

# THE SPILLOVER OF NIGERIAN FOREIGN EXCHANGE POLICIES ON THE VOLATILITY OF CRYPTOCURRENCY RETURN

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**Background:** In recent years, cryptocurrencies have emerged as alternative financial assets, gaining increasing attention in Nigeria due to rising inflation, currency depreciation, and restrictions on foreign exchange (FX) access. **Aims:** The study examined the effect of foreign exchange policies' spillover on the volatility of cryptocurrency returns in Nigeria. **Methods:** The study utilised time series data, which consisted of United States dollars and Nigerian Naira, while the cryptocurrencies were extracted from the Nigerian foreign exchange market over a two-year period. Vector Autoregressive (VAR) was employed as a method of data analysis. **Results:** The findings revealed that there is a statistically significant long-run relationship between FX rates and cryptocurrency returns. The exchange rate fluctuations, reflective of FX policy shifts, generate asymmetric and persistent volatility in major cryptocurrencies, and the impact of FX policies on crypto returns varies across assets, with BTC and ETH being more responsive than USDT and SOL. **Conclusions:** Cryptocurrencies can no longer be viewed in isolation, as they are increasingly influenced by global and national economic decisions. **Implications:** There is a need to incorporate macroeconomic indicators, particularly exchange rate trends, into trading strategies to anticipate market movements and reduce risk exposure.

**Keywords:** Foreign exchange policies, Spillover effect, Cryptocurrency returns

**JEL Classification:** C32, E44, F31, G15

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## Introduction

The most significant price in the economy is the foreign exchange. A country's foreign exchange rate is the price of its currency in relation to another currency, and when it appreciates, the national currency becomes more expensive and vice versa. By carrying out complete, suitable foreign exchange rate policies, policymakers can encourage exports and international competitiveness and boost domestic macroeconomic stability (Steinberg & Walter, 2013). Socioeconomic groups have separate opinions on the right kind of foreign exchange-rate policy when the local currency appreciates, as its stability must be present to achieve specific objectives. In particular, the foreign exchange can be used to promote the competitiveness of goods produced domestically and is the instrument used for exchange. However, the significance of the international purchasing power of a currency must be considered, and the effect of the changes in the foreign exchange rate on domestic inflation (IMF, 1992).

The domestic foreign exchange rate that can be viewed in terms of a single foreign currency is characterised by the conception of the average relationship between a currency and a set of other currencies, which is referred to as the effective exchange rate, and such affects the Forex markets are not entirely immune to liquidity risk as their fluctuations can be driven by various factors, including economic indicators, political events, and central banks' policies (Charles, 2024).

Cryptocurrency is a digital payment system that does not require physical or bank verification to complete transactions. A peer-to-peer system enables individuals to send and receive payments from anywhere (Nakamoto, 2008). Modern cryptocurrencies rely on the same fundamental principle of a consensus-based, decentralised, and immutable ledger to facilitate digital value transfers between trustless parties; subtle and significant differences exist among them (CFI Team & Andrew, 2024). Prices often experience significant fluctuations within short periods due to factors such as social media trends, technological advancements, and adoption rates. The relatively lower liquidity in crypto markets than in forex can intensify this volatility. Moreover, the absence of comprehensive regulation and oversight in crypto often contributes to rapid and unpredictable price movements, just like the case of the foreign exchange rate.

Leverage in the foreign exchange market is a double-edged sword for retail traders of cryptocurrencies (Nathan et al., 2024), which allows traders to control larger positions with a smaller capital investment, and it also magnifies potential losses when the market moves against them. Foreign exchange brokers often provide high leverage options, which can be tempting but require cautious risk management, as they fluctuate dramatically within a short time, offering investors the potential for substantial gains or losses (www.bitcoin.com, 2024).

The fluctuations in foreign exchange policy uncertainty influence cryptocurrency returns, as such uncertainty negatively affects all kinds of crypto in the short and long-term returns, even though cryptocurrencies may not consistently function as reliable hedges during economic instability (Nature portfolio, 2023). If a country raises its exchange rates to control inflation, it strengthens its currency, making Bitcoin's inflation hedge appeal less attractive, and when it increases its interest rates, it tends to strengthen its local currency, which helps to curb inflation and interest rates to suit crypto returns and this implies that exchange rate volatility may preserve the capital from the cryptocurrencies (Inika, 2024).

