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Inflation, Exchange Rate Movements and Cryptocurrency Returns in Nigeria: Evidence from a Structural VAR Model

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Abstract: **This study examines the dynamic relationships between cryptocurrency returns and macroeconomic shocks in Nigeria using a seven-variable structural vector autoregressive (SVAR) model. The analysis covers Bitcoin, Ethereum, Ripple, Solana, Tron, headline inflation and the official naira/US-dollar exchange rate. The empirical procedures include unit-root testing, VAR estimation, Granger causality tests, structural impulse response functions and forecast error variance decomposition (FEVD). The reported results indicate that all variables become stationary after first differencing, while information criteria select a VAR(1) specification. Granger causality tests provide limited evidence that domestic macroeconomic variables predict cryptocurrency returns, with weak exchange-rate predictability for Solana at the 10% significance level. The FEVD reveals substantial differences across assets: inflation accounts for 60.97% of Bitcoin's one-month forecast error variance, while Ripple innovations account for 66.63% of Solana's. Ethereum and Ripple are predominantly associated with their own innovations, while Tron also exhibits substantial own-innovation dependence. The reported impulse responses vary across assets and shock types, although the absence of confidence intervals limits inference about statistical significance. The findings suggest that cryptocurrency return dynamics differ considerably across assets and that cross-cryptocurrency interactions may be important alongside domestic macroeconomic shocks. The results also underscore the importance of structural identification assumptions when interpreting shock transmission. The study offers implications for cryptocurrency risk assessment, portfolio management and financial regulation in Nigeria.**

Keywords: **Cryptocurrency returns; Structural vector autoregression; Inflation; Exchange rate.**

1. INTRODUCTION

Cryptocurrencies have emerged as alternative financial assets, attracting growing interest in their relationship with inflation, exchange-rate movements and financial stability. Their substantial price volatility raises questions about whether their returns respond to macroeconomic conditions or are driven primarily by factors within digital-asset markets. Liu and Tsyvinski (2021) find that cryptocurrency returns are associated with market-specific factors, including momentum and investor attention. These findings suggest that the relationship between cryptocurrency returns and macroeconomic fundamentals requires empirical investigation.

Whether cryptocurrencies protect investors against inflation remains contested. Le et al. (2024) examine their inflation-hedging potential using biwavelet analysis, while Sakurai and Kurosaki (2023) investigate changes in their hedging properties following the reopening of the US economy. Smales (2024) also examines cryptocurrencies as alternative inflation hedges. Gbolahan (2023) investigates Bitcoin's hedging capabilities across several economies, including Nigeria. The findings from this literature motivate further examination of cryptocurrency returns under different macroeconomic conditions.

Nigeria provides a relevant setting for this investigation because of persistent inflationary pressures and substantial naira exchange-rate movements. These conditions may encourage investors to seek alternative stores of value, although cryptocurrency returns may also respond to global liquidity, investor sentiment and asset-specific factors. Furthermore, naira depreciation may raise the domestic-currency price of a cryptocurrency without increasing its dollar-denominated value. Understanding these relationships is important for assessing cryptocurrency exposure to domestic economic disturbances. Nigeria's cryptocurrency market has also attracted regulatory attention, with the International Monetary Fund (IMF, 2023) emphasizing appropriate policy frameworks for crypto-asset risks and De Luna Martinez and Kale (2025) examining Nigeria's regulatory challenges.

Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Solana (SOL) and Tron (TRX) differ in their market structures and characteristics, making it inappropriate to assume that they respond uniformly to macroeconomic shocks. Liu and Tsyvinski (2021) identify market-specific determinants of cryptocurrency returns, supporting the need to examine differences across assets. Furthermore, interactions among cryptocurrencies may transmit shocks across markets, even when domestic macroeconomic variables have limited predictive power.

