory, therefore assuming the same methodological approach as treating traditional financial assets. Therefore, the rest of this chapter will focus on the empirical framework, in terms of the volatility dynamics of cryptocurrencies and its spillover effects on foreign exchange and other assets.

Authors like Katsiampa (2017), Wang (2018), Charles & Darné (2019), and Fakhfekh & Jeribi (2020) applied a series of conditional heteroskedastic (GARCH) models to investigate the volatility price returns of cryptocurrencies and determine the optimum model(s) most useful for modelling cryptocurrency volatilities. All indications pointed to high volatility persistence and asymmetric effect, with more response to positive shocks (i.e., good news) than negative asymmetries (i.e., bad news). While most recommendations indicate the Threshold GARCH and exponential GARCH in mean model, serve as the best options for modelling the volatility dynamics of cryptocurrencies, Charles & Darne (2019) however, recommended adopting multifractal framework and long memory neural network analysis to control a larger dataset.

Chaim & Laurini (2019) attempted to explain the changes in returns of volatility, with regards to abrupt price swings of cryptocurrency assets using a multivariate stochastic volatility model to estimate the discontinuous jumps to mean returns and volatility, capturing long memory volatilities as well. Likewise, indications pointed to a persistent volatility trend, attributed to major market developments, and collective interest of the commodity. Furthermore, long memory features of cryptocurrencies are produced and reproduced by stationary models with transitory jump components. Lahmiri, Bekiros & Salvi (2018) revealed the existence of long-range memory in seven selected bitcoin markets volatility, regardless of its distributional premise, with the application of the Fractionally Integrated GARCH model to capture the long-range memory distribution in the endogenous series.

There are a few other literatures that contributed to the analysis of cryptocurrency volatilities by adopting other empirical approaches. Bouri et al. (2019) analysed the volatility dynamics of cryptocurrencies, using the Copula-Quantile Causality Approach (CQCA), and Granger Causality to test the causal effects of trade volume and the predictability returns of the cryptocurrency markets. Findings indicate significant positive and negative causal effects of

trading volume and causal effect on three out of four cryptocurrencies, specifically towards low volatility. The literatures of Aalborg, Molnar, & Erik de Vries (2019), alongside Bouri, Roubaud & Shahzad (2020) also corroborated the importance of cryptocurrency trade volume in measuring the causal effect of cryptocurrencies, especially in times of financial uncertainty.

The literatures of Wang (2018) and Katsiampa, Corbet & Lucey (2019) took a step further by applying the Vector Autoregressive Regression Generalized Autoregressive Conditional Heteroskedastic Baba Engle Kraft Kroner (VAR-GARCH-BEKK) extension to derive covolatility spillover effects between cryptocurrencies and a set of fiat currencies. Empirical findings revealed spillover effects between cryptocurrencies and the Chinese Yuan, alongside other Chinese equities, however, the hedging abilities of cryptocurrencies against the Chinese markets remain uncertain. Similarly, Wang, et al. (2019) found volatility spillover effects between bitcoin, gold, foreign exchange, and Chinese monetary assets. Although, it rejects hedging potential against gold, but confirms the hedging capabilities of bitcoin against the SHIBOR interest rate and a diversifier against foreign exchange.

In addition, Gandal & Halaburda (2016) uncovered strong network effects between cryptocurrencies and the U.S dollar, such that Bitcoin tend to appreciate against the dollar, while altcoins tend to depreciate against the dollar, following strong evidence of cross correlation (Ciaian, Rajcaniova, & Kancs, 2018); (Bouri, Brian, & Roubaud, The volatility surprise of leading cryptocurrencies: Transitory and Permanent linkages, 2020); (Shi, Tiwari, Gozgor, & Lu, 2020), etc., hence, consistent with a winner take all dynamic. Jimoh & Benjamin (2020) sought to explain the reaction volatility of exchange rates and equities index in cryptocurrency prices, with the GARCH and e-GARCH framework, alongside granger causality for robustness purposes, and found domestic currency appreciation as a result of cryptocurrencies by 0.002%, as well as spillover effects between endogenous variables, hence, an indication of safe-haven capabilities.

Based on what was previously discussed, Dyhrberg (2016) wrote a follow up research from her previous article, 'The Hedging Capabilities of Bitcoin', to explore similarities between the gold and the U.S dollar, to replicate the findings of the previous literature. However, estimates from a more recent dataset reveals a distinctively different return, volatility, and correlation compared to the more traditional assets, implying speculation in the cryptocurrency market (Dyhrberg, Bitcoin, Gold and Dollar- A GARCH volatility analysis, 2016).

Overall, both theoretical and empirical analyses of prior literatures, pertaining to cryptocurrency volatilities and its effect on other financial assets is subject to time lag variation,

such that, findings often differ given multiple time periods, which could be attributed to the market dynamics associated with a growing cryptocurrency market, such as, public perception towards the commodity, institutional investment, regulation, utilities, technological advancement, etc.

3. Methodology

Most literatures usually apply a series of stochastic volatility modelling techniques could potentially generate a good fit for achieving the core objective of the underlying study, as it consists of a series of regression models that relaxes the assumption of a constant variance of the stochastic variable in a time series data. Hence, the takes an identical empirical approach, by adopting an Asymmetric Vector Autoregressive - Multivariate Generalized Conditional Heteroskedastic methodological framework, with the Baba, Engle, Kraft, and Kroner transformation (VAR-MGARCH-BEKK) to critically assess the volatility spillover effect between cryptocurrencies and Foreign Exchange in Nigeria.

Secondary data, consists of Foreign Exchange (FX) and four of the most traded cryptocurrencies in Nigeria, Bitcoin (BTC) Ethereum (ETH), Ripple (XRP), and Litecoin (LTC), captured within a two-year period from September 19th, 2019, to September 19th, 2021. The dataset is collected from the Central Bank of Nigeria (CBN) annual statistical bulletin to capture Foreign Exchange, and historical data from CoinGeckoLabs to capture the market prices of selected cryptocurrencies.

3.1. Model Specification

Analysing the volatility spillover effects between cryptocurrency prices and foreign in Nigeria, require estimating the parameters of the conditional mean, variance, and covariance of all five endogenous variables. Hence, the VAR-MGARCH-BEKK model is a good fit, as it satisfies all requirements to generate parameter estimates.

