

Crypto Assets Indicators and their Effect on the Market Capitalization: A Panel Data Analysis

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Abstract

Background: In this paper, four-years (21st October, 2018 – 21st October, 2022) cryptocurrencies indicators such as OPP, CPP, HGP, LOP, and ATV for six (6) crypto assets with high market capitalization based on coin categorization/utilization were considered as explanatory (independent) variables to estimate crypto assets returns. **Aim:** This study seek to evaluate the relationship between crypto asset indicators and crypto market capitalization, so as to quantitatively review and establish that crypto market capitalization can easily be influenced by crypto indicators. **Method:** The study uses three-panel data models, the pooled OLS, fixed effect (FE) and random effect (RE) changes, to evaluate crypto assets returns for the cross-sectional data of these six crypto assets. **Results:** The study revealed that all three-panel models fit the data; the result also shows that FE and RE models explain about 62% and 50%, respectively of the return variance on the total market capitalization (MCap). While, Pooled OLS model could only explain 42% variation on the total market capitalization (MCap). The Hausman test result indicates that the FE model is an appropriate model to estimate the cross-sectional variables when compared to the RE model. Also, the Lagrange Multiplier (LM) test statistic with corresponding p-value for FE and RE when compared to the pooled OLS are 32.117 (0.0000*) and 38.943 (0.0000*), respectively, indicating that both the FE and RE models are more appropriate than the Pooled OLS model when compared with each. The identified crypto indices employed are significant and positively affects the market capitalization of these crypto assets. Finally, the study reveals that crypto assets can be classified and considered as economic assets since they include monetary values and investors derive economic benefits in terms of holding gain/losses and other benefits.

Keywords: Blockchain & tokenization, Cryptocurrency, NFTs, Crypto market capitalization, Panel analysis

1. Introduction

Over the past decade, a digital revolution has evolved, referring to the establishment of financial facilities and services supported and sustained by improvements in computing power and technology which is presently classified as “financial technology”. Leading the edge of innovations in financial technology is the advent of crypto assets such as Bitcoin, Ethereum, Binance, Tether USDT, etc. that are based on blockchain technology which helps to verify and trace multistep transactions requiring verification and traceability (Houben and Snyers, 2018). Bitcoin like other digital assets are designed to serve as a medium of exchange (Dong, 2018); thus, these crypto assets are termed as “digital tokens”. Although, yet to receive significant consideration by governments of developing and developed nations consequently no “clear

policies” backing these digital tokens, crypto assets keeps on receiving high number of investors across the globe and, transactions in crypto assets are present in few countries.

As cryptocurrency, NFT and blockchain technology are becoming more integrated and prevalent in the macroeconomy, these form of digital assets may pose new opportunities for the Naira/US Dollar exchange rate which is already facing uncertainty and volatility (Ani and Mashood, 2021; Ani and Umar, 2020; Ani et al., 2020). Based on the CoinMarketCap annual reporting statement on 31st December, 2021, the market capitalization of crypto assets has seen its value grown from over \$7 billion in 2018 (Houben and Snyers, 2018) to \$100 billion in 2021. Zhao et al. (2016) stated that digital tokens such as Bitcoin and other crypto assets are a mix of currencies features, intangible assets and commodities but yet are classified as “non-financial assets and therefore, crypto assets are classified as financial assets in macroeconomic (IASB, 2018). In 2021, International Monetary Fund (IMF) warned that countries cannot stop cryptocurrencies operations in their borders on their own (Parma et al., 2022); rather, suggested a better approach for monitoring and regulating crypto assets which will require a determined global effort. Venture capitalist, investors, financiers, stakeholders, etc. are frequently searching thoroughly for financial opportunities and prospects to create streams of incomes and vary their risks (Peters and Panayi, 2016). Recently, improvements in financial advancements and innovation termed as “Financial Technology” has generated and shaped new forms of technology and securities which is in the form of cryptocurrencies or digital tokens and NFTs. These high-tech assets have recently offered and still offering investments options which have captured the financial attention of investors. These digital assets might possibly be more efficient compared to other forms of currencies and traditional supplies as a result of the form of technology behind these assets (Collomb and Sok, 2016; Zhao et al., 2016). The prospect of crypto assets and associated digital ledger technology (DLT) are given importance in many financial fields. Crypto assets sometimes called virtual or digital currency are built on Blockchain Technology and the Distributed Ledger Technology (which is used by Ripple, XRP and other financial technology developers), which out-performs the existing instant system for money transfer which consumes time in approval and transfer (Witzig and Salomon, 2018; Zhao et al., 2016). The momentum and drive for digital or virtual asset known as “Cryptocurrency” has been tremendously solid, leading the G20 nations to have series of meetings along with International Monetary Fund (IMF) and European Union (EU) to discuss crypto asset criteria and recommend regulations/protocols and conceivable implementation in the nearest future (Helms, 2020). Therefore, it is paramount for government financial institutions, commercial banks and other financial sectors/private bodies including scholars to understand the theoretical/speculative and empirical foundation of this new technology (Abdullahi et al., 2024; Goodell, 2020; Goodell and Goutte, 2020; Philippon, 2016).

Based on the review papers, however, there are a few research gaps that are not fully addressed these includes; empirical analysis of the relationship between specific cryptocurrency indicators and market capitalization over time, which will serve as instrument in the development of more sophisticated models and frameworks for using cryptocurrency indicators to forecast market capitalization and overall market trends. Therefore, giving the raising growth and usage of these digital assets, this study aims to evaluate the impact of crypto assets returns and indicators on the crypto market capitalization. The study specifically, seek to investigate the relationship between crypto asset indicators and crypto market capitalization using a panel data analysis approach and to quantitatively review and establish that crypto assets indicators can easily be influence the general market capitalization.