Despite existing research on cryptocurrency returns and inflation hedging, the joint relationship between Nigerian inflation, exchange-rate movements and multiple cryptocurrency markets warrants further investigation. Gbolahan (2023) examines Bitcoin's hedging capabilities across several economies, including Nigeria, while the present study extends the analysis to five cryptocurrencies and considers exchange-rate movements alongside inflation. It also distinguishes predictive relationships from dynamic shock transmission. Granger causality tests assess predictive relationships, structural impulse response functions (IRFs) trace the effects of identified shocks over time and forecast error variance decomposition (FEVD) quantifies the contribution of innovations to forecast uncertainty.

This study investigates the dynamic relationships between Nigerian inflation, naira exchange-rate movements and the returns of Bitcoin, Ethereum, Ripple, Solana and Tron using a seven-variable structural vector autoregressive (SVAR) framework. Specifically, it examines the statistical properties of the series, tests Granger causality from macroeconomic variables to cryptocurrency returns, traces responses to identified inflation and exchange-rate shocks and measures the contributions of macroeconomic and cross-cryptocurrency innovations to forecast error variance.

The results indicate limited evidence of Granger causality at the 5% significance level, although exchange-rate movements provide weak predictive evidence for Solana at the 10% level. The FEVD results reveal substantial differences across assets: Ripple accounts for a large share of Solana's forecast error variance, while inflation accounts for a substantial share of Bitcoin's. These findings suggest that domestic macroeconomic influences and cross-cryptocurrency interactions vary considerably across assets. Their interpretation depends on data validity, model specification and the assumptions used to identify structural shocks.

The findings are relevant to monetary policy, financial regulation and portfolio risk management. However, Granger causality and FEVD results alone cannot establish whether cryptocurrencies effectively hedge against inflation or naira depreciation. Such conclusions require separate evidence on inflation-adjusted returns and hedging performance.

2. LITERATURE REVIEW

Cryptocurrency returns may respond to macroeconomic conditions, investor sentiment and interactions within digital-asset markets. Liu and Tsyvinski (2021) associate cryptocurrency returns with momentum and investor attention, suggesting that digital assets may respond differently from conventional financial assets. Understanding their relationship with inflation and exchange-rate movements therefore requires direct empirical investigation.

Evidence on cryptocurrency inflation hedging remains mixed. Gbolahan (2023) examines Bitcoin's hedging capabilities across several economies, including Nigeria and finds limited support for its role as an inflation hedge in Nigeria. Sakurai and Kurosaki (2023) find that cryptocurrency hedging properties vary across economic periods, while Smales (2024) reports limited evidence of consistent inflation protection. Le et al. (2024) examine these relationships across time and frequency domains using biwavelet analysis. Collectively, these studies suggest that hedging performance varies across assets and market conditions.

Exchange-rate movements may affect cryptocurrency markets through changes in domestic purchasing power and the naira cost of internationally traded assets. In a depreciating-currency environment, an increase in a cryptocurrency's naira price may reflect exchange-rate changes rather than an increase in its international value. Nigeria provides a relevant setting for

examining these relationships because cryptocurrency activity has attracted regulatory and financial-policy attention. The International Monetary Fund (2023) emphasizes the need for appropriate regulatory frameworks to address crypto-asset risks. However, these concerns do not establish whether inflation and exchange-rate movements predict cryptocurrency returns, making direct empirical testing necessary.

Cryptocurrencies may also influence one another through shared investor sentiment and market participation. Liu and Tsyvinski (2021) identify market-specific determinants of cryptocurrency returns, supporting the need to examine differences across assets. Guo et al. (2024) report cross-cryptocurrency return predictability, providing further justification for modelling several cryptocurrencies jointly. Such analysis can distinguish movements associated with an asset's own innovations from those associated with shocks originating elsewhere in the cryptocurrency market.

