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CRYPTOCURRENCY AND ITS DISRUPTIVE POTENTIAL: INVESTIGATING LONG-RUN AND SHORT-RUN RELATIONSHIPS WITH SOME SELECTED MACROECONOMIC INDICATORS

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ABSTRACT

The advent of cryptocurrency and underlying blockchain technology has ushered in a new era of digital finance, challenging traditional economic frameworks and prompting a reassessment of the macroeconomic landscape. This research work delves into the multifaceted economic impact of cryptocurrency, examining its potential implications for monetary policy, financial stability, and economic growth. This study uses a time series approach, that is Johansen cointegration and Granger causality in determining both the long and short run relationship that exist between the exchange rate of cryptocurrency prices (Binance coin, Bitcoin, Dogecoin, Ethereum, And Ripple) versus the U.S dollar and GDP from January, 2018 to July, 2023. And While, it also focuses on checking the long run and short run equilibrium relationship between the economic/financial variables and cryptocurrency market capitalization from January, 2018 to July, 2023. It considers a monthly data for both the exchange rates of the selected cryptocurrency prices versus the U.S dollar and the selected economic/financial time series variables. Finally, the study reveals that the result obtained from both tests. That is, the Johansen cointegration test and Granger causality Test, shows that short run effects exist more among the studied time series variables than in the long-run, and that changes in the selected cryptocurrency prices can be used to predict changes in the macroeconomic variables and indicators.

Keywords: Cryptocurrency, Macroeconomic indicators, Economic growth, Cointigeration, Granger causality

INTRODUCTION

The rise of digital currencies like Bitcoin (BTC) has fundamentally changed how we think about money, transactions, and financial systems. Since 2009, this ecosystem has boomed, attracting interest from diverse groups. This surge in popularity stems from cryptocurrencies' unique features, transparency, and ease of use (Urquhart, 2016). Essentially, they're digital assets secured by cryptography for transactions and unit creation (*Ani* et al., 2024; Selgin, 2015; Baeck & Elbeck, 2015). Bitcoin paved the way for countless other cryptocurrencies (Yermack, 2015; Pieters & Vivanco, 2017; Katsiampa, 2017). This rapid growth has sparked debate, with some praising their financial potential while others warn of their environmental impact, particularly Bitcoin mining's potential to worsen climate change (Li et al., 2018; Mora et al., 2018).

Decentralization and transparency, key features of cryptocurrencies and blockchain technology, have opened doors for new economic activities. The past decade saw Bitcoin's surge drive wider adoption, yet most cryptocurrencies remain associated with decentralized payments despite the growing trend of centralized trading (Pattison, 2011; Hamacher & Katzenbeisser, 2011). However, the full potential of these systems remains largely unexplored. Studies on cryptocurrencies, particularly Bitcoin (market cap: $567.54B as of July 26, 2023), often focus narrowly on their economic functions, neglecting broader contexts (Zhao et al., 2022; Britto & Castillo, 2013). Bitcoin, introduced in 2008, sparked the movement and currently dominates with 48.3% of the market share (Coin Market Cap [CMC], 2023), followed by Ethereum, Binance, Ripple, and Dogecoin (CMC, July 31, 2023).

Cryptocurrencies have become a hotly debated topic due to their unique characteristics and potential impact on the financial and monetary systems. Their decentralization, anonymity, and independence from central banks, along with their reliance on cyber technology, have made them both a source of fascination and concern (Baek & Elbeck, 2015). While their economic potential is undeniable, concerns about their environmental impact, particularly their energy-intensive mining processes like Proof-of-Work (PoW), cannot be ignored (Anuyahong & Ek-udom, 2023; Kugler, 2018). Although projections by the International Energy Agency (IEA) suggest a shift towards renewable energy sources by 2040, the immediate environmental consequences of cryptocurrency mining remain a pressing issue. Careful consideration of future energy sources and their impact on cryptocurrency production is crucial in evaluating the full potential of this technology (Martynov, 2020). Furthermore, cryptocurrencies operate outside the traditional boundaries of government control and regulation (Gilbert & Loi, 2018). This has led some central banks to explore the potential of blockchain technology and cryptocurrencies for various payment systems (Bartoletti et. al., 2017). Cryptocurrency adoption in Nigeria is gaining momentum, but concerns about its operation and lack of regulatory framework from the Central Bank of Nigeria (CBN) persist. A growing call urges the CBN to implement regulations and develop its own blockchain to leverage the potential of eNaira. Ironically, CBN's foreign exchange restrictions have driven Nigerians towards Bitcoin for access, making a complete ban on cryptocurrency and blockchain technology counterproductive for a nation seeking domestic innovation. Following other countries' lead in embracing cryptocurrency, this study aims to assess the economic impact of these virtual currencies and blockchain technology from a macroeconomic digital perspective, along with potential policy implications thereby assessing key relationship with macroeconomic indicators (Jatau et al., 2025; Ani & Mashood, 2021; Rejeb et al., 2021; Ani & Hassan, 2020; Ani et al., 2020).

Therefore, the study investigates the economic impact of cryptocurrencies, particularly focusing on their relationship with macroeconomic and financial indicators. It seeks to explore both short-term and long-term relationships between these selected cryptocurrencies (Bitcoin, Ethereum, Binance Coin, Dogecoin, and Ripple) in U.S. Dollar from January 2018 to July 2023. In addition, the study will investigate whether there is a short-run or long-run relationship among the study variables employing the Johansen cointegration framework. The study will also apply the Granger causality test to investigate the direction of the study variables and lastly, the study will propose some recommendations based on the key findings from this study.