First, the conditional mean equation replicates the VAR(p) specification, a linear model that will estimate the parameters of a ($n \times 1$) vector time series endogenous variables Y_t , and its corresponding cumulative ($n \times n$) lagged operators, Y_{t-i} and ($n \times 1$) unobservable error terms, U_t , using the Ordinary Least Square (OLS) method to determine the causal relationship between variables.

$$R_t = B + \sum_{i=1}^p B_i R_{t-i} + U_t$$

$$(3.1.1)$$

$R_t = \Delta \ln Y_t \approx \ln Y_t - \ln Y_{t-1}$, for each asset in the time series. Equation (3.1.1) can be reparametrized into the following VAR(p) vector matrix,

$$\begin{pmatrix} \Delta \ln FX \\ \Delta \ln BTC \\ \Delta \ln ETH \\ \Delta \ln XRP \\ \Delta \ln LTC \end{pmatrix}_t = \begin{pmatrix} \beta_{10} \\ \beta_{20} \\ \beta_{30} \\ \beta_{40} \\ \beta_{50} \end{pmatrix}_t + \sum_{i=1}^p \begin{pmatrix} \beta_{11} & \beta_{12} & \dots & \beta_{15} \\ \beta_{21} & \beta_{22} & \dots & \beta_{25} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{51} & \beta_{52} & \dots & \beta_{55} \end{pmatrix}_i \begin{pmatrix} \Delta \ln FX \\ \Delta \ln BTC \\ \Delta \ln ETH \\ \Delta \ln XRP \\ \Delta \ln LTC \end{pmatrix}_{t-i} + \begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \end{pmatrix}_t \quad (3.1.2)$$

$\Delta \ln FX$ represent the foreign exchange returns, while $\Delta \ln BTC$, $\Delta \ln ETH$, $\Delta \ln XRP$ and $\Delta \ln LTC$ represent the price returns of Bitcoin, Ethereum, Ripple, and Litecoin, the largest cryptocurrencies in Nigeria by trade volume and market capitalization. $\beta_{10t}, \beta_{20t} \dots \beta_{50t}$ denote the y-intercept for each corresponding dependent variable; p is the lag order for parameters $\beta_{11i} \dots \beta_{55i}$ which would be determined by the recommendations of the AIC, SC or HQIC for lag selection and $\mu_1, \mu_2 \dots \mu_5$ represent the residual error terms.

The MGARCH (q, r) model captures conditional variance and covariance parameters by estimating the covolatility relationship between endogenous variables, across the vector series. The Kroner & Ng (1998) extension captures the asymmetric shock effect of among treated assets, by augmenting the GARCH series model with the Glosten-Jagannathan-Runkle Threshold GARCH specification.

$$H_t = \Psi + \sum_{i=1}^q \Theta_i H_{t-i} + \sum_{j=1}^r (B_j + Y_j D_{t-j}) \mu_{t-j}^2 + \sum_{k=1}^K \sum_{i=1}^q \eta_i \sigma_{t-i}^2 + \sum_{k=1}^K \sum_{j=1}^r X_j \varepsilon_{t-i}^2 \quad (3.1.3)$$

H_t represents the conditional variance and covariance vector matrix of heteroskedastic series in the structural equation in (3.3.1), defined as the function of the y-intercept (Ψ), the respective ($n \times n$) vector coefficient of heteroskedastic variance (GARCH), mean square error (ARCH), and asymmetric shock effects (Θ_i, B_j, Y_j), the spillover ARCH and GARCH effects of other endogenous variables on the target variable lagged to the k th order ($X_j \varepsilon_{t-i}^2, \eta_i \sigma_{t-i}^2$). The i th and j th lag order (p, q) for the GARCH and ARCH effects will be determined by a parsimonious modelling technique.

The BEKK transformation imposes a dimensionality reduction algorithm that compartmentalizes clusters of data estimates that could exist in a lower dimensional sample space, such that the original data is not significantly compromised, particularly in terms of the variance for each endogenous variable in the vector series. Hence, the MGARCH-BEKK (q, r)

framework is further simplified to a vectorized heteroskedastic variance and covariance vector series (\mathcal{H}_t), which is defined as a function of the upper triangular ($n \times n$) vector matrix of the constant (C_0), GARCH terms (G_{ik}), ARCH terms (A_{jk}), and the asymmetric effects (D_{jk}).

$$\mathcal{H}_t = C_0^T C_0 + \sum_{k=1}^K \sum_{i=1}^q G_{ik}^T \mathcal{H}_{t-i} G_{ik} + \sum_{k=1}^K \sum_{j=1}^r A_{jk}^T \mu_{t-j} \mu_{t-j}^T A_{jk} + \sum_{k=1}^K \sum_{j=1}^r D_{jk}^T \mu_{t-j} \mu_{t-j}^T D_{jk} \tag{3.1.4}$$

3.2. Model Justification

The application of the VAR(p)-MGARCH-BEKK(q, r) model is one of the numerous extensions to the original Engle (1982) ARCH specification, an empirical framework on estimating predictability return volatilities of most financial assets and securities, that is initially based on the theoretical analyses of the prior frameworks discussed earlier in the study. The model provides a richer dynamic structure than many other GARCH series, as it assumes each endogenous variable in the multivariate time series follow a conditional heteroskedastic (GARCH) process, producing a vectorized model with a structural time varying variance (VAR-MGARCH). The dimensionality reduction process parsed in the BEKK extension ensures a positive definite conditional covariance matrix, that allows easy convergence and prevents overparameterization of MGARCH series for easier analysis and interpretation (Engle & Kroner, 1995).