## Theoretical background

A managed floating exchange rate (also known as a 'dirty float') is an exchange rate regime in which the exchange rate is neither entirely free nor fixed. Rather, the value of the currency is kept in a range against another currency (or against a basket of currencies) by central bank intervention (Kantox, 2024). The higher the value of the currency, the greater the increase in the exchange rate (Kimberly & Erika, 2021). Intervention policy is when the central banks, especially those in developing countries, intervene in the foreign exchange market by buying and selling currencies in order to build reserves for themselves or provide them to the country's banks. Their aim is often to stabilise currency fluctuations during periods

of volatility (James & Charles, 2024). As a result, these cryptocurrencies are inflationary, meaning that as more tokens are created, the value of this digital asset is expected to decrease, similar to fiat currency in a country that continuously prints money, while Bitcoin is designed to provide an alternative to physical or fiat currency (Nathan & Somer, 2024).

A study was made to examine fluctuations in crypto markets and US monetary policy. They find out that US monetary policy affects the crypto cycle, contrasting starkly with claims that crypto assets provide a hedge against market risk. A one percentage point rise in the static firm frequency response (SFFR) leads to a persistent 0.15 standard deviation decline in the crypto factor over the subsequent two weeks (Rey, 2013). They find that only the US Fed's monetary policy matters, and not that of other major central banks, likely reflecting that crypto markets are highly dollarized. Evidence was found that the risk-taking channel of monetary policy is an important channel driving these results, paralleling the findings of Miranda-Agrippino and Rey (2020). In particular,

It was found that a monetary contraction leads to a reduction of the crypto factor that is accompanied by a surge in a proxy for the aggregate effective risk aversion in crypto markets. Put differently, restrictive policies render the risk positions of investors less sustainable, and thus they reduce their exposure to crypto assets. When splitting the sample in 2020, we find that the impact on risk aversion in crypto markets is significant only for the post-2020 period, consistent with the entry of institutional investors reinforcing the transmission of monetary policy to the crypto market (Natasha et al., 2023).

Gandal & Halaburda (2016) also discovered strong network effects between cryptocurrencies and the U.S dollar, such that Bitcoin tends to appreciate against the dollar, while altcoins tend to depreciate against the dollar, following strong evidence of cross correlation from (Bouri, Brian, & Roubaud, The volatility surprise of leading cryptocurrencies: Transitory and Permanent linkages, 2020). Jimoh & Benjamin (2020) sought to explain the reaction volatility of exchange rates and equity 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.

The study of Sodiq and Oluwasegun (2020) assessed the effect of cryptocurrency returns volatility on stock prices and exchange rate returns volatility in Nigeria from 2015 to 2019. They employed GARCH, EGARCH and Granger causality techniques to analyse the data. Findings from the study revealed that the stock market price is mostly affected by the price fluctuation in Bitcoin and Ethereum rather than the exchange rate in Nigeria. There was a unidirectional causality from Bitcoin and Ethereum to the stock market index. The study, therefore, established a significant effect between the volatility of Bitcoin and Ethereum on the stock market price in Nigeria. In their conclusion, cryptocurrencies were found to be highly volatile, mostly in daily prices.

## Methodology

This study uses time series Secondary data. It consists of the United States dollar and Nigerian naira (USD/NGN) exchange rate. Since foreign exchange policies are qualitative documents, the study uses the USD/NGN exchange rate as a quantitative proxy variable for foreign exchange policy in Nigeria. Movements in exchange rates often reflect the impact of government policy changes, which enables the analysis of the relationship between foreign exchange policies and the volatility of cryptocurrency returns. In the United States, the dollar serves as the global base currency for cryptocurrency pricing. While the USD/NGN exchange rate serves as a proxy for the effects of foreign exchange policy in Nigeria, no separate exchange rate is required for the US portion of the study. It consists of four of the most traded cryptocurrencies, which are Bitcoin (BTC), Ethereum (ETH), Tether (USDT) and Solana (SOL), closing price log as cryptocurrency return captured within a two-year period from January 1st, 2020, to January 1st, 2022. The historical data was from investing.com to get the closing price and the log return of the closing price of selected cryptocurrencies. The exchange rate data was obtained from the Central Bank of Nigeria, NFEM (Nigeria foreign exchange market).