MATERIALS AND METHODS

Data Source and Description

The cryptocurrency and time series datasets employed in this study includes the following 24-hours high and low prices, trading volumes, total supply and market capitalization of the five most capitalized tokens namely; BTC, ETH, BNB, XRP and Dogecoin (CMC, 31 July 2023; 12:30pm); dataset on five central exchanges based on the following; traffic, liquidity, trading volumes, and confidence in the legitimacy of trading volumes these are Binance (BnEx), Coinbase (CoEx), Kraken (KrEx), Kucoin (KuEx) , and Bybit (ByEx) (CMC, 31 July 2023; 12:30pm); datasets on macroeconomic and financial indicators such as currency in circulation, exchange rate (NGN/USD), inflation rate, monetary policy rate on interest rates, money supply, net domestic assets, net domestic credit, net foreign assets, and real GDP as well as cryptocurrency market capitalization were retrived. The cryptocurrencies ecosystem, economic factors and indices datasets for the study are obtained as secondary data from CMC and the Nigeria Apex Bank. The CMC and CBN website from which datasets were collected are https://coinmarketcap.com/ and www.cbn.gov.ng/rates/exrate.asp. The data comprises of daily and monthly frequency. The daily datasets are high frequency data ranging from 01 January, 2018 – 31 July, 2023 with a total of 2037 observations while, the monthly datasets are low frequency data ranging from January, 2018 – July, 2023 with a total of 67 months. The monthly data set is utilized since structural breaks/shifts/change can be detected more evidently when a low frequency period is employed.

Augmented Dickey-Fuller (ADF) test

To compute the test statistics, the following augmented Dickey–Fuller regression model which is a generalized autoregression model formulated by Dickey and Fuller (1979), is used. Dickey and Fuller (1979) in differentiating a unit root, the following regression can be run:

$$\Delta Y_t = b_0 + \sum_{j=1}^{k} b_j \Delta Y_{t-j} + \beta_t + \gamma Y_{t-1} + \varepsilon_t \qquad (1)$$

The regression comprises sufficient lags of ΔY_t as a result ε_t comprises no autocorrelation. If a time trend is not required then the model can be used without *t*. In the wake of a unit root, differentiating Y_t is paramount which should result in a white-noise series (no correlation with Y_{t-1}). The Augmented Dickey-Fuller (ADF) test; $H_0: \gamma = 0$ against $H_1: \gamma \neq 0$. According to Dickey and Fuller (1979), the test statistic for $H_0: \gamma = 0$ is

$$Z_t = \frac{\hat{\gamma}}{\hat{\sigma}_\gamma} \qquad (2)$$

Where $\hat{\sigma}_\gamma$ is the standard error of $\hat{\gamma}$.

Johansen Cointegration Test

If in a long-run, two variables shares in a conjoint stochastic movement then, one can conclude that both variables are cointegrated. The Johansen cointegration test states that the method can only be applied on data sets that are integrated of the same order. A Vector Autoregressive based cointegration analysis techniques by Johansen (1991) is given below: Consider a vector autoregressive (VAR) model of order p:

$$Yt = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p \qquad (3)$$

Where Yt is the k – vector of non-stationary (1) variables, Xt is the d – vector of deterministic variables and εt is a vector of innovations. We may rewrite this (p) as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + BX_t + \varepsilon_t \qquad (4)$$

Where, $\Pi = \sum Ai - I, p\ i{=}1\ \Gamma i = -\sum Aj\ p\ j{=}i{+}1$ The Granger's theorem states that if the coefficient matrix Π has reduced rank $r < k$, then there exist $k \times$ r matrices $\alpha\ and\ \beta$ each with rank r such that $\Pi = \alpha\beta'$ and $\beta' yt$ is (0). r is the number of cointegration relations and each column of β is the cointegration vector. Johansen cointegration test computes two statistics: trace statistic and maximum eigenvalues statistic. The trace statistic for the null hypothesis of r cointegration relations in computed as:

$$LR_{tr}(r|k) = -T \sum_{i=r+1}^{k} log(1 - \lambda_I) \qquad (5)$$

While, the maximum eigenvalue test statistic is computed as:

$$LR_{max}(r|r+1) = -Tlog(1 - \lambda_{r+1}) = LR_{tr}(r|k) - LR_{tr}(r+1|k) \qquad (6)$$

Where λi is the i-th largest eigenvalue of the Π matrix in (w), $r = 0,1,2, \ldots, k-1$. 2.4.

Granger Causality Test

Cointegration shows presence of a long run relationship amongst variables (Ani et al., 2020). Note that, even if the variables are not cointegrated in the long run, it is very possible they may be interrelated in the short-run. Hence, to properly comprehend the short-run interdependence between variables, Granger causality tests might be suitable to explain these relationship dynamics. This test rely on a standard F-test to investigate whether variations in one variable cause changes in another variable. Let us start with a simple VAR model:

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_k y_{t-k} + \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_k x_{t-k} + \varepsilon_t \qquad (7)$$

If all α coefficients on lagged values of X are significant in this equation, then "X Granger causes Y". If X Granger causes Y and not vice-versa, it is called unidirectional causality. But, when the causality is vice versa, then it is refers to as bidirectional (Brooks, 2008). The hypotheses for the test is stated as follows: H0: $\alpha 1 = \alpha 2 = \cdots = \alpha k = 0$ ("X does not Granger causes Y") H1: $\alpha 1 \neq \alpha 2 \neq \cdots \neq \alpha k \neq 0$, for at least one of αi coefficients ("X does Granger Cause Y"). Though, if causality exist in one or both ways among two variables, it does not necessary mean that they are both cointegrated (Granger, 1988).