The model consists of 5 endogenous variables, classified into one control/ target variable $\Delta \ln FX_t$, and four model variables $\Delta \ln BTC_t$, $\Delta \ln ETH_t$, $\Delta \ln XRP_t$, and $\Delta \ln LTC_t$. The relative valuation of the Nigerian Naira (NGN), with respect to the U.S Dollar (USD) is an appropriate tool for measuring the purchasing power of the domestic currency, as its market valuation freely floats against foreign counterparts, including the U.S. (Central Bank of Nigeria, 2016). Hence, the data on foreign exchange consist of FX returns of the Nigerian Naira against the U.S dollar (USD/NGN). The other four model variables proxy cryptocurrency transactions in Nigeria, as they are the most traded cryptocurrencies in Nigeria (Luno exchange, 2021) and the largest cryptocurrencies by market capitalization (CoinMarket Cap, 2021). Hence, the study considers the naira value of each cryptocurrency price return as part of the treatment experiment. Moreover, the suggested period was deliberately constructed to reflect the recent uncertainties that has hindered the domestic financial market and the decentralized finance in general such as the spillover effects of COVID-19, oil price fluctuation, regulatory sanctions against cryptocurrencies, etc.

To avoid a spurious regression and ensure the fundamental premise of the underlying model hold, estimation diagnostics are conducted. The Portmanteau Ljung-Box (Q) diagnostic is carried out to determine random walks, whether each linear equation or the structural model have residual disturbances. Although, the inclusion of the time varying variance (\mathcal{H}_t), across the vector matrix already relaxes the assumption of stationarity, because of the application of the Quasi-Maximum Likelihood Estimation (QMLE) technique, however, the Augmented Dickey Fuller (ADF) test is also carried out to check for unit root presence to empirically validate the VAR(p) model, as it requires the Least Square (LS) technique to estimate parameters. Lastly, post-estimation diagnostics consist of the Durbin Watson (D-W) and Multivariate Portmanteau Ljung-Box (Q) test statistic to check for autocorrelated residuals and heteroskedasticity for each equation and the entire vector series respectively.

4. Empirical Results and Discussion

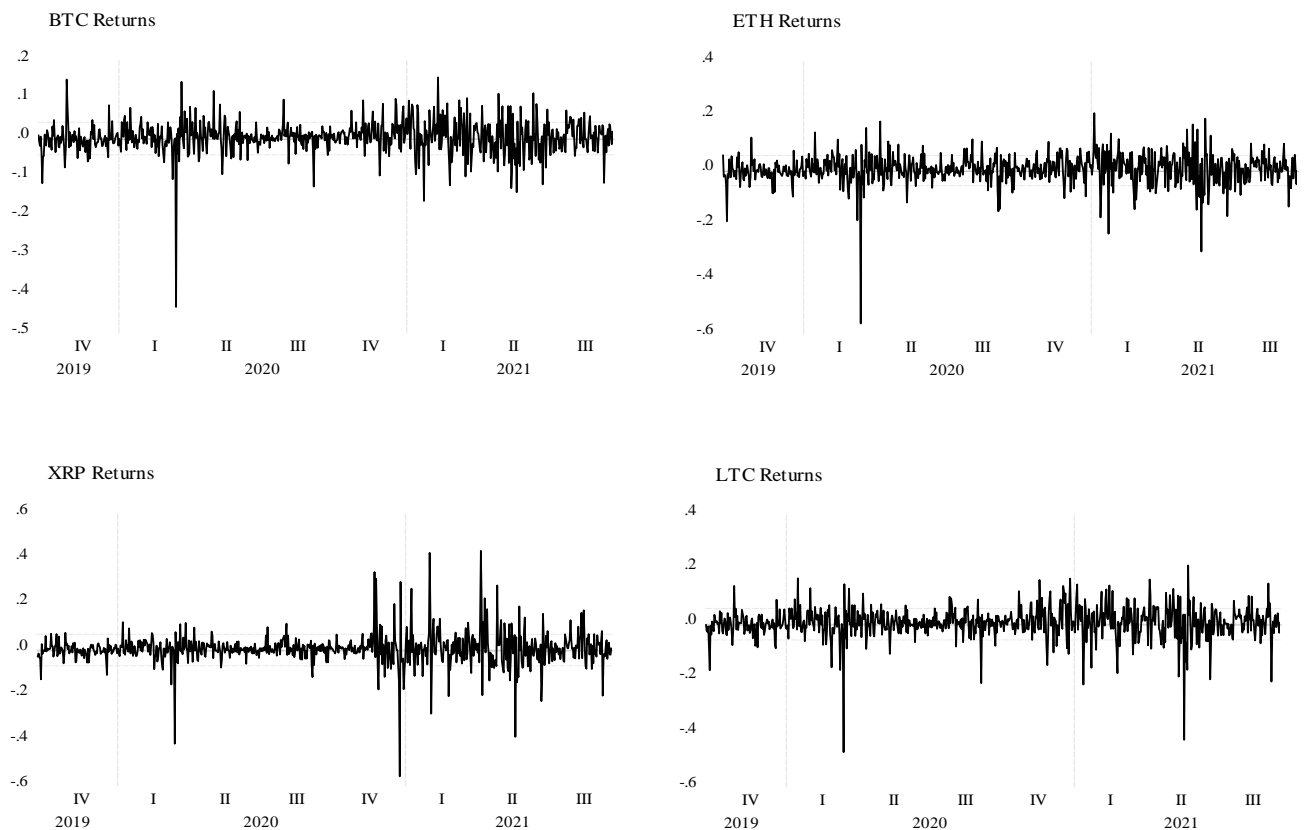
4.1. Descriptive Analysis

Table 4.1.1: Summary statistics and Unit root tests (R_t)

Variable	FX	BTC	ETH	XRP	LTC
Obs. (n)	733	733	733	733	733
Mean	0.000403	0.00227	0.00396	0.00196	0.00135
S.D.	0.008085	0.04179	0.05541	0.06923	0.05795
Minimum	-0.3279	-0.4323	-0.5617	-0.5707	-0.47
Maximum	0.1953	0.1568	0.2166	0.4314	0.2389
ADF (Z_t)	- 20.786***	-19.540***	-19.162***	-19.733***	-19.269***
PP (Z_τ)	- 31.101***	-29.653***	-30.597***	-27.663***	-29.916***
Univariate Ljung-Box (Q)	14.0313	56.8884**	92.1986***	53.3208*	60.8032**
Multivariate Ljung-Box (Q_{t-1})	56.204***	Multivariate Ljung-Box (Q_{t-20})	775.738***	Multivariate Ljung-Box (Q_{t-40})	1356.63***

