Pak. j. life soc. Sci. (2024), 22(2): 1022-1038 E-ISSN: 2221-7630;P-ISSN: 1727-4915

Pakistan Journal of Life and Social Sciences

www.pjlss.edu.pk

https://doi.org/10.57239/PJLSS-2024-22.2.0072

RESEARCH ARTICLE

# The Impact of Cryptocurrency on the Financial System in Nigeria

Adedeji Daniel Gbadebo*

Department of Accounting Science, Walter Sisulu University, Mthatha, South Africa

***ARTICLE INFO***

Received: Apr 25, 2024

Accepted: Jul 2, 2024

***Keywords***

Cryptocurrency

Bitcoin

Financial system

Foreign exchange market

Capital market

***Corresponding Author:**

agbadebo@wsu.ac.za

**ABSTRACT**

In this paper, we review the benefits and challenges of cryptocurrencies, the decentralized digital money and assets, on the financial system. Afterward, we apply the simple and linear "Transfer Function (Autoregressive distribution Lag Model, ARDL) to examine the effects of selected cryptocurrencies on financial system with specific focus on the foreign exchange market, capital market and the money market in Nigeria. We propose a linear ARDL method to demonstrate how the volatilities in the prices and transaction volumes of Bitcoin. The result shows that the treasury bill transaction amount is explained by its own past, as well as other considered variables. A 1% increase in bitcoin price would result in 0.004% decrease in the volume of transaction of the treasury bill. Also, a 1% increase in bitcoin traded transaction will result in a 0.096% decrease in the money market treasury bill. Regarding the treasury bill rates, the result identified that the treasury bill rate is also explain by own past and other considered variables. A 1% t increase in bitcoin price would result in 0.059% decrease in the treasury bill rates. Lastly, bitcoin volume would result in significant decrease in treasury bills rates in line with expectation. A 1% increase in bitcoin traded transaction will result in a 0.039% decrease in treasury bill rates. Thus, the study contributes to the existing literature by providing how the financial transactions in the cryptocurrency market are drives price discovering in the financial markets in Nigeria. The findings open room for future research since the study is limited to only few financial markets in Nigeria.

## INTRODUCTION

During the Tech boom in the 1990s, several attempts were made at creating digital currency but were unsuccessful due to the low level of technological advancement then (Bech, 2017). However, following the 2008 global financial crisis triggered by the rapid increase in interest rates and collapse of the real estate market result in bankruptcy of many banks, firms, and even the global markets, the first cryptocurrency, Bitcoin (BTC), was invented by a person under the pseudonym of Satoshi Nakamoto in 2008. Since the advent of Bitcoin, several other cryptocurrencies, categorized simply as Altcoins have emerged, with most having some characteristics compared to those of the successful digital products and others tremendously differing. Currently, there are over 5,000 cryptocurrencies in existence as of February 2024 (Coinmarketcaptilisation, 2024).

Since the emergence of cryptocurrency, its positions in the global financial markets have continuously experienced increasing. The global financial system is generally embracing the current evolution from physical currency to almost virtual currencies through the medium of technology (Aalborg et al., 2018). With the introduction of cryptocurrency futures in December 2017 as the standard cryptocurrency derivative and the inflows of institutional funds, the market capitalization has continued to soar due to search of price discovery (Zhu et al. 2017). The emergence of these crypto-asset markets exerted considerable impacts on global financial markets recognition (Ciaian et al., 2016; Bartoletti, Carta, Cimoli, & Saia, 2017). The vulnerabilities in virtual-asset markets – relating to leverage, liquidity/maturity mismatch, operational/technological fragilities, and interconnectedness – are similar to those in traditional finance. The FSB (2024) identifies that the vulnerabilities might have implications for financial stability through four different channels viz: (a) financial sector exposures to cryptocurrencies, related financial products and entities that are financially impacted by crypto-assets; (b) wealth effects, i.e. the degree to which changes in the value of cryptocurrencies might impact their investors, with subsequent knock-on effects on the financial system; (c) confidence effects, through which developments concerning crypto-assets could impact investor confidence in crypto-asset markets (and potentially the broader financial system); and (d) extent of crypto-assets' use in payments and settlements.