The study employed the Augmented Dickey-Fuller (ADF) test to test for stationarity of the variables, the Johansen Cointegration test and Vector Autoregressive (VAR) through VECM, Variance Decomposition and impulse response test for the response of the variables to a shock.

Analysing the spillover of foreign exchange rate between the United States dollar and Nigerian naira and their effect on the volatility of cryptocurrency return. This requires estimating the parameters of the conditional mean, variance, and covariance of all five endogenous variables. Hence, the VAR model is a good fit, as it satisfies all requirements to generate parameter estimates. First, the conditional mean equation replicates the VAR(p) specification. This linear model will estimate the parameters of an (n×1) vector of endogenous variables  $Y_t$  (the foreign exchange index and cryptocurrency return), and its corresponding cumulative (n×n) lagged operators,  $Y_{t-i}$ , and (n×1) unobservable error terms,  $U_t$ , using the Ordinary Least Squares (OLS) method to determine the causal relationship between variables.

$$Y_t = \beta_0 + \sum_{i=1}^p \beta_i Y_{t-i} + \sum_{i=1}^p \beta_i X_{t-i} + U_t \tag{1}$$

$Y_t$  is a vector of the endogenous variables at time  $t$ ,  $B$  is a vector of intercepts,  $B_i$  are matrices of coefficients at lag  $i$ ,  $U_t$  is a vector of error terms and  $p$  is the lag length. The Vector Autoregressive VAR(p) model is reparameterized into returns of foreign exchange (FX) and four major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Tether (USDT), and Solana (SOL). This study adopted the model used in the study of Ajayi et al. (2022). The exchange rate was logged to be in the same proportion as other variables.

$$LEXR_t = y_{10} + y_{11}BTC_{t-1} + y_{12}ETH_{t-1} + y_{13}USDT_{t-1} + y_{14}SOL_{t-1} + U_{10t} + \sum LEXR_t \tag{2}$$

$$BTC_t = y_{20} + y_{21} LEXR_{t-1} + y_{22}ETH_{t-1} + y_{23}USDT_{t-1} + y_{24}SOL_{t-1} + U_{20t} + \sum BTC_t \tag{3}$$

$$ETH_t = y_{30} + y_{31} LEXR_{t-1} + y_{32}BTC_{t-1} + y_{33}USDT_{t-1} + y_{34}SOL_{t-1} + U_{30t} + \sum ETH_t \tag{4}$$

$$USDT_t = y_{40} + y_{41}EXR_{t-1} + y_{42}BTC_{t-1} + y_{43}ETH_{t-1} + y_{44}SOL_{t-1} + U_{40t} + \sum USDT_t \tag{5}$$

$$SOL_t = y_{50} + y_{51}EXR_{t-1} + y_{52}BTC_{t-1} + y_{53}ETH_{t-1} + y_{54}USDT_{t-1} + U_{50t} + \sum SOL_t \tag{6}$$

LEXR represents the Exchange rate

BTC represents Bitcoin

ETH represents Ethereum

USDT represents US Tether

SOL represents Solana

$Y_{10} - Y_{50}$  = Constant Parameter

$Y_{11} - Y_{50}$  = Coefficients of Estimates

$U$  = Stochastic Term

## Results

Table 1: Descriptive Analysis Results

	EXR	ETH	BTC	SOL	USDT
Mean	393.2262	0.4354	0.2640	0.9112	-9.67E-05
Median	380.0000	0.7177	0.2825	0.4186	0.000000
Maximum	413.4900	23.0772	17.7424	49.9914	0.3096
Minimum	361.0000	-32.6921	-15.5474	-45.1738	-0.2296
Std. Dev.	15.4709	5.2818	3.9057	8.8761	0.0550
Skewness	0.2154	-0.4959	-0.1378	0.1987	0.2792
Kurtosis	1.1662	7.2658	4.9527	7.1085	7.4479
Jarque-Bera	76.4387	413.1906	83.7782	367.0261	432.9060
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	203298.0	225.1297	136.5040	471.0967	-0.0499
Sum Sq. Dev.	123504.2	14394.89	7871.293	40652.91	1.5615
Observations	517	517	517	517	517