The summary statistics depicted in table 4.1.1 captured $n = 733$ observations for each variable in the time series, aggregating up to $N = 3665$ observations for the entire population between 19th September 2019 and 19th October 2021. Furthermore, all cryptocurrencies are

observed to be appreciating on an average daily basis, against both domestic and foreign fiat currencies, with ethereum having the highest daily returns of 0.004%, compared to the fiat currency that has diminished in value within the sample period, with depreciation rising at a daily average of 0.0004%. The standard deviation of all endogenous variables in the time series are observed to exceed the corresponding mean, signalling strong positive skewness within the specified t period. Both Augmented Dickey Fuller (Z_t) and the Philips Perron (Z_τ) test statistics reject unit root at less than 1% statistically significant level, confirming stationarity between the assets from the first order. Except for the foreign exchange, the univariate Portmanteau Ljung Box (Q) tests rejected White noise for all cryptocurrencies, implying some degree of disturbances between the error terms of the model variables (i.e., cryptocurrencies). This is corroborated by the volatility clusters found in the linear plot for each corresponding asset returns (figure 4.1.3). The multivariate Ljung-Box Q- statistic also confirmed residual disturbances across the vectorized model from the first to the 40th lag, hence, justifying the need to endogenize the residual error terms by assuming conditional heteroskedasticity (H_t).



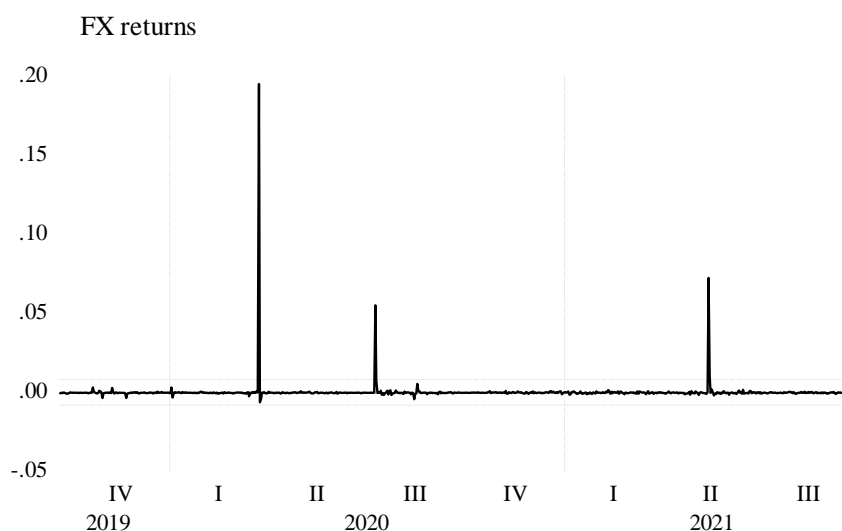


Figure 4.1.3: Historical volatility trend of return assets (R_t)

Source: Author’s compilation from EViews 12

4.2. Mean Volatility Spillover Effects: VAR estimation

Table 4.2.1 Vector Autoregressive Model

Variable	$\Delta \ln FX_t$	$\Delta \ln BTC_t$	$\Delta \ln ETH_t$	$\Delta \ln XRP_t$	$\Delta \ln LTC_t$
$\Delta \ln FX_{t-1}$	-0.1371 (0.3664)***	0.4816 (0.1891)**	0.6332 (0.2504)**	0.3759 (0.3156)	0.5324 (0.2628)**
$\Delta \ln BTC_{t-1}$	-0.0169 (0.0138)	0.0113 (0.0709)	-0.0687 (0.0939)	0.0217 (0.1184)	0.0298 (0.0986)
$\Delta \ln ETH_{t-1}$	0.013 (0.0113)	-0.1152 (0.0582)**	-0.0867 (0.077)	0.0093 (0.0971)	-0.1206 (0.0809)
$\Delta \ln XRP_{t-1}$	-0.0002 (0.0058)	-0.0311 (0.0299)	-0.0662 (0.0395)*	0.0508 (0.0498)	-0.0317 (0.0415)
$\Delta \ln LTC_{t-1}$	-0.0072 (0.011)	0.0408 (0.0569)	0.0639 (0.0753)	-0.1539 (0.0949)	0.0029 (0.079)
B	-0.0005 (0.0003)	0.0025 (0.0015)	0.0042 (0.002)**	0.0017 (0.0026)	0.0016 (0.0021)
R²	0.0238	0.0265	0.0296	0.01	0.0215
Wald (χ^2)	17.845***	19.92***	22.354***	7.366	16.069***
LM_{t-1}	22.378	AIC	-29.8421	FPE	2.5×10^{-16}

Note: Lag length selection based on AIC & FPE recommendations

(*), (**), (***) standard errors, reject H_0 at 10%, 5% & 1% significant level respectively

Source: Author’s compilation from Stata 16

It was earlier mentioned that to determine the overall volatility spillover effects between cryptocurrencies and foreign exchange in Nigeria require estimating the parameters of the conditional mean, variance, and asymmetric effect of all return endogenous variables. Table 4.2.1 provides the results of the VAR specification modelled in equation (3.1.2).

Overall empirical findings suggest a univariate causal (mean spillover) relationship between the Nigerian foreign exchange and cryptocurrencies. Although, there is no evidence to support the notion of cryptocurrencies having an impact on domestic depreciation, however, there is statistically significant evidence of domestic currency depreciation having a mean spillover effect on cryptocurrency purchases, at less than 5% level for Bitcoin, Ethereum and Litecoin. Hence, the consistent depreciation of the domestic currency tends to reflect on the popular perception of cryptocurrencies in Nigeria. Although there is no sufficient evidence to confirm interdependencies among cryptocurrencies, however, the negative mean spillover effect of Ethereum on Bitcoin, as well as Ripple on Ethereum at 5% and 10% significant level respectively, could imply the large market altcoins like Ethereum and Ripple are independent from the influence of Bitcoin prices, compared to smaller market altcoins like Litecoin that remains inconclusive as well as validating the three-factor model.

Wald test statistic (χ^2) confirmed statistical significance for each equation in the structural model, at less than 1% level, except the XRP variable. Overall, the model specification is an indication of a well-fitted regression model for the underlying research objective. Finally, the Lagrange Multiplier (LM) tests confirm absence of serially correlated residual error terms in the linear model.