2. Related Works

Even though the cryptocurrency ecosystem is just over ten years and new ideas and technology are still evolving, while existing technology within the ecosystem are been made robust and sophisticated to accommodate the growing needs of users and investors, there has been wide-range of research in this field of financial technology already. Bitcoin has enormous influence on the over-all cryptocurrency market-capitalization, which has shown times without number that bubbles activities are visible (Burggraf et al., 2021). The literature review highlights the importance of market capitalization (market cap) in the cryptocurrency space. Market cap is a crucial metric that measures the total value of a cryptocurrency and is used to assess its relative size, liquidity, and investor confidence. It is calculated by multiplying the current price of a token by the total number of coins in circulation. Market cap is relevant because it helps investors evaluate a cryptocurrency's worth, assess its risk profile, and gauge its popularity. It is also used to compare and evaluate the long-term growth potential of different cryptocurrencies.

Cristina et al. (2023) identified that macroeconomic factors have less impact on prices of crypto assets than those of traditional financial assets using a mix analysis approach; that is, inflation and interest rates can easily affects traditional financial assets. Their study showed that significant drivers' for virtual currencies (crypto assets) include acceptance, market buoyancy, liquidity conditions and technological approach. Karlström (2014) identified that the basic characteristics of cryptocurrencies such as Bitcoin are as follows: An algorithm controls its supply; its network and operations is in the public sphere which generally is free from central bank's monetary policy; authentication of transactions is decentralized and distributed; eWallets where these currencies are stored are not directly linked to owners' identity data. Tommaso et al. (2023) paper centers on macro-financial effects that stems as a result of the technological approach and design of crypto assets based on the assumption these assets have satisfied legal requirements applying a qualitative and quantitative approach. Their paper also contends that alleged profits of crypto assets may include faster and cheaper cross border payments, amplified financial annexation, and more integrated financial market-space but still are yet to be recognized. Jakhongir (2023) paper seeks to evaluate the effect of cryptocurrency marketplace on stock market performance. Employing the simple regression model, the study detects significantly negative effect of cryptocurrency marketplace on stock market performance. Dumitrescu et al. (2023) study investigate the inter-linkages between fiat currencies and cryptocurrencies by evaluating whether the price fluctuations of Bitcoin affects exchange rates of 9 sampled European nations with non-euro currencies. Their findings indicate that there is a statistically significant relationship between Bitcoin price changes in relation to nominal exchange rates fluctuations. Gerald (2015) noted that modern innovations have led to a more feasible and faster way to transfer digital currencies without any form of third party such as a bank. Pavel et al. (2016) produces the first article that evaluated the price of Bitcoin formation taking into consideration traditional elements of currency price, digital assets precise factors, market drivers of supply and demand etc. Guinda and Bhattacharyya (2021) paper presented an efficient correlation examination of 31 crypto assets along with gold indices and some other equity. They conducted a principal component analysis (PCA) to categorize various groups of crypto assets that shows different correlation patterns to enable investors build an expanded portfolio. Ogunode et al. (2022) investigated cryptocurrency and global practices: lessons for Nigeria. Their findings revealed mistrust in political structure, unstable local currency as well as high inflation rates as these is vital indicators driving the awareness and progression of cryptocurrency adoption and usage in Nigeria thereby encouraging more persons to adopt cryptocurrencies and NFT as another stream of income and wealth creation, alternative stream of income and inflation hedge. Dănilă and Robu (2019) examined the

requirement of cryptocurrency being regarded as alternative to financial opportunities. The results showed that cryptocurrency can be used as an additional asset to expand investment portfolio. Huynh (2022) noted that speculations can simply influence bitcoin price. Bitcoin has enormous influence on the over-all cryptocurrency market-capitalization, which has shown times without number that bubbles activities are visible.

Acho (2021) studied the effects of legitimizing cryptocurrency in Nigeria to serve as a payment tool. The findings showed that cryptocurrency has some level of risks nonetheless there are still large room of benefits ensuing to contributing to economic development. Chukwuere (2021) carry out an evaluation of the eNaira launch in-terms its perspectives, opportunities and challenges. The findings indicates that the launch make available opportunities for regulators, SMEs, the banking public etc. Nandal and Jora (2020) the study evaluated the change in cryptocurrency movement whenever household income increases in India. The result suggests that both sexes are keen to investing in cryptocurrencies which sole purpose is for money transfer and make return. Sun et al. (2020) evaluated the dynamics stakeholders' follows in making uncertain investments in cryptocurrency. The study revealed investors innovativeness is the key driver in investing in risky portfolios. Their study further revealed that investors have less worries and anxiety investing in cryptocurrency than in the stock market where both established and influential investors participate with private investors making the stock market a tougher ground to invest on-like the cryptocurrency market space where these form of established institutions are in-active. Jimenez et al. (2022) assert that a major problem present with risk in cryptocurrency is the inability of investors to design a proper risk assessment system and undertaking an appropriate risk assessment, even though several scholars have strived to work-out a suitable system for risk assessment not much have been done. Ogunode et al. (2022) in a study on lessons for Nigeria on cryptocurrencies and global practices showed that Africa is world third crypto users after Asia and Europe with about 32%. While, among the top ten (10) countries with crypto users Nigeria is ranked first with about 32% followed by Vietnam and Philippines with about 21% and 20%, respectively. Luther (2016) asserts that government support to any new financial system is instrumental to its success. Poor government support in the acceptance of cryptocurrency makes it very clear that its implementation and government full approval will still take some time than expected.