### Source: Author's computation

Table 1 presents a summary of the descriptive statistics indicating different distributions of the variables. The skewness statistic revealed that all the variables are positively skewed. The kurtosis statistic shows that EXR, BTC, ETH, USDT and SOL are leptokurtic (fat-tailed). The normality test from Jarque-Bera (JB) showed that EXR, BTC, ETH, USDT and SOL were not normally distributed.

### 4.1 Impulse Response Analysis

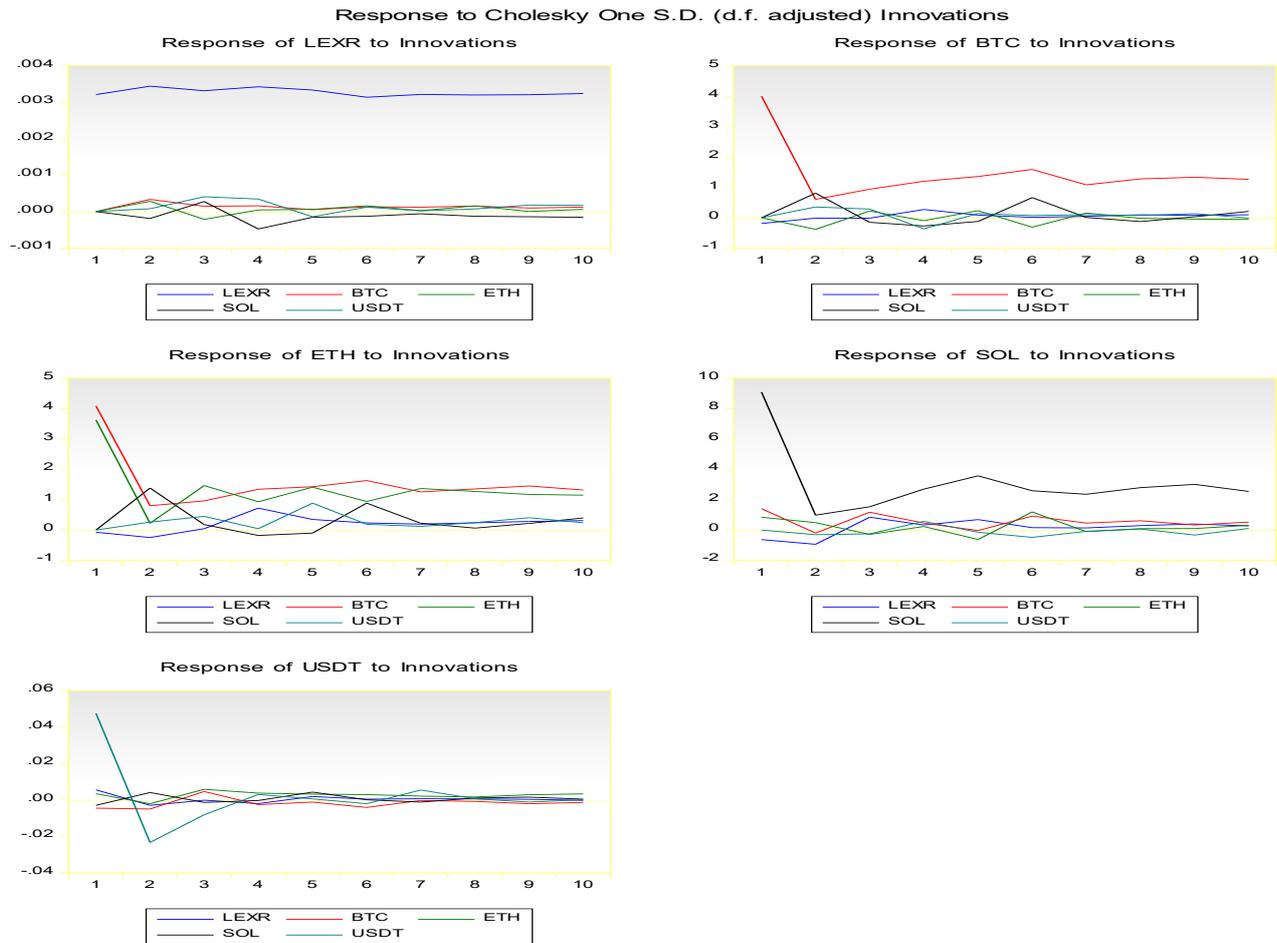


Figure 1: Impulse Response Results

The impulse response analysis indicates that shocks to the Nigerian exchange rate generate minimal and short-lived impacts on cryptocurrency returns, suggesting limited short-run spillover effects from the foreign exchange market to the cryptocurrency market. Notably, Bitcoin and Ethereum exhibit significant mutual responses to shocks, underscoring their interconnectedness within the crypto ecosystem. In contrast, Solana demonstrates somewhat higher sensitivity to exchange rate shocks, whereas USDT remains largely stable, reflecting its pegged nature. These results highlight the dominant role of internal cryptocurrency market dynamics and the relatively modest influence of exchange rate fluctuations.

The unit root tests were conducted to determine the stationarity properties of the series. Results from both the ADF and PP tests indicate that the exchange rate series (LEXR) is non-stationary at the level but becomes stationary after first differencing, suggesting it is integrated of order one,  $I(1)$ . In contrast, the cryptocurrency return series (LogBTC, LogETH, LogSOL, and LogUSDT) were found to be stationary at a level, implying they exhibit constant mean and variance over time. These outcomes confirm the appropriateness of employing VAR techniques for further analysis.

Table 2: Unit Root Test Results

		<b>At Level</b>					
		LEXR	BTC	ETH	SOL	USDT	