4.3. Asymmetric Volatility Spillover Effects: MGARCH-BEKK estimation

The ARCH, GARCH, and TGARCH estimates are derived by fitting their corresponding parameters into the model specified in equation (3.1.4). The study adopts the restricted BEKK framework due to its relative simplicity, as the conditional covariance (σ_{mn}) parameters are derived from the joint statistical significance of conditional variances (σ_{mn}^2) of each contemporaneous endogenous and exogenous variables classified in the vector series, avoiding overparameterization in the process.

$$\sigma_{m,t}^2 = c_m^2 + b_m^2 \mu_{m,t-1}^2 + \gamma_m^2 D_{m,t-1} + \theta_m^2 \sigma_{m,t-1}^2 \quad (4.3.1)$$

$$\sigma_{mn,t} = c_m c_n + b_m b_n \mu_{m,t-1} \mu_{n,t-1} + \gamma_m \gamma_n D_{m,t-1} D_{n,t-1} + \theta_m \theta_n \sigma_{mn,t-1} \quad (4.3.2)$$

Note that; $\sigma_t^2 = h_t$; and $c_m c_n = C_0^T C_0$ for each $m \neq n$ asset. However, $C_0^T C_0$ coefficient matrix is omitted because it does not affect the volatility spillover effect between return assets.

Table 4.3.1 Multivariate GARCH-BEKK Diagonal (restricted) Matrix

Variable		$\Delta \ln FX_t$	$\Delta \ln BTC_t$	$\Delta \ln ETH_t$	$\Delta \ln XRP_t$	$\Delta \ln LTC_t$
Panel A: Conditional Variance with Asymmetry						
$\hat{\mu}_{t-1}^2$		-0.00012 (0.1589)	0.32985 (0.0245)***	0.32956 (0.0213)* **	0.77295 (0.0219)***	0.36248 (0.0206)** *
\hat{D}_{t-1}		0.01609 (4.5515)	0.26314 (0.0433)***	0.16972 (0.0597)* **	0.29379 (0.1197)**	0.12434 (0.0629)** *
\hat{H}_{t-1}		0.99213 (0.0028)** *	0.89303 (0.0109)***	0.89903 (0.0095)* **	0.69501 (0.0169)***	0.88512 (0.0098)** *
Panel B: Spillover regressors (σ_t)						
$\Delta \ln FX_{t-1}$	b_j	0.00000001				
	γ_j	5				
	θ_i	0.00026				
		0.9843				
$\Delta \ln BTC_{t-1}$	b_j	-0.000035	0.1088			
	γ_j	0.00424	0.0629			
	θ_i	0.886	0.7975			
$\Delta \ln ETH_{t-1}$	b_j	-0.000039	0.1087	0.1086		
	γ_j	0.00273	0.04466	0.0288		
	θ_i	0.89195	0.80296	0.8083		
$\Delta \ln XRP_{t-1}$	b_j	-0.000093	0.25496	0.2547	0.5975	
	γ_j	0.00386	0.06309	0.0407	0.0575	
	θ_i	0.68953	0.62067	0.6248	0.483	
$\Delta \ln LTC_{t-1}$	b_j	-0.000044	0.11956	0.1195	0.2802	0.1314
	γ_j	0.002	0.03272	0.0211	0.0298	0.0155
	θ_i	0.87815	0.79044	0.7957	0.6152	0.7834

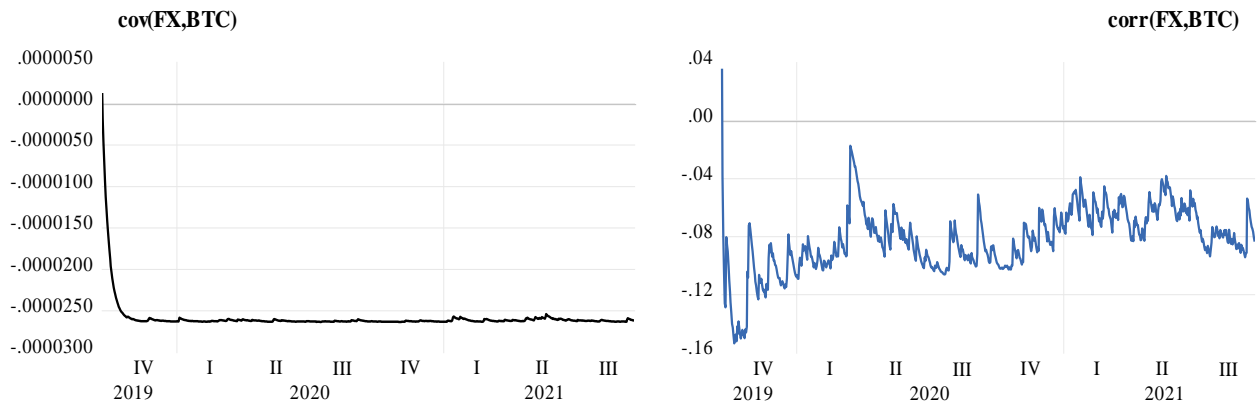
Durbin Watson	2.0002	1.8692	1.9617	1.9103	1.8747
Ljung Box (Q_{t-1})	24.3442	Ljung Box (Q_{t-9})	226.0671	Ljung Box (Q_{t-12})	378.231** *
LL	8518.965	<i>Note: Convergence achieved after 212 iterations (*), (**), (***) standard error of parameters, reject H_0 at 10%, 5% & 1% significant level respectively Source: Author's compilation from EViews 12</i>			
AIC	-23.1435				
SC	-22.7664				
HQIC	-22.9981				

Interpretations on the asymmetric volatility spillover effects between cryptocurrencies and foreign exchange in Nigeria is based on the spillover regressors specified in equations (4.3.1) and (4.3.2), which led to the empirical results illustrated in panel B, table 4.3.1 above. Although, the ARCH and TARARCH estimates of foreign exchange appear to be statistically insignificant, however Allen & McAleer (2018) proposed the parameters of the QMLE model in a restricted BEKK framework as illustrated, allow statistical inferences on hypotheses testing to be consistent and asymptotically normally distributed, hence, valid. The degree of volatility spillovers between cryptocurrencies and FX in Nigeria is therefore, measured by making comparative analysis between the lagged own volatility, lagged cross volatilities, and relative asymmetry between asset returns.