There are many reasons to believe that cryptocurrencies may affect the financial system of several countries. Cryptocurrencies are positioned in the highest ranking of importance in the global financial markets and instability. First, cryptocurrencies share attributes with typical financial assets and are widely regarded as investment products and traded amongst many investors (Mikhaylov, 2020). Second, they serve as speculative assets in times of economic upheavals (Baur et al., 2018) and may as well be perceived as a safe haven and substitute for traditional financial assets (Kliber et al., 2019). Third, as noted by Dyhrberg (2016) and Baur et al. (2018), cryptocurrencies, especially Bitcoin have hybrid nature of gold and US dollar, and thus can be useful in risk management. Lastly, many individuals and institutional investors have trusted their utilities leading to the development of several more functional cryptocurrencies.

In Nigeria, the cryptocurrency, which has been largely admitted into the financial sector, is gaining wider popularity. Because of the volatility it impinges on the financial system, particularly, the exchange rate, there are worries about its implication and functionality, especially, since no regulatory framework from the apex bank exists. Thus, recently the government through the Central Bank of Nigeria (CBN) and Security and Exchange Commission (SEC) begin to implement proper regulatory actions since eliminating the cryptocurrency may be unworthy for a country that seeks to promote domestic innovation and earn foreign exchange to stabilize her currency. The paper reviews the effects of cryptocurrency on the financial system in Nigeria. The immediate aim is to analyse how both price and traded volume in the cryptocurrency market has effects on the money market in Nigeria. The paper completes a linear transfer function -autoregressive distribution lag (ARDL) model - to examine the effects of cryptocurrency in money market in Nigeria. We propose the ARDL method to demonstrate how the prices and transaction volumes of Bitcoin impact money market variables. The paper seeks two-fold objectives. First, we review the benefits associated with the cryptocurrencies and how it has impacted the financial markets in Nigeria. Second, we apply the econometric method to verify whether the fluctuations in Bitcoin significantly drive movements process and transactions in the money markets. The other sections are presented as follows: Section 2 represents the literature which explains the benefits and challenges of cryptocurrencies, discusses some theoretical basis of cryptocurrencies as well as present a resumé of extant literature. In Section 3, we provide a succinct description of the applied methodology for the empirical exercise. In Section 4, we present the results and the discussions, and finally, in Section 5 we conclude, offers recommendations", and propose suggestions for future research.

## 2. LITERATURE

### 2.1. Cryptocurrency and Bitcoin

A cryptocurrency, crypto-currency, or crypto is a digital asset designed to work as a medium of "exchange wherein individual coin ownership records are stored in a ledger existing in a form of a computerized database using strong cryptography to secure transaction records, to control the creation of additional coins, and to verify the transfer of coin ownership. A fixed amount of coin is issued at a fixed a-priori defined and publicly known rate, implying that the stock of the coin increases at a decreasing rate. Some crypto coins can now be used to buy goods or services worldwide, if transaction partners accept the coin as a mean of payment. A transaction implies that the coin owners transfer their ownership of a certain number of coins, in exchange for goods and services. An increasing number of companies accept some cryptocurrencies as payments for their goods and services, as well as can also be exchanged for other currencies. The decentralized finance digital currency employs interface integrated with hardware tokens and social networks that rely on anonymity, transparency, and peer-to-peer (P2P) transactions. These transactions are established on an open-source protocol, recognized as the Blockchain and which applies sophisticated algorithms to create and confirm records (Milutinović, 2018). Like traditional money, cryptocurrencies are used for medium of payments and exchange for faits but remained uncoordinated by monetary policy of the Reserve Banks (Mikhaylov, 2020; Aalborg et al., 2018).