<b>Phillip Perron Test</b>	t-Statistic	-2.1487	-30.0811	-30.5099	-24.8807	-41.7813	
	<b>Prob.</b>	<b>0.2258</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0001</b>	
		no	***	***	***	***	
	<b>At First Difference</b>						
		d(LEXR)	d(BTC)	d(ETH)	d(SOL)	d(USDT)	
	t-Statistic	-27.1695	-207.6398	-271.9721	-268.8784	-86.3676	
<b>Prob.</b>	<b>0.0000</b>	<b>0.0001</b>	<b>0.0001</b>	<b>0.0001</b>	<b>0.0001</b>		
	***	***	***	***	***		
		<b>At Level</b>					
		LEXR	BTC	ETH	SOL	USDT	
<b>Augmented Dickey Fuller Test</b>	t-Statistic	-2.1490	-30.2559	-30.6820	-24.8575	-17.6182	
	<b>Prob.</b>	<b>0.2257</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	
		no	***	***	***	***	
	<b>At First Difference</b>						
		d(LEXR)	d(BTC)	d(ETH)	d(SOL)	d(USDT)	
	t-Statistic	-27.1693	-13.7213	-16.2590	-14.3083	-13.0913	
<b>Prob.</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>	<b>0.0000</b>		
	***	***	***	***	***		

\*MacKinnon (1996) one-sided p-values.

Source: Author's computation

Table 3: Lag Length Selection Criterion

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-5889.273	NA	9454.719	23.3437	23.3855	23.3601
1	-4589.052	2569.545	60.5758	18.2933	18.5442*	18.3917
2	-4517.048	140.8716	50.2881	18.1071	18.5672	18.2876*
3	-4484.902	62.2546	48.8884	18.0788	18.7481	18.3413
4	-4448.403	69.9619	46.7183*	18.0333*	18.9117	18.3778

Source: Author's computation

The optimal lag length for the VAR model was determined using the Akaike Information Criterion (AIC), the Schwarz Criterion (SC), and the Hannan-Quinn Criterion (HQ). The AIC and HQ indicated that a lag length of four provided the best model fit, as evidenced by the lowest criterion values at lag 4. Although the SC suggested a more parsimonious lag structure, the AIC and HQ were prioritized given the relatively large sample size and the need to capture complex dynamic interactions among the variables. Consequently, a lag length of four was selected for estimating the VAR model.