Based on the reviewed papers, it can be deduced that most articles seek to establish that crypto assets fluctuations are due to indicators within the crypto ecosystem. Thus, this study therefore addresses the following; the relationship between crypto asset indicators and crypto market capitalization using a panel data analysis approach and also, to quantitatively review and establish that crypto assets prices can easily be influenced by crypto indicators.

3. Methodology

3.1 Data

This study employs a secondary source of data which were obtained from CoinMarketCap and Yahoo Finance cryptocurrency's financial statements and related websites, available online (<https://coinmarketcap.com/> and <https://finance.yahoo.com/crypto/?guccounter=1>). The data were collected at a regular daily frequency exhibiting high volatility spinning from 21st October, 2018 to 21st October, 2022. In this paper, four-year cryptocurrencies indicators for six (6) crypto assets with high market capitalization based on coin categorization/utilization (i.e. payment tokens, utility tokens, asset tokens and hybrid tokens) are considered as explanatory variables to estimate crypto assets returns. The selected

cryptocurrencies are valued in US dollar and they include the following; Bitcoin (BTC), Ethereum (ETH), Binance (BNB), Binance-peg Cardano (ADA), Litecoin (LTC) and DASH (DASH). Table 1 below gives the description and measurement of the study's response and explanatory variables.

Table 1: Description of Study Variables

Abbreviations	Variables	Variable description & measurement
Response variable		
MCap	Market capitalization	cryptocurrency and NFT market capitalization is simply an indicator of dominance/popularity of a cryptocurrency/NFT which is described as the total value of a coin mined or in supply.
Explanatory variable		
OPP	Opening price	The Open/close price of crypto coin is said to be the price at which a token or non-fungible token (NFT) opens at a specified time period while, the price for which a token or related asset closes at a specified period as well is termed as closing price.
CPP	Closing price	
HGP	High price	The high/low is the highest and lowest price for which a cryptocurrency and NFT has been traded over 52weeks.
LOP	Low price	
ATV	Asset volume	The Asset volume is a pointer that absolutely accelerates investment in the cryptocurrency exchange.

Table 2: Total Market Capitalization (As at 31st December, 2022)

Token	Symbol	Industry/Category/Sector	Algorithm	Summary Statistics
Bitcoin	BTC	Payments; Delivering Interest	Proof-of-Work (PoW); SHA-256	Market Cap – \$324.62 Bn Volume 24h – \$16.19 Bn Maximum Supply – 21.00 M Circulating Supply – 19.25 M All Time High – \$68,789.63 All Time Low – \$65.53 Market Dominance – 39.62%
Ethereum	ETH	Smart Contracts; Payments; Marketplace; Delivering Interest	Proof-of-Stake (PoS)	Market Cap – \$153.05 Bn Volume 24h – \$5.24 Bn Maximum Supply – N/A Circulating Supply – 122.37 M All Time High – \$4,891.70 All Time Low – \$0.4209 Market Dominance – 18.68%
Binance	BNB	Smart Contracts; Payments; Marketplace: Asset	Proof-of-Stake Authority	Market Cap – \$40.81 Bn Volume 24h – \$562.83 M Maximum Supply – 200 M

Binance-peg Cardano	ADA	Research; Assets; Smart Contracts; Staking; Delivering Interest	(PoSA) (i.e. combines both DPoS and PoA) Delegated PoS; Proof- of-Stake (DPoS)	Circulating Supply – 159.96 M All Time High – \$690.93 All Time Low – \$0.09611 Market Dominance – 4.98% Market Cap – \$9.151 Bn Volume 24h – \$254.263 M Maximum Supply – 45.00 Bn Circulating Supply – 34.519 Bn All Time High – \$3.099 All Time Low – \$0.01735 Market Dominance – 1.117%
Litecoin	LTC	Medium of Exchange/Payments	Proof-of- Work (PoW); Scrypt	Market Cap – \$5.49 Bn Volume 24h – \$643.204 M Maximum Supply – 84.00 M Circulating Supply – 71.978 M All Time High – \$412.96 All Time Low – \$1.114 Market Dominance – 0.671%
Dash	DASH	Medium of Exchange/Payments; Hybrid token for Payments	Hybrid - Proof-of- Work (PoW) & Proof-of- Stake (PoS)	Market Cap – \$492.85 M Volume 24h – \$72.79 M Maximum Supply – 18.90 M Circulating Supply – 11.08 M All Time High – \$1,642.22 All Time Low – \$0.2139 Market Dominance – 0.06%

Source: Coin Market Cap and Yahoo Finance (Bn - billion; M - million; h – hours; N/A – not applicable)

3.2 Model Specification

Panel data techniques are widely used econometric tools employed in estimating parameters with partial effects in a nonlinear process, compute inference on data exhibiting repeated cross sections and measure dynamic linkages across variables. Distinct from cross sectional data analysis, panel datasets permits the occurrence of systematic and undetectable variances across-units with high possibility of association amongst identified variables or observed factors whose effects are to be evaluated. The specifications of the study techniques are outlined in the sub-sections below.

Panel Data Structures

A panel dataset also known as longitudinal dataset has a combination of a cross sectional and time series dimensions such that all the cross-section units are observed over a time period.

$$\begin{array}{c}
 \text{Cross-section} \\
 \left[\begin{array}{ccccccc}
 x_{11} & x_{21} & x_{31} & \cdots & x_{i1} & \cdots & x_{M1} \\
 x_{12} & x_{22} & x_{32} & \cdots & x_{i2} & \cdots & x_{M2} \\
 \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\
 x_{1t} & x_{2t} & x_{3t} & \cdots & x_{it} & \cdots & x_{Mt} \\
 \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\
 x_{1T} & x_{2T} & x_{3T} & \cdots & x_{iT} & \cdots & x_{MT}
 \end{array} \right] \\
 \text{Time series}
 \end{array}$$

Thus, $X_{it}, i = 1, 2, 3, \dots, M; t = 1, 2, 3, \dots, T$.