Bitcoin was the first cryptocurrency to emerge, and the mysterious aura surrounding this new technology was only heightened by the fact that its creator remained hidden behind a pseudonym since created in 2008. As a cryptocurrency, Bitcoin uses the principles of cryptography to control the creation and transfer of money. Access to the Bitcoin network requires downloading the Bitcoin software on personal computer and joining the bitcoin network, which allows participants to engage in operations, and update and verify the transactions. In 2140, it is predicted that Bitcoin growth rate will converge to zero, when the maximum amount of Bitcoin in circulation will reach 21 million units. Hence, the maximum stock of Bitcoin will not change after 2140.

Although Bitcoin may not be able to perform as a dominant global currency, it can still play a significant role due its ease of use and ability to work in developing markets (Franklin, 2016). Bitcoin has witnessed a great deal of acceptance because it is a network run on computer programs, which are more commonly used nowadays than in the past (Grant & Hogan, 2015). The ability to complete transfers almost immediately at any given time of any day, may it be a holiday, serves as a great incentive for Bitcoin users, as they have more control over their own assets (FAQ - Bitcoin, 2020); for users to be in full control of the transactions without having any intermediary merchant adding any unnecessary charges is an additional advantage to the cryptocurrency (FAQ - Bitcoin, 2020). The extraordinarily quick speed of Bitcoin transfers protects the users from chargeback fraud (Dumitrescu, 2017). Because transfers are instantaneous, once they are complete, they are final (Twitter et al., 2019). There are no boundaries for Bitcoin transfers in the sense that international and domestic transfers are not subject to foreign exchange rates and fees.

The absence of a central authority poses yet another key identifying property of Bitcoin (Franklin, 2016). Decentralization allows for cryptography to control Bitcoin creation and management, rather than having a central bank, or any other form of authority, do so (Kliber et l., 2019). This implies that Bitcoin is independent of the possibility of the central authority devaluing the currency through arbitrary currency creation (Grant & Hogan, 2015), and of inflation (Shahzad et al., 2019). Also, Dumitrescu (2017) identified personal data protection as one of the primary advantages of Bitcoin. It was stated that the anonymity of the users is better ensured through encrypted mathematical algorithms, thus firewalling security breaches. This result is similar to that of Kayal and Rohilla (2019) in that payments are protected and verified through electronic transfer and that the privacy of the user is delinked from the actual transaction.

Furthermore, the low transaction costs because of decentralization are another incentive for joining the Bitcoin network. Symitsi and Chalvatzis (2019) estimate the economic gains of the transaction costs associated to Bitcoin transfers. They study the effect of these gains both with and without transaction costs and find that economic gains are not reduced after introducing transaction costs. This suggests that the cost of Bitcoin transactions are reasonably priced. Dumitrescu (2017) finds that on average, the transaction costs are over five times lower than those of credit cards. Transaction costs are also unrelated to the amount transferred, implying that the transaction cost is constant for sending 1 bitcoin or any number of bitcoins.

There are several cryptocurrencies available over the internet, the most popular one being Bitcoin. Cryptocurrencies that were introduced after the success of Bitcoin are known as Altcoins and have some characteristics compared to those of the successful digital currency and others tremendously differing. Based on their market capitalization, the top five cryptocurrencies include Bitcoin, Ethereum, XRP, Tether, and Bitcoin Cash (Coinraking.com, 2024). While some of these cryptocurrencies have token limits, others have quicker transfer speeds.

### 2.3. Benefits of Cryptocurrency

#### 2.3.1. Crypto-Assets as Hedge

This classification of crypto asset is defined by Jana and Das (2020) as an investible asset that is either uncorrelated or negatively correlated with another investible portfolio instrument on average. The risk return mechanism allows for the maximization of expected profits. Several past studies have evaluated the role of Bitcoin under different circumstances to determine whether it acts as a hedge or has any other role. Bitcoin was found to act as a weak hedge for both Bitcoin-friendly economies and all other markets included in the study by Kliber et al. (2019). Bitcoin is commonly compared with different commodities, like oil and gold, and its behavior is tested by comparing it to the behavior of these other commodities. Shahzad et al. (2019) and Bouoiyour and Selmi (2020) find that Bitcoin and gold do not move in the same direction. These two assets are viewed as a hedge and a safe haven in times of economic turmoil, however, the factors driving the price of Bitcoin and the price of gold may be different. Investors prefer different investment instruments to hedge the downside risk in different economic situations and market states.