#### 4.2 Estimates results

Table 4. VECM Long-Run and Error Correction Term (ECT) Estimates Results

Cointegrating Eq:	CointEq1				
LEXR(-1)	1.000000				
BTC(-1)	0.113475				
	(0.07643)				
	[ 1.48463]				
ETH(-1)	0.022689				
	(0.05960)				
	[ 0.38069]				
SOL(-1)	-0.079771				
	(0.02579)				
	[-3.09305]				
USDT(-1)	105.5359				
	(5.41474)				
	[ 19.4905]				
C	-5.937841				
Error Correction:	D(LEXR)	D(BTC)	D(ETH)	D(SOL)	D(USDT)
ECT	0.000224	0.14301	-0.001971	0.399755	-0.018437
	(7.9E-05)	(0.086)	(0.11778)	(0.19935)	(0.00097)
	[ 2.82554]	[ 1.650]	[-0.01674]	[ 2.00528]	[-18.9157]

Source: Author’s computation, 2025

The VECM results reveal significant short-run and long-run dynamics among the exchange rate and cryptocurrency returns. The error correction term for the exchange rate is positive and significant, suggesting that deviations from long-run equilibrium influence short-term adjustments in the exchange rate. USDT exhibits a strong and significant negative error correction coefficient, indicating it plays a critical role in restoring equilibrium after a shock. Short-run dynamics are evident across equations, particularly for BTC, ETH, and SOL, with several lagged differences significantly impacting current movements. These results support the presence of both short-term spillover effects and long-term linkages between foreign exchange rates and cryptocurrency markets.

#### 4.3 Variance Decomposition Analysis

Table 5: Variance Decomposition Result

Variance Decomposition of LEXR:						
Period	S.E.	LEXR	BTC	ETH	SOL	USDT
1	0.003859	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.005604	99.60253	0.143315	0.000269	0.195992	0.057893
3	0.006838	98.29986	0.165239	1.022954	0.255992	0.255957
4	0.007941	97.62175	0.302831	1.220913	0.580938	0.273569
5	0.008977	96.77152	0.909012	1.374773	0.470958	0.473738
6	0.009798	96.46701	1.381992	1.287491	0.437533	0.425976
7	0.010566	96.09997	1.786925	1.320709	0.380229	0.412165
8	0.011277	95.96417	2.025220	1.293285	0.342362	0.374961
9	0.011942	95.75140	2.263397	1.326287	0.305268	0.353644
10	0.012554	95.62857	2.427855	1.336603	0.277274	0.329697
Variance Decomposition of BTC:						
Period	S.E.	LEXR	BTC	ETH	SOL	USDT