As earlier explained in this section and subsection above, the panel data provides us that system to study cross-section properties that is, along M , deviations across time series properties that is, along T , signifying variations across time.

The datasets below gives the typical form of a panel data structure;

$$x_1 = \begin{bmatrix} x_{11} \\ x_{12} \\ \vdots \\ x_{1t} \\ \vdots \\ x_{1T} \end{bmatrix}; \dots; x_i = \begin{bmatrix} x_{i1} \\ x_{i2} \\ \vdots \\ x_{it} \\ \vdots \\ x_{iT} \end{bmatrix} \quad Z_1 = \begin{bmatrix} z_{11} & z_{21} & \dots & z_{p1} \\ z_{12} & z_{22} & \dots & z_{p2} \\ \vdots & \vdots & \dots & \vdots \\ z_{1t} & z_{2t} & \dots & z_{pt} \\ \vdots & \vdots & \dots & \vdots \\ z_{1T_1} & z_{2T_1} & \dots & z_{pT_1} \end{bmatrix}; \dots; Z_i = \begin{bmatrix} s_{11} & s_{21} & \dots & s_{p1} \\ s_{12} & s_{22} & \dots & s_{p2} \\ \vdots & \vdots & \dots & \vdots \\ s_{1t} & s_{2t} & \dots & s_{pt} \\ \vdots & \vdots & \dots & \vdots \\ s_{1T_j} & s_{2T_j} & \dots & s_{pT_j} \end{bmatrix}$$

Thus, a classic panel dataset model stacks up the x_i 's and Z_i 's:

$$x = Z\theta + c + \epsilon \tag{1}$$

Z – $\sum_i T_i \times p$ matrix

θ – $p \times 1$ matrix

c – $\sum_i T_i \times p$ matrix, related with unobservable variables

x and ϵ are $\sum_i T_i \times 1$ matrices

It is important to note that, the panel dataset can be categorize in two forms namely “Balanced” and “Unbalanced” panels.

Thus, if $X_{it}, i = 1, 2, 3, \dots, M; t = 1, 2, 3, \dots, T_i$; then, Balanced panel = MT (there is no missing values) while, Unbalanced panel = $\sum_{i=1}^M T_i$ (there are missing values). In this study, the panel dataset used is a balanced panel case as there are no missing values across the observed variables both in-terms of time (years and months) observed values.

3.3 Estimation Techniques

In this study, we have employed three (3) panel data models that is, Pooled OLS, Fixed Effects (FE) and Random Effects (RE), to evaluate selected crypto assets returns for the cross sectional data of six selected crypto assets.

The simplified form of the panel data regression equation can be given as;

$$x_{it} = c_i + \theta Z_{it} + \epsilon_{it} \tag{2}$$

Where, x specifies the ‘response variable’, Z specifies the ‘explanatory variables’. While, ‘ c ’ is the entity-specific effect; ‘ θ ’ is a vector of coefficients for the independent variables; Z_{it} is a vector of independent variables for entity ‘ i ’ at time ‘ t ’; ‘ i ’ and ‘ t ’ are specific elements and time, respectively. The specific element is identified as the cross-sectional influence from the selected crypto assets. And, the time component ‘ t ’ refers the time series datasets order as observed. In the FE model structure, ϵ_{it} exhibits and follows a non-stochastic process over ‘ i ’ and ‘ t ’, while, ϵ_{it} follows a stochastic process in an RE process.

The OLS model takes into account homogeneity which implies that, the model doesn’t differentiate amid the panel segments; consequently, the pooled OLS method does not consider distinctive features of each element in the dataset and hence, omits these unique features of the respective element within the panel dataset over the time period ‘ t ’. The FE allows for heterogeneity across the panel datasets permitting sections to have their respective constant or intercept, nonetheless time invariant. While, the RE model has a common ‘ c ’ value across the cross section. The error term in RE model fluctuates in a stochastic pattern and is not correlated with the explanatory variables such that, ϵ_{it} is normally distributed with zero mean.

This study employed the Hausman test to investigate if there is no correlation between the unique errors with the regressors. This test also determines the suitability of the FE or RE models. H_0 , i.e., if $p > 0.05$ we choose the RE model. The secondary data obtained were analyzed using E-view software (version 10) and STATA.