Empirical findings of the underlying study suggest a bidirectional volatility spillovers (ARCH effect) between cryptocurrencies and FX trend, as own volatility spillovers exceed cross volatility spillovers for all contemporaneous variables. In other words, cryptocurrencies have a volatility spillover effect on the FX market and vice versa. Findings also pointed out that cryptocurrencies, overall have had a significant influence over domestic markets within the sample period, as ARCH coefficient of own volatilities in cryptocurrencies exceed that of the fiat currency. Furthermore, TARARCH coefficients confirm all assets respond more to negative shock effect (bad news) than positive asymmetries, which is usually common in most conventional financial assets. Specifically, there is an indication to unidirectional asymmetric influence between cryptocurrencies and FX, such that the influence of negative asymmetries the cryptocurrency market tends to subdue the volatilities of the FX market, signalling hedging opportunities in times of financial uncertainties.

Overall, there is evidence of stronger volatility persistence (GARCH effect) in the presence of weaker volatility spillovers (ARCH effect) in all return assets, except the XRP prices that indicate otherwise. Hence, there is statistically significant covariation in shocks that

are influenced on past innovations, rather than past error terms. However, there is also evidence of cross volatility persistence between domestic depreciation and cryptocurrencies, such that the volatilities of cryptocurrency prices in Nigeria are partly influenced by past innovations of its foreign exchange, which is attributed to the causal relationship between FX and cryptocurrencies, as FX markets show relative resistance to external influence.



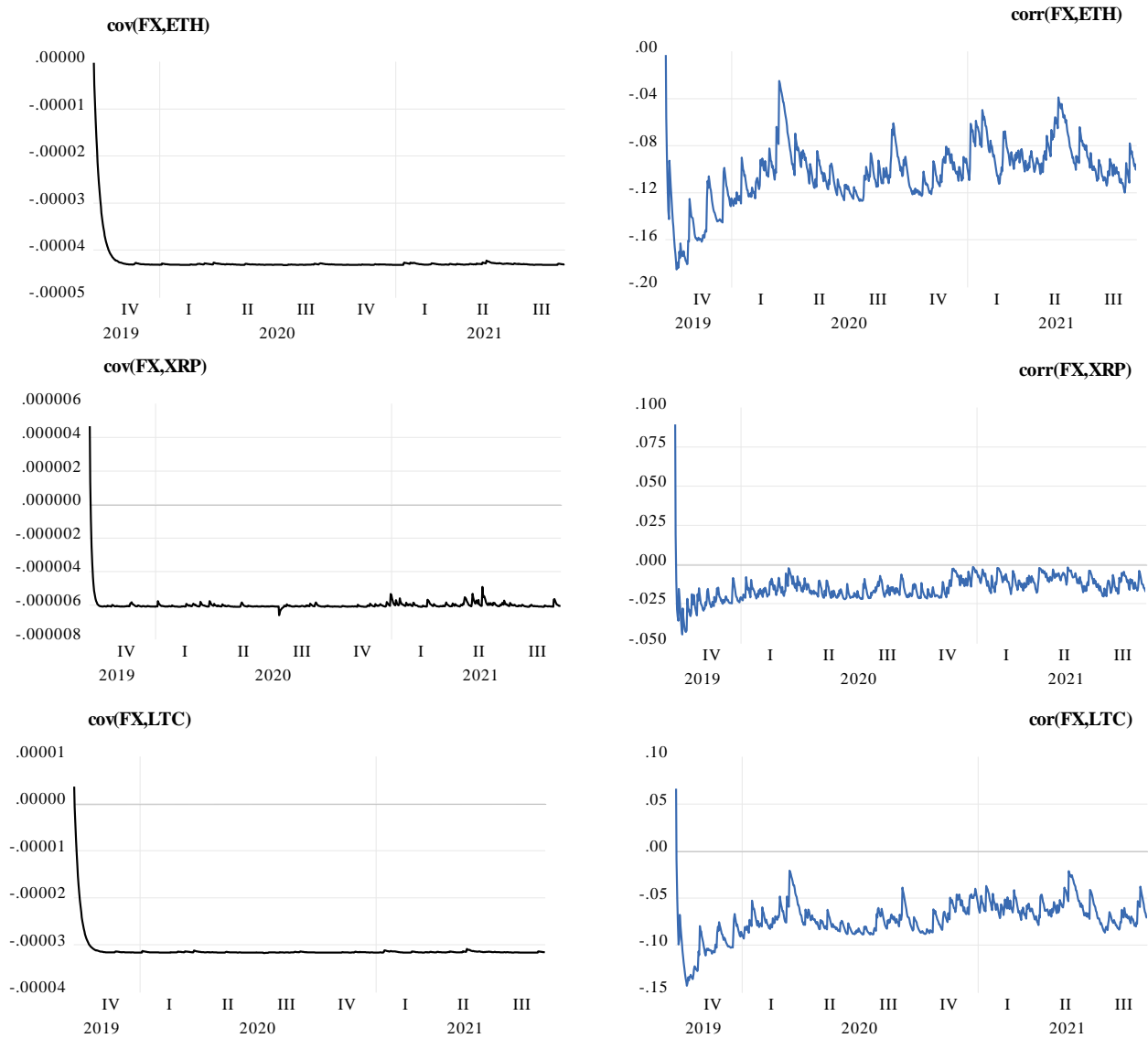


Figure 4.3.1 Conditional covariances and Correlations between Foreign Exchange and Cryptocurrencies

Source: Author’s compilation from EViews 12

The conditional covariance (black) and correlation (blue) between the contemporaneous exogenous variables and endogenous variable indicate dynamic comovements between cryptocurrencies and foreign exchange, and a relatively low volatile trend, especially during the fourth quarter of 2019. The overall negative hedge ratio between domestic currency depreciation and cryptocurrencies, both illustrated in table 4.3.1 and figure 4.3.1 signal hedging capabilities of cryptocurrencies against uncertainties emanating from the foreign exchange market, such that a risk averse investor can place a short position on the domestic currency, while placing a long position on cryptocurrencies amid a period of financial uncertainties in the domestic market. Moreover, the lowered volatility trend in conditional

covariance, alongside the sharp increase in conditional correlation between FX and cryptocurrencies, particularly between the first and second quarter of 2020, as well as the second quarter of 2021, show safe haven potentials of cryptocurrencies against FX volatilities. Finally, the negative relationships make cryptocurrencies an effective portfolio diversifier for foreign exchange, as gradual market integration is already implied.