Methodologically, previous studies have employed vector error correction models and biwavelet analysis to examine cryptocurrency and macroeconomic relationships (Gbolahan, 2023; Le et al., 2024). Chen (2025) uses a Bayesian structural vector autoregressive model to examine cryptocurrency shocks and their transmission to other markets. An SVAR provides a complementary framework for tracing responses to identified shocks and estimating their contributions to forecast uncertainty. Granger causality tests assess predictive relationships, impulse response functions trace dynamic responses and forecast error variance decomposition measures the relative contributions of innovations. These methods address different questions and structural interpretations depend on the identification restrictions imposed on the model.

Despite existing research on cryptocurrency returns and inflation hedging, further evidence is needed on the joint relationship between Nigerian inflation, exchange-rate movements and multiple cryptocurrency markets. This study addresses this gap by estimating a seven-variable SVAR comprising inflation, the naira exchange rate and the returns of Bitcoin, Ethereum, Ripple, Solana and Tron. It examines predictive causality, responses to identified macroeconomic shocks and the relative contributions of domestic and cross-cryptocurrency innovations to forecast error variance. By examining five assets jointly, the study assesses whether their relationships with Nigerian macroeconomic conditions differ across cryptocurrencies.

3. METHODOLOGY

3.1. Research Design and Data

The study adopts a quantitative, ex post facto time-series design to examine the relationships between Nigerian macroeconomic conditions and cryptocurrency returns. The dataset is reported to cover January 2010 to December 2024, with monthly observations. The variables comprise Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Solana (SOL), Tron (TRX), the official naira/US-dollar exchange rate (EXR) and headline inflation (INF). Cryptocurrency prices are sourced from Investing.com, exchange-rate data from the Central Bank of Nigeria and inflation data from the National Bureau of Statistics.

Cryptocurrency prices and the exchange rate are transformed into logarithmic first differences, while inflation is first-differenced to achieve stationarity. The empirical analysis comprises descriptive statistics, correlation analysis, Ljung–Box tests, Augmented Dickey–Fuller (ADF) tests, VAR estimation, Granger causality tests, structural impulse response functions (IRFs) and forecast error variance decomposition (FEVD). Estimation is conducted in Python using NumPy, Pandas, SciPy, Statsmodels and Matplotlib.

3.2. VAR Specification and Structural Identification

The study employs a seven-variable structural vector autoregression (SVAR) to examine dynamic interactions among the five cryptocurrency return series and the two macroeconomic variables. Following Lütkepohl (2005), the reduced-form VAR is specified as:

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + u_t \qquad (1)$$

where yt is the vector of stationary variables, c is the intercept vector, A_i denotes the autoregressive coefficient matrices and ut is the vector of reduced-form innovations with covariance matrix Σu.

The endogenous vector follows the ordering:

$$yt = [\Delta \ln XRP_t \ \Delta \ln ETH_t \ \Delta \ln SOL_t \ \Delta \ln TRX_t \ \Delta \ln BTC_t \ \Delta INF_t \ \Delta ln \ EXR_t]'$$

The optimal lag length is selected using the Akaike information criterion (AIC), Bayesian information criterion (BIC), Hannan–Quinn criterion (HQIC) and final prediction error (FPE), with candidate lag lengths from zero to five. Model adequacy is assessed through the stability of the companion matrix and residual autocorrelation diagnostics. The selected VAR(1) specification is retained for the subsequent analysis.

To identify structural shocks, the reduced-form innovations are related to mutually orthogonal structural shocks through:

$$u_t = B\varepsilon_t, \Sigma u = BB' \qquad (2)$$

where B is the contemporaneous impact matrix and εt is the vector of structural shocks, with $E(\varepsilon t \varepsilon t') = I$. Identification follows recursive Cholesky restrictions, with the five cryptocurrency variables ordered before inflation and the exchange rate. This ordering assumes that contemporaneous effects operate recursively from earlier to later variables. Consequently, the estimated structural responses depend on the ordering and its identifying assumptions (Sims, 1980).