4. Results and discussion

4.1 Descriptive Statistics

Table 3: Descriptive and Summary of Observed Variables

Measures	CCP	HGP	LOP	OPP	ATV
BTC/USD					
Mean	22891.56	23456.08	22247.15	22885.75	3.05E+10
SD	17975.54	18455.72	17432.93	17985.47	1.93E+10
Skew.	0.719693	0.712876	0.728920	0.720402	3.983591
Kurt.	2.123013	2.099852	2.149715	2.123227	56.12366
J-B (P-value)	173.06 (0.0)	173.18 (0.0)	173.50 (0.0)	173.28 (0.0)	175781.1 (0.0)
Obsn.	1462	1462	1462	1462	1462
ETH/USD					
Mean	1256.421	1295.991	1210.442	1255.916	1.55E+10
SD	1304.737	1345.472	1259.130	1305.576	1.06E+10
Skew.	0.900945	0.893009	0.915043	0.903061	1.644727
Kurt.	2.518298	2.495298	2.556228	2.523059	7.448965
J-B (P-value)	211.92 (0.0)	209.83 (0.0)	216.02 (0.0)	212.57 (0.0)	186.89 (0.0)
Obsn.	1462	1462	1462	1462	1462
BNB/USD					
Mean	172.4334	178.1118	165.9037	172.2933	1.17E+09
SD	192.3907	198.8722	185.2922	192.5103	1.54E+09
Skew.	0.775235	0.776864	0.777994	0.778744	3.220504
Kurt.	2.188766	2.196313	2.186603	2.195710	21.02988
J-B (P-value)	186.53 (0.0)	186.40 (0.0)	187.79 (0.0)	187.18 (0.0)	22329.80 (0.0)
Obsn.	1462	1462	1462	1462	1462
ADA/USD					
Mean	0.557165	0.580063	0.532506	0.556939	1.41E+09
SD	0.686111	0.714965	0.655311	0.686073	2.25E+09
Skew.	1.325095	1.320268	1.331241	1.324517	2.955275
Kurt.	3.864076	3.834592	3.899367	3.861276	14.35496
J-B (P-value)	473.33 (0.0)	467.17 (0.0)	481.10(0.0)	472.66 (0.0)	9982.40 (0.0)
Obsn.	1462	1462	1462	1462	1462
LTC/USD					
Mean	96.28702	99.89968	92.40774	96.30762	2.85E+09
SD	61.84768	65.19060	58.22450	61.88822	2.49E+09
Skew.	1.344265	1.394736	1.287249	1.345768	1.954873
Kurt.	4.672999	4.908242	4.381217	4.681528	8.216491

J-B (P-value)	614.16 (0.0)	699.63(0.0)	522.82(0.0)	616.90 (0.0)	2603.0 (0.0)
Obsn.	1462	1462	1462	1462	1462
DASH/USD					
Mean	113.5935	118.1403	108.8846	113.6978	4.66E+08
SD	62.99932	67.10059	58.76884	63.02051	8.46E+08
Skew.	1.619575	1.705861	1.539080	1.619541	11.57252
Kurt.	6.309869	6.762013	5.909803	6.315022	172.2810
J-B (P-value)	1306.5 (0.0)	1571.20(0.0)	1092.97(0.0)	1308.5(0.0)	1778264 (0.0)
Obsn.	1462	1462	1462	1462	1462

Table 3 gives the descriptive and summary statistics of the selected cryptocurrencies across the observed explanatory variables (CCP, HGP, LOP, OPP and ATV). The result shows wide-range difference across the series mean. While, the values of the SD across the observed explanatory variables indicates that the crypto market is also more volatile as well and exhibiting high risk since the market is highly volatile, this may be due to the fact that there are other variables such as macroeconomic variables that might be responsible for this high volatility towing the line of Dumitrescu (2023) and Karlstrøm (2014) whose findings revealed that Bitcoin price fluctuations are in line with sampled countries monetary policy suggesting that investors in cryptocurrencies and different traditional financial assets can benefit from diversification thereby including both forms of assets in their portfolios. The skewness values obtained for all the observed variables across the selected cryptocurrencies shows that the shape of each series is positively skewed. And, the kurtosis values of the observed variables for ADA/USD, LTC/USD and DASH/USD suggest that their observed variables are highly peaked with fat-tailed distribution beyond the normal distribution while, the observed variables except for ATV for BTC/USD, ETH/USD and BNB/USD are below the normal distribution suggesting a flatten-tailed distribution, this result suggest the volatility and unpredictability of crypto assets which is in-line with Cristina et al. (2023) that identified that crypto assets exhibits uncertainties due to their attractiveness and market speculations. The highly significant p-values of the Jarque – Bera statistic further confirm that none of the series are normally distributed which indicates that the series are basically exhibiting asymmetric, jumps or regime switch, this result is in agreement with Tommaso et al. (2023) as well as Dănilă and Robu (2019) specifying and suggesting that domestic stability, external stability, and structure of financial systems are features that characterize crypto assets price stability prompting these assets to display structural breaks which can be attached to specific economic phenomenon. These facts are evident from the time-plot of the observed variables for each selected cryptocurrency as shown in figure 2.0 below.