RESULTS AND DISCUSSION

Descriptive Statistics

The selected cryptocurrency exchange rates versus the U.S Dollar were obtained from CMC while the economic/financial variables datasets were obtained from the official CBN website. The descriptive statistics of the selected cryptocurrency exchange rates versus the U.S Dollar are given in table 1.

Table 1: Summary statistics of daily exchange rates of Binance, Bitcoin, Dogecoin, Ethereum and Ripple versus the U.S. Dollar (01 January 2018 to 31 July 2023)

Measures	BNB Price	BTC Price	DOGECOIN Price	ETH Price	XRP Price
Mean	165.6240	20942.35	0.063975	1210.311	0.517496
Median	30.71218	13547.77	0.005652	727.3373	0.407328
Maximum	675.0990	67617.02	0.681842	4815.005	3.398450
Minimum	4.470332	3216.627	0.001483	83.78596	0.137830
Std. Dev.	179.8085	16244.76	0.094268	1154.877	0.340717
Skewness	0.745687	0.955124	2.158895	1.030149	2.496940
Kurtosis	2.307476	2.780375	8.792992	3.177808	14.03615
Jarque-Bera	229.5967	313.9607	4432.825	363.1412	12460.28
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	337541.8	42680514	130.3820	2466614.	1054.657
Sum Sq. Dev.	65858436	5.38E+11	18.10161	2.72E+09	236.4713
Observations	2038	2038	2038	2038	2038

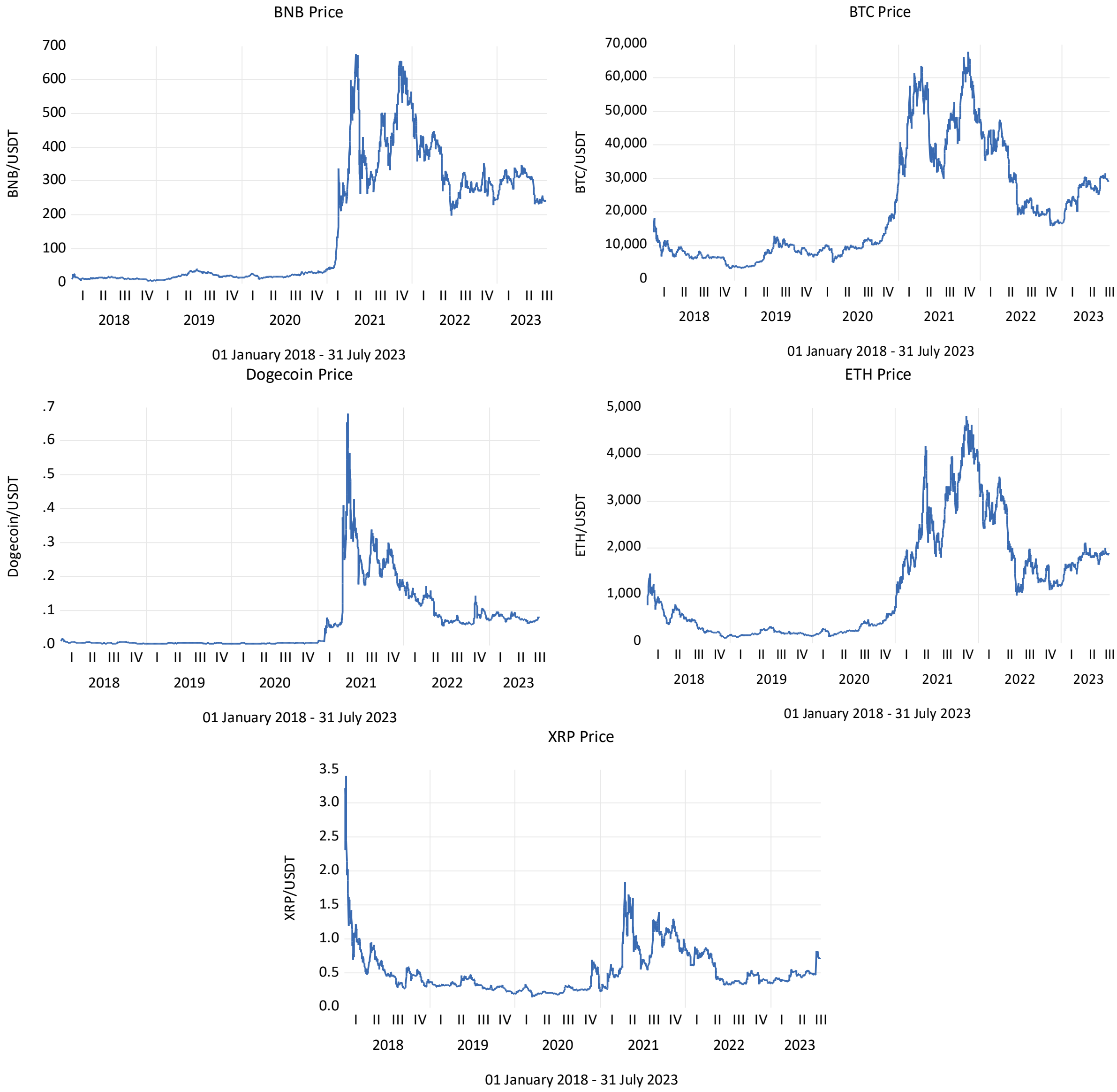

Figure 1: Time-plots of daily exchange rates of Binance, Bitcoin, Dogecoin, Ethereum and Ripple versus the U.S. Dollar (01 January 2018 to 31 July 2023)