3.3. Stationarity and Granger Causality

The Augmented Dickey–Fuller test is used to assess whether each series contains a unit root (Dickey & Fuller, 1979, 1981). The null hypothesis of non-stationarity is tested in levels and after transformation. The Ljung–Box test evaluates serial dependence at lag 12. These diagnostics inform the transformations and model specification used in the VAR estimation.

Granger causality tests examine whether lagged values of one variable provide additional predictive information for another, conditional on the remaining variables in the system (Granger, 1969). The analysis focuses on whether inflation and exchange-rate movements predict the returns of each cryptocurrency. Statistical significance is assessed at the 5% level, while results significant only at 10% are treated as weaker evidence. Granger causality is interpreted as predictive precedence rather than proof of structural causation.

3.4. Impulse Response Functions and Forecast Error Variance Decomposition

Impulse response functions trace the effects of identified structural shocks on cryptocurrency returns over time. The structural moving-average representation is:

$$y_t = \sum_{s=0}^{\infty} \Theta s \varepsilon t - s, \Theta s = \Psi_s B \qquad (3)$$

where Ψs denotes the moving-average coefficient matrices derived from the estimated VAR. The element $[\Theta_s]_{ij}$ measures the response of variable i at horizon s to a structural shock in variable j. The analysis examines responses to one-standard-deviation inflation and exchange-rate shocks, focusing on their direction, magnitude and persistence.

FEVD quantifies the share of forecast error variance attributable to each structural shock:

$$FEVD_{ij}(h) = \frac{\sum_{s=0}^{h-1}[\Theta s]_{ij}^2}{\sum_{s-0}^{h-1}(\Theta s \Theta s')_{ii}} \times 100 \qquad (4)$$

where h denotes the forecast horizon. The decomposition is evaluated at one, six and twelve months to quantify the relative contributions of domestic macroeconomic and cross-cryptocurrency shocks to forecast uncertainty. The IRFs and FEVD are interpreted conditional on the estimated model and its structural identification restrictions.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the five cryptocurrencies, the naira/US dollar exchange rate and headline inflation. The coefficient of variation (CV) indicates substantial differences in relative dispersion across the variables. Among the cryptocurrencies, Solana records the highest CV (0.201), followed by Ripple (0.153), Bitcoin (0.109), Tron (0.097) and Ethereum (0.040). The exchange rate and inflation record CVs of 0.424 and 0.413, respectively.

These differences suggest that the variables exhibit distinct distributional characteristics. The relatively high dispersion of the macroeconomic series reflects considerable variation in the reported exchange rate and inflation data, while the differences among cryptocurrencies indicate that their price distributions are not uniform. These descriptive patterns motivate an examination of the extent to which domestic macroeconomic variables account for cryptocurrency return dynamics.

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Table 1. Descriptive Statistics of Cryptocurrency and Macroeconomic Variables

Variable	Mean	Standard deviation	Minimum	Maximum	CV
Bitcoin (BTC)	98,582.594	10,708.155	76,271.950	119,995.415	0.109
Ethereum (ETH)	162.158	6.470	150.390	174.870	0.040
Ripple (XRP)	2.436	0.372	1.795	3.556	0.153
Solana (SOL)	165.444	33.235	105.512	261.869	0.201
Tron (TRX)	0.257	0.025	0.212	0.338	0.097
Exchange rate (EXR)	188.830	80.139	0.000	381.000	0.424
Inflation (INF)	13.453	5.549	5.400	32.770	0.413

Note: CV denotes the coefficient of variation.

4.2. Stationarity and VAR Model Diagnostics

The Augmented Dickey-Fuller (ADF) tests indicate that the unit-root null cannot be rejected for any of the seven variables in levels at the 5% significance level. Following logarithmic first differencing, all transformed series are stationary at the 1% level, according to the reported test results.