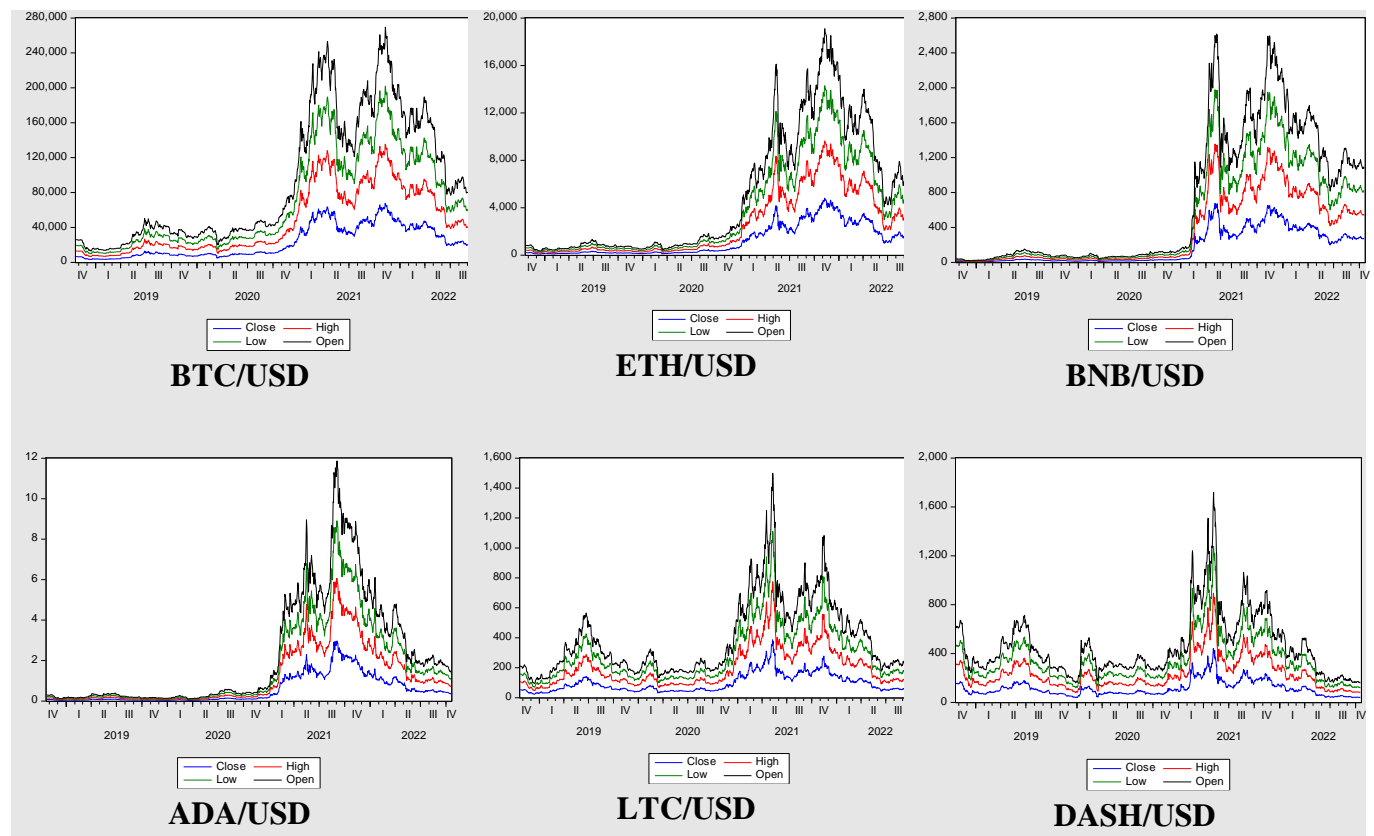


Figure 1. Time Plot for Selected Cryptocurrencies as regards CPP; HGP; LOP; OPP

4.2 Panel Unit Root Test

The study utilizes both the first and second generation panel unit root testing methods. The choice for using both approaches is to allow for both cross-sectional dependence and independence. Since, the crypto market is highly volatile couple with no policy-framework in the industry using the second generation unit root test is ideal as it assumes heterogeneity and accordingly, autoregressive structure may not be common across the series. Table 4 and 5 summarizes the results of the first and second generation test used, respectively.

Table 4: Levin, Lin and Chu (First Generation) Panel Unit Root Test

Variable	Constant (C)		Constant and Trend (CT)	
	<i>I</i> (0)	<i>I</i> (1)	<i>I</i> (0)	<i>I</i> (1)
CCP	1.37	-9.11**	-0.21	-8.22**
HGP	2.34	-6.89**	-0.07	-9.19**
LOP	-0.01	-8.45**	1.89	-9.67**
OPP	-0.65	-7.34**	2.02	-4.72*
ATV	1.06	-6.77**	-0.98	-4.12*

*Denote significance level at 5%; *I*(0) and *I*(1) symbolize test at level and first difference, respectively

Table 4 reports the first generation panel unit root test of the study using the (Levin et. al., 2002). This test principle suggests that the cross-section units are homogeneous and more importantly, this unit root under

the first generation test is ideal for a balance panel dataset which categorizes this study. Thus, the H_0 for this test specifies that the panel dataset has unit root (i.e. common unit root process). The results are given at both level and first difference across the study variables. The result generally suggest that all the variables are not stationary at level i.e. $I(0)$ while, at first difference the result showed that all the variables under study are stationary for both test specification (i.e. C and CT).

Table 5: Pesaran (Second Generation) Panel Unit Root Test

Variable	Constant (C)		Constant and Trend (CT)	
	$I(0)$	$I(1)$	$I(0)$	$I(1)$
CCP	-1.81	-6.11**	-0.02	-5.23**
HGP	-0.21	-3.09*	-0.76	-2.99*
LOP	-0.98	-5.31**	-0.11	-6.73**
OPP	-0.87	-3.81*	-0.31	-3.21*
ATV	-2.01	-5.77**	-1.34	-6.10**

*Denote significance level at 5%; $I(0)$ and $I(1)$ symbolize test at level and first difference, respectively

Table 5 reports the second generation panel unit root test in a cross sectional Augmented DF regression i.e. CADF. This test allows for cross section correlation and is suitable for panel balance series where H_0 for the test specifies that the panel dataset has unit root. The results are given at both level and first difference across the study variables. The result generally suggest that all the variables are not stationary at level i.e. $I(0)$ while, at first difference the result showed that all the variables under study are stationary for both test specification (i.e. C and CT).