From table 1 it is observed that the exchange rates of Binance, Bitcoin, Dogecoin, Ethereum And Ripple versus the U.S Dollar from the period under study ranges from 4.470332 to 675.0990, 3216.627 to 67617.02, 0.001483 to 0.681842, 83.78596 to 4815.005, and 0.137830 to 3.398450, respectively with a mean value of 165.240, 20942.35, 0.063975, 1210.3.11, and 0.517496, respectively and a standard deviation of 179.8085, 16244.76, 0.094268, 1154.877 and 0.340717, respectively. With the exception of first moment statistics of the series, Figure 1 clearly shows the time plot of the exchange rates of Binance, Bitcoin, Ethereum, Dogecoin and Ripple versus the U.S Dollar. The results of alternative statistical analyses are also observable in figure 1. The results reveal a high standard deviation, indicating a lot of variability in the series, the time plots show a massive uptrend in the last quarter of 2020 and a little downtrend in the last quarter of 2023. The statistic for skewness shows that the variable is positively skewed, implying that the distribution has long right tail, this further signify that the series is non-symmetric. While, the kurtosis value obtained for the exchange rates of Binance, Bitcoin, Dogecoin, Ethereum and Ripple versus the U.S Dollar are 2.307476, 2.780375, 8.792992, 3.177808 and 14.03615, respectively which exceeds 0, and are positive, this shows that the normal curve is peaked (i.e Leptokurtic). The Jarque-Bera test statistic obtained for the exchange rates of Binance, Bitcoin, Dogecoin, Ethereum and Ripple versus the U.S Dollar are 229.5967, 313.9607, 4432.825, 363.1412, and 12460.28, respectively with a p-value of 0.000000, this result indicates that the null hypothesis of normal distribution for the series are rejected, signifying that the time series data set exhibit nonlinearity. By implication, structural break/changes/or shifts occurs in the exchange rates of Binance, Bitcoin, Dogecoin, Ethereum and Ripple versus the U.S Dollar. The current study confirms Urquhart's findings that cryptocurrency prices exhibit high volatility and non-stationarity. The Jarque-Bera test results indicate that cryptocurrencies do not follow a normal distribution, which aligns with Urquhart's (2016) analysis of Bitcoin's price dynamics. The high standard deviations in exchange rates found in this study support previous research stating that cryptocurrencies experience significant fluctuations over short periods. Katsiampa (2017) highlights excess kurtosis and skewness in Bitcoin prices, indicating fat-tailed distributions; the current study finds similar results, particularly for Dogecoin and Ripple, which exhibit high kurtosis values, confirming their non-symmetric and peaked price distribution.

Table 2: Summary statistics of economic/financial and crypto market capitalization variables (January, 2018 to July, 2023)

Measures	Crypto mcap	Currency Circulation	Exch Rate NGN USD	Inflation Rate	Monetary Policy Rate on Interest Rates	Money Supply	Net Domestic Assets	Net Domestic Credit	Net Foreig Assets	Real GDP
Mean	1.93E+10	2468165.	374.9	15.3	13.6	39873164	28738863	43900898	10436934	17869.9
Median	1.16E+10	2370886.	379.0	14.9	13.5	36813448	28777280	39849572	8087752.	17861.6
Max	6.15E+10	3350615.	769.3	24.1	18.5	64906931	53414464	84045544	19100004	18166.4
Min	3.02E+09	982097.7	304.6	11.0	11.5	28207927	4555768.0	24691470	4252035.	17630.4
Std. Dev.	1.61E+10	535568.6	78.6	3.9	1.9	8340353.	12496526	14966510	5088164.	119.2
Skewness	0.9	-0.020827	2.2	0.6	1.01	0.807403	0.133123	0.751173	0.588666	0.3
Kurtosis	2.6	2.486817	11.2	2.1	3.7	2.908365	2.028521	2.703376	1.687392	2.6
Jarque-Ber	9.2	0.740049	238.2	6.3	12.6	7.302983	2.832588	6.546540	8.679434	1.3
Prob.	0.01	0.690717	0.0	0.04	0.0	0.025952	0.242611	0.037882	0.013040	0.5
Sum	1.30E+12	1.65E+08	25119.3	1027.2	908.0	2.67E+09	1.93E+09	2.94E+09	6.99E+08	1197223.
Sum Sq. De	1.71E+22	1.89E+13	407702.4	1003.8	233.6	4.59E+15	1.03E+16	1.48E+16	1.71E+15	937658.0
Obs	67	67	67	67	67	67	67	67	67	67