Table 2. Augmented Dickey-Fuller Unit-Root Tests

Variable	ADF statistic, levels	p-value, levels	ADF statistic, first differences	p-value, first differences
BTC	1.940	0.3135	−16.887	1.05×10^{-29}
ETH	1.956	0.3062	−14.633	3.73×10^{-27}
XRP	2.731	0.0688	−16.469	2.29×10^{-29}
SOL	1.730	0.4159	−15.978	6.88×10^{-29}
TRX	2.761	0.0641	−10.197	6.10×10^{-18}
EXR	2.582	0.0968	−9.757	7.72×10^{-17}
INF	2.840	0.0528	−3.460	0.00908

The results support the use of stationary transformations for the subsequent VAR analysis. However, the transformation of inflation requires explicit documentation because differencing an inflation rate measures changes in inflation rather than changes in the price level.

The lag-selection criteria unanimously select a VAR(1) specification. The maximum eigenvalue modulus is 0.924, satisfying the reported stability condition. The residual autocorrelation test produces a p-value of 0.472, so the null of no residual serial correlation cannot be rejected at conventional significance levels.

Table 3. VAR Lag Selection and Model Diagnostics

Panel A. Lag-order selection criteria

Lag	AIC	BIC	HQIC	FPE
0	7.241	8.134	7.602	1,396.0
1	5.523*	7.197*	6.200*	250.9*
2	5.759	8.213	6.751	318.7
3	5.618	8.854	6.926	278.9
4	5.813	9.830	7.437	342.9
5	5.887	10.680	7.826	375.4

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Panel B. Model diagnostics

Diagnostic	Result
Effective observations	215
Selected lag order	VAR(1)
Estimated-model AIC	−48.173
Estimated-model BIC	−47.172
Maximum eigenvalue modulus	0.924
Stability condition	Satisfied
Residual autocorrelation test, p-value	0.472

Note: indicates the selected lag. AIC denotes the Akaike information criterion, BIC the Bayesian information criterion, HQIC the Hannan-Quinn information criterion and FPE the final prediction error.*

The diagnostic results support the reported VAR specification for examining dynamic relationships among the variables. The interpretation of the structural results, however, depends on the identification restrictions used to distinguish the innovations and the ordering of variables in the system.

4.3. Granger Causality between Macroeconomic Variables and Cryptocurrency Returns

Table 4 reports Granger causality tests from exchange-rate movements and inflation to the returns of the five cryptocurrencies. The tests assess whether lagged macroeconomic variables contain additional predictive information for cryptocurrency returns within the multivariate system.

Table 4. Granger Causality Tests from Macroeconomic Variables to Cryptocurrency Returns

Null hypothesis	p-value	Decision at 5%
EXR does not Granger-cause BTC	0.338	Fail to reject
INF does not Granger-cause BTC	0.853	Fail to reject
EXR does not Granger-cause ETH	0.864	Fail to reject
INF does not Granger-cause ETH	0.584	Fail to reject
EXR does not Granger-cause XRP	0.460	Fail to reject
INF does not Granger-cause XRP	0.768	Fail to reject
EXR does not Granger-cause SOL	0.079	Fail to reject
INF does not Granger-cause SOL	0.478	Fail to reject
EXR does not Granger-cause TRX	0.383	Fail to reject
INF does not Granger-cause TRX	0.825	Fail to reject

The results provide limited evidence that domestic macroeconomic variables predict cryptocurrency returns. Neither exchange-rate changes nor inflation significantly predict Bitcoin, Ethereum, Ripple or Tron at the 5% level. For Solana, the exchange-rate test yields a p-value of 0.079, providing weak evidence of predictive causality at the 10% level, but not at the 5% level. Inflation does not significantly predict Solana returns.

These findings indicate that the predictive contribution of domestic macroeconomic variables is limited within the specified model. They do not establish that exchange-rate movements and inflation have no economic effect on cryptocurrency markets. Rather, the results indicate that the tests fail to identify statistically significant incremental predictive relationships for most assets.

The findings also raise an important distinction between predictive causality and shock transmission. A macroeconomic variable may account for part of a cryptocurrency's forecast error variance under a particular structural identification scheme even when its Granger causality test is not statistically significant. The variance decomposition therefore provides a complementary assessment of the estimated system.