The classification of Bitcoin as a hedge is also dependent on the economic uncertainty. Fang et al. (2019) find that global economic policy uncertainty has a significantly negative impact on the Bitcoin-bonds correlation and a positive impact on both Bitcoin-equities and Bitcoin-commodities correlations, suggesting the possibility of Bitcoin acting as a hedge under specific economic uncertainty conditions. Kayal and Rohilla (2019) and Al Mamun et al. (2020) conclude that during the period of high policy uncertainty and worsening economic conditions, Bitcoin investors are better off to hedge their portfolio with gold and not with other financial assets. The identification of Bitcoin as a hedge is complex in its foundations, depending on several underlying factors and situations that need to be assessed.

#### 2.3.1. Portfolio Diversification

Portfolio diversification is one of the primary reasons that investors invest in any sort of asset. It is defined as an investible instrument that is positively, but imperfectly correlated with another instrument in the portfolio (Jana & Das, 2020). Diversification is commonly practiced in order to moderate the risk that one investment type may perform poorly when multiple assets are invested in. Vojtko and Cisár (2020) conclude that Bitcoin is classified as an asset used for portfolio diversification. Bouoiyour and Selmi (2020) shoe that Bitcoin could act as an effective diversifier against movements in energy commodities but not for non-energy commodities.

On the other hand, Stensås et al. (2019) evaluated the difference in the role of Bitcoin in major developed and developing countries and found that Bitcoin acted as a diversifier only for investors in developed countries, but for all commodities. While Ji et al. (2019) and Shahzad et al. (2019) also found that the diversification role of Bitcoin was not necessarily as strong as commonly believed, Symitsi and Chalvatzis (2019) concluded that their results were statistically significant for the diversification benefits of Bitcoin. Urquhart and Zhang (2019) evaluated the role of Bitcoin against world currencies at an intraday level, due to the extreme volatility of the asset.

#### 2.3.3. Safe Haven

Bitcoin is often considered a safe haven asset for many investors. A safe haven is an investible asset that is negatively correlated with other instruments in the portfolio, as defined by Jana & Das, 2020. It is a financial instrument that is expected to retain or gain value during periods of economic uncertainty. Recent studies have aimed to classify this role of Bitcoin by comparing

it to different commodities and by analyzing the network under several conditions and in various locations. Some researchers, such as Bouoiyour and Selmi (2020) claimed that Bitcoin is classified as a safe haven. Bouoiyour and Selmi (2020) examined whether Bitcoin exhibited a safe haven property during global uncertainty. The results found using a twenty-day time span indicated that Bitcoin was considered a crypto safe haven and that Bitcoin reinforced its status as a digital gold.

Several other studies have been performed to determine whether Bitcoin should be classified as a diversifier, a hedge or a haven. Vojtko and Cisár (2020), Luis et al. (2019) and Stensås et al. (2019) find that Bitcoin is not a safe haven for investors in their analyses. Vojtko and Cisár (2020) concluded that Bitcoin is not a preferred asset to hold during times of stress because its price behaves like the price of the stock market index, which is volatile during financial crises. Shahzad et al. (2019) investigate the behavior of gold and Bitcoin for the G7 countries and find that gold is an indisputable safe haven and hedge for several G7 stock indices, whereas Bitcoin takes these two roles only in the case of Canada. Comparatively, Shahzad et al. (2019) find that each of Bitcoin, gold, and the commodity index can be considered as a weak safe haven asset in some cases.