The results in table 2 indicates that the cryptocurrency market capitalization has a mean of 1.93E+10 and a standard deviation of 1.61E+10, indicating a wide range of values. The maximum market capitalization is 6.15E+10 and the minimum is 3.02E+09. The currency in circulation has a mean of 2468165 and a standard deviation of 535568.6, indicating a moderate range of values. The maximum currency in circulation is 3350615 and the minimum is 982097.7. The exchange rate against the Nigerian naira has a mean of 374.9144 and a standard deviation of 78.59586, indicating a moderate range of values. The maximum exchange rate is 769.3165 and the minimum is 304.6100. The inflation rate has a mean of 15.33164 and a standard deviation of 3.899889, indicating a moderate range of values. The maximum inflation rate is 24.08000 and the minimum is 11.02000. The monetary policy rate has a mean of 13.55224 and a standard deviation of 1.881195, indicating a narrow range of values. The maximum monetary policy rate is 18.50000 and the minimum is 11.50000. The money supply has a mean of 39873164 and a standard deviation of 8340353, indicating a moderate range of values. The maximum money supply is 64906931 and the minimum is 28207927. The net domestic assets have a mean of 28738863 and a standard deviation of 12496526, indicating a moderate range of values. The maximum net domestic assets are 53414464 and the minimum are 4555768. The net domestic credit has a mean of 43900898 and a standard deviation of 14966510, indicating a moderate range of values. The maximum net domestic credit is 84045544 and the minimum is 24691470. The net foreign assets have a mean of 10436934 and a standard deviation of 5088164, indicating a moderate range of values. The maximum net foreign assets are 19100004 and the minimum are 4252035. The real GDP has a mean of 17868.99 and a standard deviation of 119.1929, indicating a narrow range of values. The maximum real GDP is 18166.37 and the minimum is 17630.39.

In the table, the kurtosis values for all of the variables except for the exchange rate and monetary policy rate are less than 3. This suggests that the distributions of these variables are not peaked. The monetary policy rate has a kurtosis value of *3.671826*, which is slightly greater than 3, but still within the normal range. *T*he skewness values for all of the variables except for the Currency in Circulation are positive. This suggests that the distributions of these variables have long right tails. The Currency in Circulation has a skewness value of -0.020827, which is very close to 0, and the Real GDP has a skewness value of 0.289393, which is slightly positive. The p-values for all of the variables except for the Currency in Circulation, Net domestic Assets and, Real GDP are less than 0.05. This result shows that the null hypothesis for the series data set exhibit nonlinearity. The Currency in Circulation, Net Domestic Assets and Real GDP has a p-value of 0.690717, 0.242611, and 0.519295, which is greater than 0.05, so we cannot reject the null hypothesis of normality for this variables.

Unit Root Test Using Augmented Dickey-Fuller

In this section, the unit root and stationarity properties of the study variable is examined using Augmented Dickey Fuller (ADF); the null hypothesis is specified as having unit root. Table 3 shows the results of the Augmented Dickey-Fuller unit root test at constant and linear trend of the daily exchange rates of Binance, Bitcoin, Dogecoin, Ethereum, and Ripple versus the U.S. Dollar (01 January 2018 to 31 July 2023). While Table 4, shows the result of the Augmented Dickey-Fuller unit root test at constant and linear trend of Economic/Financial variables and crypto market cap (January, 2018 to July, 2023) respectively.

Table 3: Augmented Dickey-Fuller unit root test at constant and linear trend of the daily exchange rates of Binance, Bitcoin, Dogecoin, Ethereum, and Ripple and, versus the U.S. Dollar at level and first difference (01 January 2018 to 31 July 2023)

Variable	Option	ADF	
		Test Statistic	**P–Value**
BNB Price	Intercept and Trend	-2.141997	0.5214
Δ BNB Price	Intercept and Trend	-17.85536	0.0000*
BTC Price	Intercept and Trend	-1.737379	0.7344
Δ BTC Price	Intercept and Trend	-46.36499	0.0000*
DOGECOIN Price	Intercept and Trend	-3.285017	0.0690
Δ DOGECOIN Price	Intercept and Trend	-8.667387	0.0000*
ETH Price	Intercept and Trend	-1.886561	0.6611
Δ ETH Price	Intercept and Trend	-48.28833	0.0000*
XRP Price	Intercept and Trend	-5.491664	0.0000*

The ADF test results from table 3 indicate that the prices of BNB, BTC, DOGECOIN, and ETH are non-stationary at levels, while their first differences are stationary. This means that the prices of these cryptocurrencies have a unit root, which implies that they exhibit a random walk pattern and do not have a mean-reverting tendency. In other words, these prices are not predictable from their past values. On the other hand, the prices of XRP and their first differences are both stationary. This means that the prices of XRP have a mean-reverting tendency, and their past values can be used to predict their future values. These results have implications for forecasting and modeling the prices of these cryptocurrencies. For example, since the prices of BNB, BTC, DOGECOIN, and ETH are non-stationary, traditional forecasting methods that assume stationarity may not be appropriate for these currencies. Instead, more advanced forecasting methods that can handle non-stationary time series may be needed.

Table 4: Augmented Dickey-Fuller unit root test at constant and linear trend of Economic/Financial variables and crypto market capitalization (January, 2018 to July, 2023)

Variable	Option	ADF	
		Test Statistic	**P–Value**
MCAP	Intercept and Trend	-1.820812	0.6834
Δ MCAP	Intercept and Trend	-7.457730	0.0000*
CC	Intercept and Trend	-2.983275	0.1448
ΔCC	Intercept and Trend	-6.537864	0.0000*
ER	Intercept and Trend	0.186144	0.9975
ΔER	Intercept and Trend	0.341343	0.9985
ΔΔER	Intercept and Trend	-6.838013	0.0000*
INFR	Intercept and Trend	-2.356042	0.3986
ΔINFR	Intercept and Trend	-2.730144	0.2285
ΔΔINFR	Intercept and Trend	-7.562875	0.0000*
MPR	Intercept and Trend	-3.052448	0.1264
ΔMPR	Intercept and Trend	-7.973105	0.0000*
MS	Intercept and Trend	0.567260	0.9993
ΔMS	Intercept and Trend	-14.43195	0.0001*
NDA	Intercept and Trend	-7.929026	0.0000*
NDC	Intercept and Trend	0.715803	0.9996
ΔNDC	Intercept and Trend	-5.327575	0.0002*
NFA	Intercept and Trend	-2.734024	0.2269
ΔNFA	Intercept and Trend	-10.11224	0.0000*
GDP	Intercept and Trend	-2.311082	0.4221
ΔGDP	Intercept and Trend	-12.33675	0.0000*