4.4. One-Month Forecast Error Variance Decomposition

The forecast error variance decomposition (FEVD) quantifies the share of forecast uncertainty attributable to innovations in each variable. Table 5 reports the decomposition for the five cryptocurrencies at the one-month horizon.

Table 5. One-Month Forecast Error Variance Decomposition of Cryptocurrency Returns (%)

Responding asset	EXR	INF	XRP	ETH	SOL	TRX	BTC
Bitcoin (BTC)	1.66	60.97	0.88	8.15	0.45	27.88	0.41
Ethereum (ETH)	0.84	2.45	0.30	96.41	0.00	0.00	0.00
Ripple (XRP)	0.00	0.00	100.00	0.00	0.00	0.00	0.00
Solana (SOL)	0.05	1.05	66.63	0.11	32.16	0.00	0.00
Tron (TRX)	0.14	0.12	17.19	0.18	3.11	79.26	0.00

The Bitcoin decomposition is distinctive. Inflation accounts for 60.97% of its one-month forecast error variance, followed by Tron at 27.88% and Ethereum at 8.15%. The exchange rate contributes 1.66%. The large reported inflation share contrasts with the Granger causality result, which does not establish statistically significant predictive causality from inflation to Bitcoin. The two results measure different properties of the estimated system and should not be treated as equivalent tests of economic influence.

For Ethereum, own innovations account for 96.41% of forecast error variance. Inflation contributes 2.45% and the exchange rate contributes 0.84%. The other cryptocurrency contributions are reported as zero. This distribution indicates that Ethereum's one-month forecast uncertainty is predominantly associated with its own innovation under the specified decomposition.

Ripple's forecast error variance is attributed entirely to its own innovation at this horizon. None of the other variables has a reported contribution. This finding concerns the one-month variance allocation and does not establish that Ripple is independent of the other assets over longer periods.

Solana displays substantial cross-cryptocurrency dependence. Ripple innovations account for 66.63% of Solana's one-month forecast error variance, while Solana's own innovation contributes 32.16%. Inflation contributes 1.05% and the exchange rate contributes 0.05%. These estimates indicate that Ripple accounts for a much larger share of Solana's immediate forecast uncertainty than either domestic macroeconomic variable.

Tron's own innovation accounts for 79.26% of its forecast error variance. Ripple contributes 17.19%, followed by Solana at 3.11%. Inflation and the exchange rate account for 0.12% and 0.14%, respectively. Tron's immediate forecast uncertainty is therefore attributed primarily to its own innovation, with Ripple providing the largest reported contribution from another cryptocurrency.

The one-month results reveal considerable variation in the sources of forecast uncertainty across the five assets. Inflation has a large reported contribution for Bitcoin but a small or zero contribution for the other cryptocurrencies. Exchange-rate contributions are small across all five assets. The contribution of Ripple to Solana is particularly pronounced, indicating a strong dependence within the estimated cryptocurrency system at this horizon.

These findings are conditional on the structural identification scheme used in the VAR. The allocation of forecast error variance may depend on variable ordering and the restrictions imposed on contemporaneous relationships. The reported shares should therefore be interpreted as estimates from the specified model rather than direct measures of economic causation.

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4.5. Structural Impulse Responses to Macroeconomic Shocks

The structural impulse response functions describe how cryptocurrency returns respond to identified inflation and exchange-rate shocks over time. Table 6 presents the available early-horizon responses.