4.3 Model Estimation

Table 6: Regression Analysis on OLS, FE and RE Models

Variables	Measures	Pooled-OLS	Fixed-Effect	Random-Effect
Intercept	Coefficient	-0.003	0.127	-0.003
	Standard error	0.011	0.108	0.021
	t Stat.	-0.273	1.176	-0.143
	Prob.	0.121	0.091	0.101
Opening Price (OP)	Coefficient	0.015	0.020	0.016
	Standard error	0.211	0.019	0.009
	t Stat.	0.071	1.052	1.778
	Prob.	0.011*	0.012*	0.031*
High Price (HP)	Coefficient	0.002	0.003	0.002
	Standard error	0.018	0.901	0.211
	t Stat.	0.111	0.003	0.009
	Prob.	0.011*	0.012*	0.047*
Low Price (LP)	Coefficient	-0.014	-0.009	-0.016
	Standard error	0.910	0.298	0.851
	t Stat.	-0.015	-0.030	-0.019
	Prob.	0.067	0.028*	0.032*
	Coefficient	-0.075	-0.081	-0.001

Closing Price (CP)	Standard error	0.827	0.349	0.081
	t Stat.	-0.091	-0.232	-0.012
	Prob.	0.071	0.015*	0.038*
Asset Volume (AV)	Coefficient	0.013	0.011	0.013
	Standard error	0.018	0.198	0.332
	t Stat.	0.722	0.056	0.039
	Prob.	0.101	0.000*	0.001*
F stat		12.032	17.51	12.032
Prob (F)		0.0003*	0.000*	0.000*
R ²		0.4153	0.6153	0.504
Adj R ²		0.4160	0.6178	0.505
Idiosyncratic random (Rho)				1.0000

*Denote significance level at 5%

The result as shown in Table 6 above shows that all three panel models are statistically significant. Despite the limitation of the Pooled OLS model in not recognizing the distinctive elements across the panel dataset, the model adequately fit the dataset significantly at 0.05 ($F = 12.0321$, $p < 0.0003$). The R^2 of 0.4153 explains for about 42% of the return variance on the total market capitalization (market-cap). The p-values as shown in Table 6 indicate that, OPP, ATV and HGP are statistically significant at 0.05 level of significance. This implies that, one unit rise in OPP contributes to an increase in the market-cap by 0.015, a single unit upsurge in ATV adds to an increase of 0.013 and hike in price (i.e. HGP) contributes 0.002 to the total market-cap which is in-line with Huynh (2022) and Burggraf et al. (2021) that acknowledge in their respective findings that Bitcoin market indices such as its volume of trade, 24 high/low prices and total supply have enormous influence on the over-all cryptocurrency market-capitalization, which has shown times without number that bubbles activities are evident. This results further back the fact that crypto assets are economic assets as crypto users earns from these assets and the need for countries to enact financial policies backing cryptocurrencies which is in-line with the studies conducted by the following Ogunode et al. (2022). While, a unit increases in both LOP and CPP results in decrease in the total market-cap of 0.014 and 0.075, respectively as regards crypto assets over the period under review. As earlier identified, the Pooled OLS model fits the dataset but doesn't make a distinction between the six (6) selected crypto assets with high market capitalization; employing both FE and RE model is justifiable as the Pooled OLS disregards the cross-section and time-series features of panel dataset under consideration. Mutually, both FE and RE model are also found to fit the panel dataset at 0.05 level of significance. The result as reported shows FE at $F = 17.512$, $p < 0.0000$ and R^2 of 0.6153, i.e. FE explains about 62% of the total market-cap variance. RE at $F = 12.0321$ and $p < 0.0000$ and R^2 of 0.5041, explaining about 50% variations in the MCap. The Idiosyncratic random Rho coefficient for RE model is 1 demonstrating lower pooling effect but the equation is well specified for the panel data.

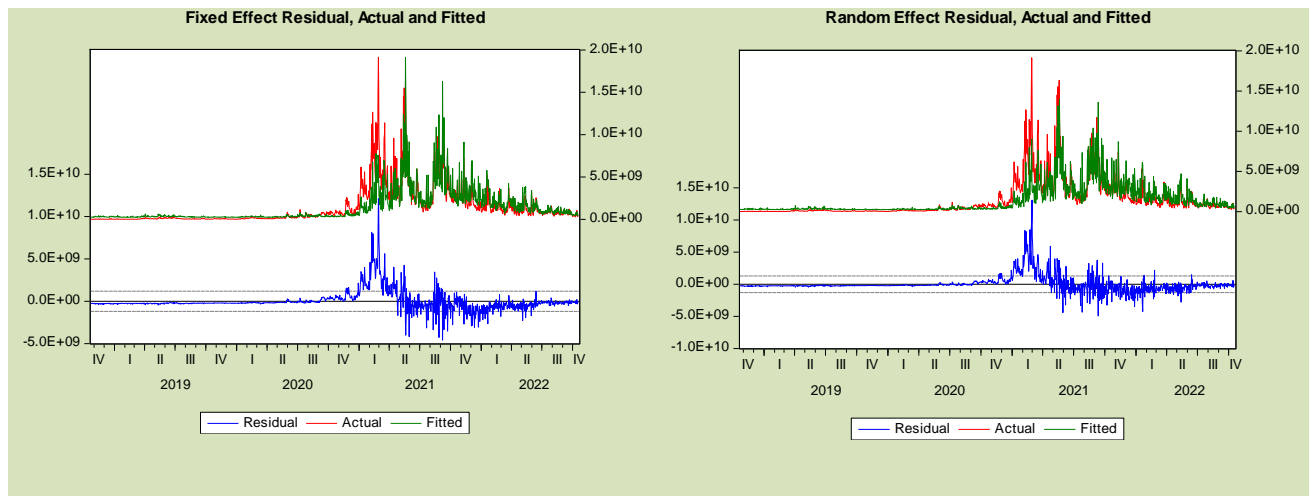


Figure 2. FE and RE Residuals (i.e. Actual and Fitted Process)

4.4 Panel Model Comparison and Selection

The Hausman test allows us to choose the better model between the random effect and the fixed effect models. The H_0 specifies that the random effects model is appropriate against the alternative that the fixed effect model is appropriate.