Furthermore, The ADF test results from table 4 indicate that most of the Economic/Financial variables are non-stationary, while their first differences are stationary. This means that these variables have a unit root, which implies that they exhibit a random walk pattern and do not have a mean-reverting tendency. In other words, these variables are not predictable from their past values. The exceptions are NDA (Net Domestic Assets), ΔMS (Money Supply), ΔΔER (Exchange Rate), ΔMPR (Monetary Policy Rate), ΔCC (Currency in Circulation), ΔINFR (Inflation Rate), ΔNDC

(Net Domestic Credit), ΔNFA (Net Foreign Assets), and ΔGDP (Real GDP), which are all stationary. This means that these variables have a mean-reverting tendency, and their past values can be used to predict their future values. These results have implications for forecasting and modeling the relationships between these variables and crypto market capitalization. For example, since most of the Economic/Financial variables are non-stationary, traditional forecasting methods that assume stationarity may not be appropriate for these relationships. Instead, more advanced forecasting methods that can handle non-stationary time series may be needed.

Johansen Cointegration

Table 5: Johansen Cointegration Test (Trace) among the selected cryptocurrencies and GDP

Hypothesis $H_o H_1$	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob. Critical Value
$r = 0$ $r = 1$	0.593206	155.1194	95.75366	0.0000*
$r \leq 1$ $r > 1$	0.543400	97.55473	69.81889	0.0001*
$r \leq 2$ $r > 2$	0.355750	47.38209	47.85613	0.0554
$r \leq 3$ $r > 3$	0.167481	19.24334	29.79707	0.4755
$r \leq 4$ $r > 4$	0.085849	7.512198	15.49471	0.5189
$r \leq 5$ $r > 5$	0.027241	1.767610	3.841465	0.1837

Trace test indicates 2 cointegrating equation(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level

Table 6: Johansen Cointegration Test (Maximum Eigen Value) among the selected cryptocurrencies and GDP

Hypothesis $H_o H_1$	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob. Critical Value
$r = 0$ $r = 1$	0.593206	57.56471	40.07757	0.0002*
$r \leq 1$ $r > 1$	0.543400	50.17263	33.87687	0.0003*
$r \leq 2$ $r > 2$	0.355750	28.13875	27.58434	0.0425*
$r \leq 3$ $r > 3$	0.167481	11.73114	21.13162	0.5744
$r \leq 4$ $r > 4$	0.085849	5.744588	14.26460	0.6462
$r \leq 5$ $r > 5$	0.027241	1.767610	3.841465	0.1837

Max-eigenvalue test indicates 3 cointegrating equation(s) at the 0.05 level * denotes rejection of the hypothesis at the 0.05 level

Table 7: Normalized Cointegrating Coefficients among the selected cryptocurrencies and GDP

BNB	BTC	DOGECOIN	ETH	GDP	XRP
1.000000	0.040689	-0.815705	-0.329247	-684853.3	1.280763
Standard Error	(0.00889)	(0.17500)	(0.02361)	(229271.)	(0.12341)

Table 8: Johansen Cointegration Test (Trace) among the Economic/Financial Variables and Market Capitalization of the selected cryptocurrencies

Hypothesis $H_o H_1$	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob. Critical Value
$r = 0$ $r = 1$	0.858986	410.0039	239.2354	0.0000*
$r \leq 1$ $r > 1$	0.643995	284.6346	197.3709	0.0000*
$r \leq 2$ $r > 2$	0.611401	218.5346	159.5297	0.0000*
$r \leq 3$ $r > 3$	0.545195	158.0414	125.6154	0.0001*
$r \leq 4$ $r > 4$	0.418086	107.6167	95.75366	0.0060*
$r \leq 5$ $r > 5$	0.402582	72.96505	69.81889	0.0274*
$r \leq 6$ $r > 6$	0.253973	39.99617	47.85613	0.2227
$r \leq 7$ $r > 7$	0.204468	21.24460	29.79707	0.3426
$r \leq 8$ $r > 8$	0.097962	6.604965	15.49471	0.6240
$r \leq 9$ $r > 9$	0.000104	0.006688	3.841465	0.9342

Trace test indicates 6 cointegrating equation(s) at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level

Table 9: Johansen Cointegration Test (Maximum Eigen Value) among the Economic/Financial Variables and Market Capitalization of the selected cryptocurrencies

Hypothesis $H_o H_1$	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob. Critical Value
$r = 0$ $r = 1$	0.858986	125.3693	64.50472	0.0000*
$r \leq 1$ $r > 1$	0.643995	66.09993	58.43354	0.0074*
$r \leq 2$ $r > 2$	0.611401	60.49325	52.36261	0.0060*
$r \leq 3$ $r > 3$	0.545195	50.42469	46.23142	0.0168*
$r \leq 4$ $r > 4$	0.418086	34.65163	40.07757	0.1800
$r \leq 5$ $r > 5$	0.402582	32.96888	33.87687	0.0639
$r \leq 6$ $r > 6$	0.253973	18.75157	27.58434	0.4339

$r \leq 7$ $r > 7$	0.204468	14.63963	21.13162	0.3149
$r \leq 8$ $r > 8$	0.097962	6.598277	14.26460	0.5377
$r \leq 9$ $r > 9$	0.000104	0.006688	3.841465	0.9342