While the Durbin-Watson (D-W) test statistics found little to no evidence of serially correlated residuals for each equation, the Ljung-Box Q statistics showed no evidence of autocorrelation in the standardized residuals across the vector series, up until the 9th lag (see table 4.3.1). Hence, the conditional mean returns, and volatility spillovers are correctly specified with the Multivariate GARCH-BEKK model.

5. Conclusion

Although, the empirical findings of the mean volatility spillovers (VAR) could not find any evidence of cryptocurrencies having a causal impact on the fiat currency, however, it was uncovered that the domestic currency depreciation had an overall positive effect on the price of cryptocurrencies in Nigeria. In addition, empirical research findings were also able to confirm bidirectional volatility spillover effects between cryptocurrencies and foreign exchange, with negative asymmetric influence, where cryptocurrencies have more market influence on the past errors of the fiat currency. However, the FX market indicated relative high resistance to external shocks from cryptocurrencies and was able to show that cryptocurrencies prices are partially influenced by the past volatilities of the fiat currency. Finally, the dynamic comovements between cryptocurrencies and foreign exchange signal hedging, safe haven capabilities as well as a diversification instrument and risk minimizer against uncertainties in the domestic market.

Therefore, the study recommends potential investors to exercise caution in patronizing a growing market like cryptocurrencies due to its high volatility and susceptibility to speculative attacks. Nevertheless, having confirmed hedging and safe-haven properties of digital currencies, the study further recommends potential investors to adopt optimal portfolio diversification strategies, for the treated assets, specific to the stated recommendations of the positions of a risk averse investor, and low leverage contracts to avoid incurring large debts. In addition, the institutional framework of financial regulators should be able to satisfy the requirements of developing the digital currency infrastructure of the Nigerian Financial System. Finally, the recurrent changes in the volatility dynamics of cryptocurrencies warrant further investigation with regards to both short- and long-range memories, and its impact on

other regulated financial asset, as it is a fairly new concept of decentralized financing that has rapidly gained massive retail and institutional adoption across the globe.

REFERENCES

- Aalborg, H. A., Molnar, P., & Erik de Vries, J. (2019). What can explain the price, volatility and trading volume of Bitcoin? *Finance Research Letters*, 255-265.
- Allen, D. E., & McAleer, M. (2018). Theoretical and Empirical Differences between Diagonal and Full BEKK for Risk Management. *Energies*, 1-19.
- Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 3-18.
- Basu, S. (1977). Investment Performance of Common Stocks in Relation to their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis. *The Journal of Finance*, 663-682.
- Baydakova, A. (2021, July 06). *Thriving Under Pressure: Why Crypto Is Booming in Nigeria Despite the Banking Ban*. Retrieved from CoinDesk: <https://www.coindesk.com/markets/2021/07/06/thriving-under-pressure-why-crypto-is-booming-in-nigeria-despite-the-banking-ban/>
- Bornholt, G. (2013). The Failure of the Capital Asset Pricing Model (CAPM): An Update and Discussion. *A Journal of Accounting, Business and Finance* , 36-43.
- Bouri, E., Brian, L., & Roubaud, D. (2020). The volatility surprise of leading cryptocurrencies: Transitory and Permanent linkages. *Finance Research Letters*.
- Bouri, E., Roubaud, D., & Shazard, S. H. (2020). Do Bitcoin and other Cryptocurrencies Jump together? *The Quarterly Review of Economics and Finance*, 396-409.
- Central Bank of Nigeria. (2016). *Foreign Exchange Rate*. Abuja FCT: CBN Research Department.
- Central Bank of Nigeria. (2021, October 04). *Exchange Rates by Currency*. Retrieved from Central Bank of Nigeria: <https://www.cbn.gov.ng/rates/exchratesbycurrency.asp>
- Chaim, P., & Laurini, M. P. (2019). Nonlinear dependence in cryptocurrency markets. *The North American Journal of Economics and Finance*, 32-47.
- Charles, A., & Darné, O. (2019). Volatility estimation for Bitcoin: Replication and robustness. *International Economics*, 23-32.

- Chaum, D. L. (1983). Blind Signatures for Untraceable Payments. *Advances in Cryptology* (pp. 199-203). Boston, MA: Springer.
- Ciaian, P., Rajcaniova, M., & Kancs, d. (2018). Virtual relationships: Short- and long-run evidence from Bitcoin and Altcoin markets. *Journal of International Financial Markets, Institutions and Money*, 173-195.
- CoinMarket Cap. (2021, September 13). *Today's Cryptocurrency Prices by Market Cap*. Retrieved from CoinMarket Cap: <https://coinmarketcap.com>
- Czapliński, T., & Nazmutdinova, E. (2019). Using fiat currencies to arbitrage on cryptocurrency exchanges. *Journal of International Studies*, 184-192.
- Dempsey, M. (2013). The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance? *A Journal of Accounting, Finance, and Business Studies*, 49.
- Dyhrberg, A. H. (2016). Bitcoin, Gold and Dollar- A GARCH volatility analysis. *Finance Research Letters*, 85-92.
- Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, 139-144.
- Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of UK Inflation. *Econometrica*, 987-1008.
- Engle, R. F., & Kroner, K. F. (1995). Multivariate Simultaneous Generalized ARCH. *Cambridge University Press*, 122-150.
- Fakhfekh, M., & Jeribi, A. (2020). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, 1-10.
- Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 383-417.
- Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, 427-465.
- Fischer, T. G., Krauss, C., & Deinert, A. (2019). Statistical Arbitrage in Cryptocurrency Markets. *Journal of Risk and Financial Management*, 1-15.
- Gandal, N., & Halaburda, H. (2016). *Can We Predict the Winner in a Market with Network Effects? Competition in Cryptocurrency Market*. Tel Aviv: NET Institute Working Paper No 14-17.
- Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics*, 1308-1321.