Table 7: Hausman Test Summary between Fixed or Random Effect Model

Test	Chi-Square statistic	P-value
Cross-section random	18.233	0.006*

*Denote significance level at 5%

Hausman test result as shown in Table 7 indicates that the fixed effect model is an appropriate model to estimate the cross-sectional variables since the $p\text{-value} > 0.05$. The result as reported implies the allowance of heteronomy in the panel datasets that is, allowing for individual intercept values across the selected cryptocurrencies. This result further indicates that, the average price of the selected tokens upon listing differs significantly.

The Lagrange Multiplier (LM) test as reported in Table 8 & 9 is employed to further decide the appropriate model between the fixed and random effects regression with the pooled OLS regression by comparing the FE and RE each with the pooled OLS. The H_0 for the LM test is specified such that, there is no significant difference across the cross-sectional units (i.e. no panel effect) which implies that the FE and RE model is inappropriate; that is, reject FE and RE model if $p > 0.05$.

Table 8: Lagrange Multiplier (LM) Test between Random Effects Regression and the Pooled OLS Regression

Test	Normal	P-value
Cross-sectional Units	32.117	0.0000*

*Denote significance level at 5%

Based on the result in Table 8, it can be seen that test statistic is 32.117 with a corresponding $p\text{-value}$ of 0.0000 which is less than 0.05. The result shows that the test statistic obtained is significant at 5% and the

H_0 in favour of OLS is rejected; thus, the RE model is more appropriate than the OLS model. And also, Table 8 also shows the comparison between the fixed effect model and pooled OLS model using the Lagrange Multiplier (LM) test.

Table 9: Lagrange Multiplier (LM) Test between Fixed Effects Model and the Pooled OLS Regression

Test	F-Statistic	P-value
Cross-sectional Units	38.943	0.0000*

*Denote significance level at 5%

Thus, the result as reported in Table 9 shows that the H_0 is rejected, implying that the fixed-effect model is also appropriate over the pooled OLS model. This result further established that the fixed effect model should be used instead of OLS model. As earlier stated in the conceptual review, this study acclaims that crypto assets should be classified as non-financial assets since there aren't any policies guiding its existence in Nigeria which is of the view with studies conducted by (Tommaso et al., 2023; Ogunode et al., 2022). Still yet, these non-financial assets are used by individuals in economic activity and also, serve as store-of-value; this view is in-line with Ogunode et al. (2022) study on cryptocurrency and global practices: lessons for Nigeria. This study also agrees with Marcelo et al., 2019, that crypto assets have no counterpart liability which are not issued or legally approved by a central bank or any financial institution recognized by government as highlighted in this study in respect to crypto assets classification in macroeconomic. Though, it is important to state that, one of the major reasons crypto assets are not classified as financial assets is due to the fact that this new ecosystem of medium of exchange is yet to be endorsed by world leaders may be due to its volatile nature compared to fiat currencies and that, terrorists see it as an easy flow to finance their activities; corrupt individuals sees it as a means to launder money or even evade taxes.

5. Conclusion

This study seeks to investigate the relationship between crypto asset indicators and crypto market capitalization using a panel data analysis approach and also, to quantitatively review and establish that crypto assets prices can easily be influenced by macroeconomic variables indicating that it can be classified as an economic asset. The study findings shows wide-range difference across the series mean of the explanatory variables (CCP, HGP, LOP, OPP and ATV). While, the standard deviation values across the explanatory variables showed that the crypto market is a volatile market-space as well and exhibiting high risk. Our study reveal that macroeconomic variables may also be responsible for the crypto price fluctuations since Bitcoin price movements are in-line with the monetary policies of countries already having cryptocurrency's regulatory framework. Our findings also showed that the crypto indicators as identified and used in this study (CCP, HGP, LOP, OPP and ATV) were not stationary; this maybe as a result of the unpredictable nature of this digital assets suggesting that this assets exhibits structural breaks and jumps. But, stationairty for the study variables were achieved at first difference for both test specification. In addition, this study revealed that, an increase in the explanatory variables leads to an increase in the crypto market capitalization. Our findings in-line with other studies as identified in the result and discussion section shows that crypto indicators such as volume of trade, 24 high/low prices and total supply have enormous influence on the over-all cryptocurrency market-capitalization. This results further

back the fact that crypto assets are economic assets as crypto users earn from these assets and the need for countries to come up with financial policies backing cryptocurrencies. As identified by this study, the Pooled OLS model fits the dataset but doesn't make a distinction between the six (6) selected crypto assets with high market capitalization suggesting level of same association between the crypto assets indicators selected for this study. The crypto ecosystem is categorized significantly from other financial markets which are approved and recognized by the government. Nonetheless, the development of cryptocurrencies and its usage of blockchain technology and still evolving innovations around it is really changing the world's perception and dividing opinions about fiat currencies. In addition to these the blockchain structure allows an enormous number of people to join in this market, start a trade and complete several transactions with minimal efforts. Unfortunately, may cause numerous forms of jumps or asymmetries leading to structural break patterns known as "Pumps & Dumps". The significance of all the explanatory variables as highlighted in both the FE and RE models suggest that the selected variables are suitable indices for predicting the MCap of the identified tokens in this study and also, point towards the requisite to implement more analysis (comprising qualitative aspect) of the variables, incentive and crypto use case, financial policies, regulations and practices.

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