Max-eigenvalue test indicates 4 cointegrating equation(s) at the 0.05 level. * denotes rejection of the hypothesis at the 0.05 level

Table 10: Normalized Cointegrating Coefficients among the Economic/Financial Variables and Market Capitalization of the selected cryptocurrencies

Crypto mcap	Currency in circulation	Exch rate NGN/USD	Inflation rate	Monetary policy rate on interest rates	Money supply	Net domestic assets	Net domestic credit	Net foreign assets	Real GDP
1.0000	-63392.87	2.44E+08	-3.44E+09	2.70E+09	-27485.04	15182.87	8269.398	17057.61	11817204
Standard Error	(7547.47)	(7.0E+07)	(9.1E+08)	(8.4E+08)	(3210.72)	(1167.14)	(2322.65)	(1402.04)	(2.0E+07)

From the Johansen Multivariate Cointegration technique in Table 5 and 6 above, both indicate at least two cointegrating equation, the normalized cointegrating equation is obtained which shows the long run relationship between the Selected cryptocurrencies prices and GDP. The Table 7 below contains the coefficients of the first normalized cointegrating equation. The results from Table 5 and 6 both indicate cointegration between cryptocurrency price and GDP at 5% significance level. That is, the causes of increase or decrease in the Real GDP can be linked to Cryptocurrency prices. The normalized coefficients in Table 7, shows that BNB price has a positive and direct relationship with BTC price and XRP price. Also BNB price has a negative and inverse relationship with Dogecoin price, ETH price and Real GDP. That is, the price of BNB can influence Bitcoin Price, and Ripple price but it might not necessarily influence Dogecoin price, Ethereum price and Real GDP. Furthermore, based on the result obtained from this study, it can be deduced that for the period under review 40.6% and 12.8% of Bitcoin and Ripple, respectively are linked to BNB Price.

Additionally, table 8 and 9 shows that there are at least four cointegrating equation in both the trace and maximum eigenvalues. By implication there is a long run equilibrium relationship between the Economic/Financial variables and their relation to cryptocurrency market capitalization at 5% level of significance. That is the Economic/Financial variables and their relation with cryptocurrency market capitalization can be linked to GDP. Furthermore, it is very possible that the time series variables may share common stochastic trend in the long run. The normalized coefficient in table 10 show that Crypto Market Capitalization has a positive and direct relationship with Exchange Rate, Monetary policy Rate, Net Domestic Assets, Net Domestic Credit, Net Foreign Assets and Real GDP. Also, Crypto Market Capitalization has negative and inverse relationship with Currency in Circulation, Inflation Rate, and Money Supply. That is the influence Currency in Circulation, Inflation rate, and Money Supply might not necessary be linked to Crypto Market Capitalization as that of Exchange Rate, Monetary policy Rate, Net Domestic Assets, Net Domestic Credit, Net Foreign Assets and Real GDP which coefficients indicate a positive and direct relationship. Furthermore, it can be deduced that the for the time period under review 24,.4%, 27%, 15.18%, 82.69% 17.05% and 11.18% of Exchange Rate, Monetary policy Rate, Net Domestic Assets, Net Domestic Credit, Net Foreign Assets and Real GDP, respectively are linked to Crypto Market Capitalization. The Johansen Cointegration Test confirms the existence of at least two cointegrating equations between selected cryptocurrency prices and GDP. This is in line with Johansen's (1991) findings, which state that economic and financial variables often share long-run equilibrium relationships. The results also mirror those of Ani & Hassan (2020)**,** who used cointegration techniques to analyze exchange rates in Nigeria. The study finds that exchange rates and monetary policy rates share a long-run relationship with cryptocurrency market capitalization**,** which aligns with Pieters & Vivanco (2017), who demonstrated that crypto prices are linked to traditional currency fluctuations. Yermack (2015) argues that cryptocurrencies may significantly influence GDP and economic growth due to their increasing adoption. However, this study finds that the relationship between GDP and cryptocurrency prices is weak**,** suggesting that despite crypto's rapid expansion, it does not yet play a central role in driving economic growth. Ani et al. (2024) suggest that crypto assets indicators significantly impact market capitalization, but this study finds mixed results regarding their influence on GDP. While Bitcoin and Binance Coin have a short-run impact, their long-run contribution to GDP remains uncertain. Kugler (2018) argues that inflation rates have a strong influence on cryptocurrency prices, as investors use Bitcoin as a hedge against inflation. However, the results in this study indicate a negative relationship between inflation and crypto market capitalization, implying that higher inflation does not necessarily drive cryptocurrency investments. Gilbert & Loi (2018) suggest that central banks' monetary policy directly affects cryptocurrency adoption. While, this study finds some correlation between monetary policy rates and market capitalization, the effect is weaker than expected, suggesting that cryptocurrencies may operate outside traditional monetary policy channels.