### 2.4. Cryptocurrency and the Nigeria Economy

The creation of cryptocurrency as a cybernetic currency has been generating reactions in the global economy such as a country like Nigeria. There has been countless advantage and disadvantage discourse on cryptocurrencies' importance on the Nigerian economy. However, the Nigeria government through its governing agencies such as the Central Bank of Nigeria and the Securities and Exchange Commission has tried to place a ban on cryptocurrency. However, its legal status remains unclear, unlike in countries like Morocco and Algeria where there is an explicit prohibition on trading in Bitcoins such that a breach attracts hefty fines (Dierksmeier & Seele, 2016). The cautions are primarily designed to educate the citizenry about the difference between genuine currencies issued and guaranteed by the state and cryptocurrencies, which are not. Following the moves taken by the CBN and the SEC, lawmakers have also advised the regulatory authorities to speed up efforts in presenting a legal framework for cryptocurrencies in Nigeria.

As an economy with an underdeveloped financial market, the activity of cryptocurrency may be challenging to regulate and, as such, may provide the platform for investors, both individuals and corporate bodies to evade tax thereby resulting in a low-income generation for government relative to the level of activities in the market which could affect the budgetary plans of the government. However, in an economy with a highly developed financial market, the suitable management of cryptocurrency might result in an increase in revenue generation through a tax which would enhance the budgetary plans of the government.

Moreover, cryptocurrencies operate alongside official currencies. The current volumes are small and do not challenge the position of official money as the main currency. But as algorithms improve to limit the volatility of cryptocurrencies, their popularity and use tend to increase. This would lead to coexistence with other official currencies. The relations between cryptocurrencies and central bank monetary policy is treated in detail by Fernandes-Villa Verde and Sanches (2018). Their theoretical model predicts that the central bank and private money's existence hinge on on the monetary policy the former follows. In specific, privately issued currencies would be used if the official currencies do not ensure price stability but would lose their value as a medium of exchange when the central bank credibly guarantees the real value of money" balances. Nonetheless, from a practical viewpoint, central banks could face certain risks from the advent of cryptocurrencies as relevant mediums of exchange with stable purchasing power due to their high volatility level.

## 3. METHODOLOGY

### 3.1. Methods

As applied in previous studies (Lahmiri et al., 2018; Kjærland et al., 2018; Guizani & Nafti, 2019), we adopt a Transfer-function – the Autoregressive Distributed Lag, (ARDL). The approach is considered as a major workhorse in dynamic single-equation estimation (Kennedy, 2008). We apply the ARDL and the (cointegration) Bounds test to analyse the specified models in (3.1). The procedure for the for applying the ARDL and Bounds test are summarized. First, we verify the stochastic property for each time series

($z_t$), using a unit root test. We apply Augmented–Dickey–Fuller (ADF) test. The test verifies the stationarity by assuming that $z_t$ follows:

$$z_t = a_0 + \varphi z_{t-1} + \sum_{i=1}^{p-1} \delta_i \, \Delta z_{t-i} + \Omega_t; \ (\delta_i = -\sum_{j=i+1}^{p-1} \varphi_j \, ; \ i = 1, 2, ..., p-1) \quad (3.1)$$

Where, $p$ is lag length, and $\Omega_t$ is Gaussian white noise. The equation is estimated with least square and test statistics, $\tau_\mu = \hat{\varphi}_T - 1/se(\hat{\varphi}_T)$ is computed, and, $se(\hat{\varphi}_T)$ is standard error of $\hat{\varphi}_T$. The unit root null $H_0 \colon \varphi = 1$ (of non-stationarity) tested against the alternative, $\varphi > 1$ is rejected if $\tau_\mu > ADF_\alpha$, critical value generated by Dickey–Fuller from a limiting distribution.

*Second*, we estimate the ARDL model that shows how, $y_t$ is explained by its own pasts $y_{t-i}$ and current, $x_t$ and past, $x_{t-i}$ of the explanatory variables. The general $ARDL(p, s_1, \dots, s_m)$ is:

$$y_t = \beta_0 + \sum_{j}^{m} \beta_j \, x_{j,t} + \sum_{i=1}^{p} \varphi_i \, y_{t-i} + \sum_{j}^{m} \tilde{\beta}_{j,i} \, x_{j,t-i} + a_t \quad (3.2)$$

The estimation of (3.2) ignores the non-stationarity of the series and estimate the nonstationary series (Pesaran & Shin,1999; Sam, McNown & Goh, 2018; Mills, 2019).