Table 6. Structural Responses of Cryptocurrency Returns to Inflation and Exchange-Rate Shocks

Cryptocurrency	Horizon	Inflation shock	Exchange-rate shock
Bitcoin (BTC)	0	0.002963	0.000195
Bitcoin (BTC)	1	−0.000660	0.001515
Ethereum (ETH)	0	0.001297	0.000761
Ethereum (ETH)	1	0.000293	−0.000032
Ripple (XRP)	2	0.000335	−0.000580
Solana (SOL)	2	0.001171	0.0000538
Tron (TRX)	3	−0.000110	−0.000019

Bitcoin's response to an inflation shock is positive on impact but negative at horizon one. Its response to an exchange-rate shock remains positive over the two reported horizons, increasing from 0.000195 to 0.001515. Ethereum responds positively to an inflation shock at impact and at horizon one, although the magnitude declines from 0.001297 to 0.000293. Its response to an exchange-rate shock changes from positive on impact to a small negative value at horizon one.

The reported responses for Ripple and Solana at horizon two are positive for inflation shocks. Ripple's response to the exchange-rate shock is negative, whereas Solana's is positive. Tron's reported responses at horizon three are negative for both shocks. These differences indicate that the direction of the estimated response varies across assets and shock types.

The available estimates do not establish whether these responses are statistically different from zero because confidence intervals are not reported. Moreover, the reported figures for Ripple, Solana and Tron begin at later horizons than those for Bitcoin and Ethereum. Consequently, the table does not permit a complete comparison of impact responses across all five assets.

The impulse response results provide a complementary description of the estimated dynamic relationships. They should not be interpreted as proof that a shock has a statistically significant economic effect unless the corresponding uncertainty estimates support that conclusion.

4.6. Discussion

The empirical results reveal three main features of the relationship between Nigerian macroeconomic variables and cryptocurrency returns. First, the Granger causality tests provide little evidence that exchange-rate movements and inflation consistently predict returns across the five assets. Solana exhibits weak evidence of exchange-rate predictability at the 10% level, but the result does not meet the 5% threshold.

Second, the one-month FEVD reveals marked differences in the allocation of forecast uncertainty. Inflation accounts for a large reported share of Bitcoin's forecast error variance, whereas Ethereum and Ripple are dominated by their own innovations. Solana exhibits a substantial contribution from Ripple and Tron is predominantly associated with its own innovation. These differences caution against treating cryptocurrency markets as a homogeneous asset class.

Third, the available impulse responses indicate that cryptocurrency responses differ according to the type of shock and the period examined. The evidence does not support a single response pattern across all five assets. The results also show why Granger causality and FEVD should be interpreted separately: one assesses incremental predictive content, while the other allocates forecast error variance under the chosen identification scheme.

The findings do not establish that any of the five cryptocurrencies provides an effective hedge against Nigerian inflation or naira depreciation. Such a conclusion would require evidence directly relating to hedging performance. The large inflation contribution reported for Bitcoin also warrants verification against the original model output before it is used to support substantive economic claims.

Taken together, the results suggest that the immediate relationship between domestic macroeconomic variables and cryptocurrency returns differs considerably across assets. Domestic macroeconomic innovations account for a large share of Bitcoin's reported forecast uncertainty but relatively small shares for the other cryptocurrencies. At the same time, the contribution of Ripple to Solana indicates that interactions within cryptocurrency markets may be important for understanding short-horizon forecast uncertainty.

5. CONCLUSION

This study examines the dynamic relationships between Nigerian macroeconomic shocks and the returns of five cryptocurrencies using a seven-variable SVAR model. Granger causality tests reveal limited predictive relationships between inflation, exchange-rate movements and cryptocurrency returns, with weak exchange-rate predictability for Solana at the 10% significance level. The FEVD results reveal substantial differences across assets. Inflation accounts for a large share of Bitcoin's forecast error variance, while Ripple contributes considerably to Solana's. Ethereum and Ripple are predominantly associated with their own innovations, indicating heterogeneous return dynamics across cryptocurrency markets. These findings suggest that investors should consider asset-specific risks and cross-cryptocurrency interactions when managing portfolios. However, the results do not establish that cryptocurrencies provide reliable hedges against Nigerian inflation or naira depreciation. Further research should examine alternative identification schemes and assess hedging performance directly.

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