1	3.728194	0.509725	99.49028	0.000000	0.000000	0.000000
2	3.852129	0.560587	93.30993	1.331130	4.118961	0.679394
3	3.876670	0.745819	92.15450	1.587205	4.496725	1.015751
4	3.931060	1.127428	89.83326	1.626900	5.406951	2.005463
5	3.958697	1.127160	88.77094	1.909439	6.158296	2.034162
6	3.970585	1.151921	88.29326	1.973668	6.555796	2.025352
7	3.974312	1.157989	88.13009	1.995191	6.686891	2.029843
8	3.976525	1.170896	88.03204	1.994169	6.704737	2.098158
9	3.978030	1.177015	87.96795	2.005689	6.704168	2.145173
10	3.978942	1.181585	87.93282	2.012786	6.725118	2.147695
<b>Variance Decomposition of ETH:</b>						
Period	S.E.	LEXR	BTC	ETH	SOL	USDT
1	4.980117	0.441874	56.04943	43.50870	0.000000	0.000000
2	5.207543	1.245730	51.26104	40.94156	6.537882	0.013790
3	5.245266	1.412528	50.52837	41.44585	6.444462	0.168795
4	5.312682	2.669494	49.41868	40.53785	6.968737	0.405237
5	5.365610	2.629524	48.47668	39.74398	7.574560	1.575255
6	5.383452	2.619325	48.20143	39.67517	7.871892	1.632184
7	5.389284	2.625220	48.09798	39.60450	8.039859	1.632450
8	5.393007	2.621694	48.04534	39.55111	8.033475	1.748382
9	5.394914	2.632321	48.01365	39.55058	8.027992	1.775450
10	5.395664	2.634998	48.00366	39.54498	8.041006	1.775352
<b>Variance Decomposition of SOL:</b>						
Period	S.E.	LEXR	BTC	ETH	SOL	USDT
1	8.679885	0.115636	2.419768	0.886743	96.57785	0.000000
2	8.788588	1.588097	2.462065	1.042833	94.84049	0.066518
3	8.896866	2.453197	3.760284	1.080076	92.59574	0.110702
4	8.954621	2.506360	3.864966	1.111268	91.48940	1.028002
5	9.031392	2.503473	3.949380	1.683121	90.82327	1.040757
6	9.060622	2.489419	3.966666	1.697750	90.81211	1.034053
7	9.066069	2.507890	3.962126	1.698039	90.70992	1.122020
8	9.071163	2.536563	3.959167	1.709031	90.64103	1.154212
9	9.072634	2.538663	3.962462	1.714370	90.61834	1.166169
10	9.074502	2.538910	3.965494	1.719696	90.60949	1.166408
<b>Variance Decomposition of USDT:</b>						
Period	S.E.	LEXR	BTC	ETH	SOL	USDT
1	0.048331	0.548512	1.116210	0.038206	0.137206	98.15987
2	0.054359	0.453389	1.466966	0.609083	0.810010	96.66055
3	0.055439	0.493459	2.371288	1.425913	0.882185	94.82715
4	0.055717	0.751160	2.610645	1.500999	0.873473	94.26372
5	0.055935	0.749881	2.590806	1.494098	1.580813	93.58440
6	0.055975	0.786610	2.591593	1.515148	1.648199	93.45845
7	0.055986	0.792347	2.596230	1.521923	1.667195	93.42231
8	0.055991	0.792964	2.596933	1.522842	1.673784	93.41348
9	0.055998	0.795702	2.601269	1.523777	1.675842	93.40341
10	0.056002	0.795753	2.601079	1.527226	1.679698	93.39624
<b>Cholesky Ordering: LEXR BTC ETH SOL USDT</b>						

Source: Author's computation, 2025

The variance decomposition analysis reveals that the majority of forecast error variance for each cryptocurrency is explained by its own innovations, highlighting the dominance of internal market dynamics in driving crypto volatility. However, a modest proportion of variance in cryptocurrencies, particularly SOL, is attributable to shocks in the exchange rate, indicating the presence of spillover effects from foreign exchange markets. Conversely, the exchange rate variance remains predominantly self-determined, with negligible contributions from cryptocurrencies. These findings underscore the limited but observable interdependence between the Nigerian foreign exchange market and cryptocurrency returns.

## Discussion

Based on the analysis of data consisting of the log of the exchange rate of USD/NGN (LEXR), Bitcoin log return (BTC), Ethereum log return (ETH), Solana log return (SOL), and Tether log return (USDTs), the following findings emerged with respect to the objective of the study;

There is a moderately high positive correlation of 0.7660 between ETH and BTC, which is statistically significant at 5% level. Other correlations between the cryptocurrencies are relatively low and statistically insignificant except for the positive correlation of 0.1170 between SOL and ETH and the negative correlation of -0.1059 between USDTs and BTC, both of which are statistically significant at 5% level. This suggests that both ETH and BTC returns move in the same direction. Similarly, ETH and SOL have a positive association in that they both make gains or losses together.

On the other hand, USDTs are a stable currency, have a negative association with BTC, suggesting that they move in opposite directions. The Johansen cointegration Trace test statistics results established a long-run relationship between the variables, with 4 cointegrating equations, which was also corroborated by the Max-Eigen statistics. This suggests that foreign exchange policy changes have enduring effects on cryptocurrency behaviour. Furthermore, the VECM results found that the D(LEXR) equation's R-squared is 0.175869, while the D(BTC) equation has an R-squared of 0.518807. The Durbin-Watson statistics range from 1.947 to 2.084, indicating the absence of significant autocorrelation in the residuals. Several coefficients, such as C(28) through C(32) in the D(BTC) equation and C(54), C(55), C(56) in the D(ETH) equation, are statistically significant at 5% level.