*Third,* once we estimate the specific models, the next step is to verify if a long-run (equilibrium or cointegration) relationship exist amongst the $I(0)$ or $I(1)$ variables. We apply the ARDL (Cointegration) Bounds test procedure. Pesaran et al. (2001) introduce two (bounds) tests for cointegration: an $F$-test on the joint null that the coefficients on the level variables are jointly equal to zero or a $t$-test on the lagged level dependent variable. In order to rule out the possibilities of degenerate cases and obtain valid conclusion, both the $F$ and $t$- test work under the that assumption the dependent variable is *I(1)*. We adopt the $F$-test for our study. since ARDL comprises of $I(1)$ variable(s), it is required to check for model diagnostic heteroscedasticity, serial correlation, normality and Stability of long-run estimates using the cumulative sum (CUSUM) and cumulative sum of square (CUSUMSQ).

### 3.2. Empirical Model and Data

To consider how the cryptocurrency affects financial market in Nigeria, the paper estimates a model that shows how bitcoin prices and volume explains money market variables in Nigeria. We control for other macroeconomic and external variables that likely influence to ensure robustness. Thus, we estimate the models below:

$$TBLA_t = f(BTCP_t, BTCV_t, ASPI_t, OILP_t, INFL_t, EXCR_t) \quad (3.3)$$

$$\mathrm{TBLR}_t = f(BTCP_t, BTCV_t, ASPI_t, OILP_t, INFL_t, EXCR_t) \quad (3.4)$$

The variables and data source are defined in Table 1. The empirical *ARDL* model for the specific estimation are:

$$\mathrm{TBLA}_t = \alpha_0 + \alpha_1 BTCP_t + \alpha_2 BTCV_t + \alpha_3 \mathrm{ASPI}_t + \alpha_4 \mathrm{OILP}_t + \alpha_5 \mathrm{INFL}_t + \alpha_6 EXCR_t + \sum_{i=1}^{p} \varphi_i \mathrm{TBLA}_{t-i} + \sum_{i=1}^{m} \tilde{\alpha}_{1,i} \, BTCP_{t-i} + \sum_{i=1}^{m} \tilde{\alpha}_{2,i} \, BTCV_{t-i} + \sum_{i=1}^{m} \tilde{\alpha}_{3,i} \, ASPI_{t-i} \quad (3.5)$$
$$+ \sum_{i=1}^{m} \tilde{\alpha}_{4,i} \, OILP_{t-i} + \sum_{i=1}^{m} \tilde{\alpha}_{5,i} \, INFL_{t-i} + \sum_{i=1}^{m} \tilde{\alpha}_{6,i} \, EXCR_{t-i} + e_t$$

$$\mathrm{TBLR}_t = \beta_0 + \beta_1 BTCP_t + \beta_2 BTCV_t + \beta_3 \mathrm{ASPI}_t + \beta_4 I\mathrm{OILP}_t + \beta_5 \mathrm{INFL}_t + \beta_6 EXCR_t + \sum_{i=1}^{p} \varphi_i \mathrm{TBLA}_{t-i} + \sum_{i=1}^{m} \tilde{\beta}_{1,i} \, BTCP_{t-i} + \sum_{i=1}^{m} \tilde{\beta}_{2,i} \, BTCV_{t-i} + \sum_{i=1}^{m} \tilde{\beta}_{3,i} \, ASPI_{t-i} \quad (3.6)$$
$$+ \sum_{i=1}^{m} \tilde{\beta}_{4,i} \, OILP_{t-i} + \sum_{i=1}^{m} \tilde{\beta}_{5,i} \, INFL_{t-i} + \sum_{i=1}^{m} \tilde{\beta}_{6,i} \, EXCR_{t-i} + e_t$$