Granger Causality Test

Table 11: Granger Causality Test among the selected cryptocurrencies and GDP

Null Hypothesis:	Obs	F-Statistic	Prob.
BTC does not Granger Cause BNB	65	28.2182	2.E-09
BNB does not Granger Cause BTC		12.6814	3.E-05
DOGECOIN does not Granger Cause BNB	65	6.62936	0.0025
BNB does not Granger Cause DOGECOIN		2.42095	0.0975
ETH does not Granger Cause BNB	65	2.83477	0.0666
BNB does not Granger Cause ETH		0.13486	0.8741
GDP does not Granger Cause BNB	65	0.45778	0.6349
BNB does not Granger Cause GDP		0.94405	0.3948
XRP does not Granger Cause BNB	65	0.50593	0.6055
BNB does not Granger Cause XRP		4.55968	0.0143
DOGECOIN does not Granger Cause BTC	65	11.6401	5.E-05
BTC does not Granger Cause DOGECOIN		11.2698	7.E-05
ETH does not Granger Cause BTC	65	7.65879	0.0011
BTC does not Granger Cause ETH		11.4961	6.E-05
GDP does not Granger Cause BTC	65	0.34592	0.7090
BTC does not Granger Cause GDP		0.47447	0.6245
XRP does not Granger Cause BTC	65	5.45875	0.0066
BTC does not Granger Cause XRP		17.9162	8.E-07
ETH does not Granger Cause DOGECOIN	65	0.72960	0.4863
DOGECOIN does not Granger Cause ETH		2.15413	0.1249
GDP does not Granger Cause DOGECOIN	65	0.33626	0.7158
DOGECOIN does not Granger Cause GDP		0.47749	0.6227
XRP does not Granger Cause DOGECOIN	65	1.88663	0.1605
DOGECOIN does not Granger Cause XRP		2.89605	0.0630
GDP does not Granger Cause ETH	65	0.17809	0.8373
ETH does not Granger Cause GDP		0.64268	0.5295
XRP does not Granger Cause ETH	65	0.17765	0.8377
ETH does not Granger Cause XRP		4.01714	0.0231
XRP does not Granger Cause GDP	65	0.21724	0.8054
GDP does not Granger Cause XRP		0.03943	0.9614

The cointegration test performed revealed that long-run effects exist between Cryptocurrencies prices and GDP. It is also very important to also investigate the short run relationship/effect between the variables being studied by applying Granger causality test. From Table 11 the Granger causality tests reveals that BTC Granger causes BNB, meaning that past values of BTC help predict future values of BNB. However, BNB Granger causes BTC, Dogecoin Granger causes BNB, BNB Granger causes XRP, Dogecoin Granger causes BTC, BTC Granger causes Dogecoin, ETH Granger causes BTC, BTC Granger causes ETH, GDP Granger causes BTC, XRP Granger Causes BTC and BTC Granger causes XRP, and Lastly ETH Granger causes XRP. The results obtained from conducting this test revealed that only unidirectional causality is established in the sample period. By implication, short run effects exist more among the studied variables than in the long-run. Furthermore, the cointegration detected by the Johansen cointegration test between the selected Cryptocurrency prices and GDP is supported with the Granger causality test. Consequently, the prior values of the selected Cryptocurrency prices can be used to forecast the GDP. The study finds that cryptocurrencies, particularly Bitcoin and Binance Coin, have significant short-run effects on macroeconomic variables. The Granger Causality Test shows that Bitcoin Granger-causes Binance Coin, Dogecoin, and Ripple, supporting previous research indicating Bitcoin's dominant influence over other cryptocurrencies. This aligns with Engle & Granger (1987), who stated that short-run relationships may exist even if long-run relationships are weak. This study supports Ani & Mashood's (2021) conclusion that cryptocurrency prices can influence macroeconomic indicators in the short term, but their long-run impact remains uncertain. Mora et al. (2018) highlight the environmental concerns of cryptocurrency mining, particularly Bitcoin's high energy consumption. While, this study acknowledges environmental concerns, it does not directly measure or analyze their economic impact, creating a gap in the discussion. Rejeb et al. (2017) argue that regulatory uncertainty limits cryptocurrency adoption. However, this study suggests that despite the absence of regulations in Nigeria, crypto adoption continues to rise, indicating that regulatory barriers may not always limit adoption.

CONCLUSION

The findings of this study highlight the significant impact that cryptocurrencies, particularly Bitcoin, Ethereum, Binance Coin, Dogecoin, and Ripple, have on macroeconomic indicators such as exchange rates and GDP. Through rigorous analysis using Johansen Cointegration and Granger Causality tests over the period from January 2018 to July 2023, the study reveals that short-run effects are more pronounced than long-run relationships among the examined variables. This indicates that fluctuations in cryptocurrency prices can serve as predictors for changes in macroeconomic conditions. The results demonstrate a notable correlation between cryptocurrency market capitalization and key economic indicators, suggesting that as digital currencies gain traction, they increasingly influence traditional financial metrics. The evidence of non-stationarity in the time series data further highlights the volatility inherent in cryptocurrency markets, which poses both risks and opportunities for investors and policymakers alike. Moreover, the implications of these findings extend beyond mere economic analysis; they call for a reevaluation of existing regulatory frameworks governing cryptocurrencies. As these digital assets continue to disrupt traditional financial systems, there is an urgent need for comprehensive policies that can harness their potential while mitigating associated risks. The study also emphasizes the necessity for further research into the environmental impacts of cryptocurrency mining and its sustainability, especially given the growing concerns about energy consumption. In summary, this study contributes to a deeper understanding of how cryptocurrencies are reshaping the economic landscape. It highlights their potential to drive innovation and growth while also posing challenges that require careful consideration by stakeholders in both the financial sector and governmental institutions. As the cryptocurrency ecosystem evolves, ongoing analysis will be essential to fully grasp its implications for future economic stability and growth.

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Datasets Declaration and Accessibility
The datasets utilized in this study, which were generated and analyzed, can be accessed through the CMC and CBN websites (https://coinmarketcap.com/ and www.cbn.gov.ng/rates/exrate.asp., respectively).

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