The VECM long-run and error correction term (ECT) estimates reveal the cointegrating equation (CointEq1) with normalized coefficients for LEXR(-1), BTC(-1), ETH(-1), SOL(-1), and USDT(-1), along with a constant. The coefficients indicate the long-run relationships between these variables, with USDT(-1) having a notably high coefficient of 105.5359 and SOL(-1) showing a negative coefficient of -0.0798. The error correction terms show how each variable adjusts to restore equilibrium, with D(SOL) having the largest adjustment coefficient of 0.3998 and D(ETH) showing a minimal adjustment of -0.001971. The statistical significance, as indicated by the t-statistics, varies across the ECTs, with D(USDT) being highly significant at -18.9157.

The variance decomposition analysis illustrates the percentage of variance in each cryptocurrency explained by shocks to itself and other cryptocurrencies over a 10-period horizon. Initially, LEXR's variance is almost entirely explained by itself (100%), but over time, the influence of other cryptocurrencies like BTC and ETH increases, although LEXR remains the dominant factor. Similarly, BTC's variance is primarily explained by itself, starting at 99.49% in period 1 and decreasing to 87.93% by period 10, with SOL contributing a significant portion (6.73%) by the end of the period.

For ETH, its own shocks explain 43.51% of its variance in period 1, but BTC's influence is considerable at 56.05%. Over time, ETH's self-explanation remains relatively stable, while BTC's influence decreases slightly. SOL's variance is predominantly explained by itself, starting at 96.58% and remaining above 90% throughout the 10 periods. USDT's variance is also largely explained by itself, starting at 98.16% and remaining above 93%. The Cholesky ordering used is LEXR, BTC, ETH, SOL, and USDT.

The Impulse responses to Cholesky One S.D. (d.f. adjusted) Innovations vary among the cryptocurrencies, with LEXR showing a consistent positive response, BTC and SOL displaying large initial positive responses followed by stabilization, ETH exhibiting a large initial positive response followed by a negative response, and USDT having a small initial positive response followed by stabilization.

## Conclusion

This study rigorously examined the interaction between foreign exchange policies and cryptocurrency market volatility, using the USD/NGN exchange rate as a proxy for Nigeria's FX policy. The findings reveal that there is a statistically significant long-run relationship between FX rates and cryptocurrency returns. The exchange rate fluctuations, reflective of FX policy shifts, generate asymmetric and persistent volatility in major cryptocurrencies, and the impact of FX policies on crypto returns varies across assets, with BTC and ETH being more responsive than USDT and SOL. These outcomes underscore the growing interconnectivity between traditional macroeconomic policies and emerging digital asset markets. Cryptocurrencies can no longer be viewed in isolation, as they are increasingly influenced by global and national economic decisions.

Recognising that FX policy adjustments now affect not only traditional financial markets but also digital assets, the following recommendation can mitigate their adverse effects and further aid financial inclusion and development in the economy. There is a need to monitor cryptocurrency markets more closely when implementing FX or monetary policy changes. Developing a regulatory framework that reflects the integration between local currency policies and cryptocurrency markets can help avoid unintended consequences.

Players in the cryptocurrency industry play a crucial role due to the decentralised nature of the crypto space; hence, the need to incorporate macroeconomic indicators, particularly exchange rate trends, into trading strategies to anticipate market movements and reduce risk exposure. The use of stablecoins like USDT during periods of high volatility can help hedge against extreme market swings. Digital assets are still at their early adoption stage; therefore, a proper study should be conducted on how to capture global spillover effects more robustly by investigating the role of investor sentiment and external shocks (e.g., geopolitical tensions or regulatory changes) in amplifying the FX-crypto relationship.

However, due to the political nature of Nigeria, the study would have much appreciation by having a details comparison of most sub-Saharan foreign policies and how such has affected the cryptocurrency returns, which will likely be an area of interest in the near future and if possible make a clear comparism on how African and the European countries foreign policies span crypto returns as such will assist most nations to factor such expected return on their policies formulation.

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