- Huijbregts, M. (2020). *An Asset Pricing Model for Cryptocurrencies*. Rotterdam, Netherlands: An unpublished MSc Dissertation submitted to the department of Financial Economics, Erasmus University.
- Hussain, A. (2021, February 2). *Post-Modern Portfolio Theory (PMPT)*. Retrieved from Investopedia: <https://www.investopedia.com/terms/p/pmpt.asp>
- Jimoh, S. O., & Benjamin, O. O. (2020). The effect of Cryptocurrency returns Volatility on Stock prices and Exchange rate returns volatility in Nigeria. *Economica*, 200-213.
- Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 3-6.
- Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*, 322-335.
- Katsiampa, P., Corbet, S., & Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK-MGARCH analysis. *Finance Research Letters*, 68-74.
- Kenton, W. (2019, April 12). *Downside Risk Definition*. Retrieved from Investopedia: <https://www.investopedia.com/terms/d/downsiderisk.asp>
- Kenton, W. (2021, March 31). *Capital Asset Pricing Model*. Retrieved from Investopedia: <https://www.investopedia.com/terms/c/capm.asp>
- Krauss, C., Anh-Do, X., & Huck, N. (2017). Deep neural networks, gradient-boosted trees, random forests: Statistical arbitrage on the S&P 500. *European Journal of Operational Research*, 689-702.
- Lahmiri, S., Bekiros, S., & Salvi, A. (2018). Long-range memory, distributional variation and randomness of bitcoin volatility. *Chaos, Solitons and Fractals*, 43-48.
- Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 13-37.
- Luno exchange. (2021). *Trading volume historical data, BTC/NGN, ETH/NGN, XRP/NGN*. Retrieved from <https://www.luno.com/en/developers/api#operation/GetOrder>
- Makarov, I., & Schoar, A. (2019). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics*, 293-319.
- Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, 77-91.
- Nakamoto, S. (2008). *Bitcoin: A peer to peer Electronic Cash System*. An open source online publication.
- Petukhina, A., Trimborn, S., Härdle, W. K., & Elendner, H. (2020). *Investing with cryptocurrencies - evaluating the potential of portfolio allocation*. Social Science Research Network Publications.

- Polansek, T. (2016, May 3). CME, ICE prepare pricing data that could boost Bitcoin. *Reuters*.
- Ponto, S. C., & Rizkiant, E. (2019). Asset Pricing Analysis of 18 Cryptocurrencies. *Advances in Economics, Business and Management Research: 23rd Asian Forum of Business Education* (pp. 279-282). Jakarta, Indonesia: Atlantis Press.
- Redman, J. (2019, December 26). *Bitcoin Gained 8.9 Million Percent Over the Last Decade*. Retrieved from Bitcoin News, Archived: <https://news.bitcoin.com/bitcoin-gained-8-9-million-percent-over-the-last-decade/#:~:text=In%20the%20last%20decade%20bitcoin,to%20gold%27s%20%2B10.8%25%20increase>.
- Rom, B. M., & Ferguson, K. (1993). Post-Modern Portfolio Theory Comes of Age. *Journal of Investing*, 349-364.
- Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, 341-360.
- Sanni, S. (2019, October 19). Crypto Currency In Nigeria: Regulatory Framework & Related Issues. *Season Legal Practitioners*.
- Schmidt, M. (2020, December 13). *Taking Shots at CAPM*. Retrieved from Investopedia: <https://www.investopedia.com/articles/financial-theory/09/capm-error-problem.asp>
- Selmi, R., Mensi, W., Hammoudeh, S., & Jamal, B. (2018). Is Bitcoin a hedge, a safe haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics*, 787-801.
- Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk. *The Journal of Finance*, 425-442.
- Shen, D., Urquhart, A., & Wang, P. (2020). A three-factor pricing model for cryptocurrencies. *Finance Research Letters*, 1-6.
- Shi, Y., Tiwari, A. K., Gozgor, G., & Lu, Z. (2020). Correlations among cryptocurrencies: Evidence from multivariate factor stochastic volatility model. *Research in International Business and Finance*, 1-11.
- Stoffels, J. (2017). *Asset Pricing of Cryptocurrencies and Momentum based patterns*. Rotterdam, Netherlands: An unpublished MSc Dissertation submitted to the Department of Economics, Erasmus University.
- Thumar, C. (2021). *How Cryptocurrency will disrupt the Stock Market*. Retrieved from ReadITQuik: <https://www.readitquik.com/articles/security-2/how-cryptocurrency-will-disrupt-the-stock-market/#>

- Trimborn, S., & Härdle, W. (2018). CRIX an Index for cryptocurrencies. *Journal of Empirical Finance*, 107-122.
- Veldmeijer, Q. (2018). *The effects of cryptocurrencies in a multi-asset portfolio: A case study for Dutch pension funds*. Tilburg, Netherlands: An unpublished MSc. dissertation submitted to the school of Economics and Management, Tilburg University.
- Wang, G., Tang, Y., Xie, C., & Chen, S. (2019). Is bitcoin a safe haven or a hedging asset? Evidence from China. *Journal of Management Science and Engineering*, 173-188.
- Wang, Z. (2018). *Essays on efficiency, hedging effectiveness and volatility dynamics in cryptocurrency markets*. Bath, UK: A PhD thesis submitted to the department of Economics, University of Bath.
- Williams, M. (2020, December 19). *How Nigeria Became the Second-Largest Bitcoin P2P Market in the World*. Retrieved from CryptoPotato: <https://cryptopotato.com/how-nigeria-became-the-second-largest-bitcoin-p2p-market-in-the-world/?amp>
- Zimwara, T. (2021, February 18). *Nigeria Crypto Ban: Bitcoin Sells for \$76K as Deposits on Centralized Exchanges Plummet*. Retrieved from Bitcoin.com News: <https://news.bitcoin.com/nigeria-crypto-ban-bitcoin-sells-for-76k-as-deposits-on-centralized-exchanges-plummet/>
- Zimwara, T. (2021, May 5). *Nigeria's Cryptocurrency Traded Volumes on P2P Platform Top \$1.5 Billion*. Retrieved from Bitcoin.com: <https://news.bitcoin.com/nigerias-cryptocurrency-traded-volumes-on-p2p-platform-top-1-5-billion/>