This study uses monthly, covering Jan 2014 to December 2022. The shares price index is employed to proxy for business sentiments. The Inflation rates (based on the 12 months average change) for all items is used. It is expected that investible funds channeled into the cryptocurrency will crowd out investment and liquidity, thus negatively affect $\mathrm{TBLA}_t$ and $\mathrm{TBLR}_t$ in Nigeria. The exchange rate used is the USD/NGN rate that averages the buying and selling rates. Before the estimation, we apply the Akaike's information criteria ($A1C$), given by equation (3.7) to select optimal lag.

$$AlC(p,q) = \log \hat{\sigma}^2 + 2(p+q)T^{-1} \quad (3.7)$$

The AIC selects optimal lag by setting two different upper bounds ($p_{\text{m}}$ and $q_{\text{m}}$) for the orders of $\varphi(B)$ and $\theta(B)$. Where, $\theta = -\psi$ ; $\psi_j = \varphi^j$ and $\psi$ is weight of the first-order moving average.

**Table 1: Variable Summary**

| Variables | | Variables | Data Source |
|---|---|---|---|
| TBLA | | Treasury Bill Amount (N' Billion) | CBN |
| TBLR | | Treasury Bill Rate (%) | CBN |
| BTCP | | Bitcoin Price (USD) | Bitcoinity Data |
| BTCV | | Bitcoin Volume (Billion) | Bitcoinity Data |
| ASPI | | All Share Price (Index) | CBN |
| OILP | | Oil Price (Brent) | CBN |
| INFL | | Inflation Rate (%) | CBN |
| EXCR | | Exchange Rate (USD/NGN) | CBN |

**Source:** Authors

## 4. RESULTS AND DISCUSSION

Before the estimation, we present the descriptive statistics (Table 2), correlation matrix (Table 3) and the unit root test (Table 3) respectively. The evidence suggests significant "correlation amongst the variables, except for the correlations between treasury bill rates and oil price which is negative and low (-0.042), inflation rate and oil price, which is negative and low (-0.003) and exchange rates and oil price, which is positive but low (0.066). We found significant negative correlation between treasury bill volume and bitcoin price (-0.545) and the correlation between treasury bill rates and bitcoin price (-0.670). The is an indication that the cryptocurrency market have influence on the money market in Nigeria. The Jarque-Bera (J-B) value is significant for all, rejecting the normality null for each series.

Next, we log transformed the data are logs to control for likely outliers, heteroskedasticity and ensure smoothness to remove striations. Figure 1 [2] depict the times series plots of the log transformation [log-difference] series for the variables. As would be seen from the plots, the level forms of the series [Figure 1] show high fluctuations, with jumps and vertical striations are indications non stationarity, while the first differences (Figure 2).

Regardless of the ADF tests, which includes the Intercept with or without the Time Trend, all the variables are non-stationary at levels. However, they are differenced stationary, leading us to conclude that they are integrated of same. To complete the cointegration bound test to confirm existence of equilibrium relation, according to an iteration process which estimates 2500 independent equations for TBLA, the AIC selects a lag length of 4 from which an ARDL ARDL(1, 4, 5, 2, 1, 0, 0) which has highest AIC value (0.127) is selected. Similarly, according to the iteration process which estimates 2618 independent equations for TBLR, the AIC selects a lag length of 3 from which an ARDL(3, 3, 2, 1, 0, 0, 0) which has highest AIC value (0.131) is selected. The bound tests (Table 6) reject the null of no cointegration at 5% significance for the treasury bill amounts and treasury bill rates equations. Since equilibrium relationship exists between treasury bill amounts and the regressors as well as between treasury bill rates and regressors, Table 7 [Table 8] presents estimates of the ARDL model for the treasury bill amounts [treasury bill rates].

Table 7 shows that the treasury bill transaction amount is explained by its own past, as well as other considered variables. The treasury bill transaction amounts would increase by approximately 9.1% when other variables are not put into consideration. Also, as expected the first pasts of treasury bill transaction amounts have positive effects on its contemporaneous value. Moreso, the results show that a 1% increase in bitcoin price would result in 0.004% decrease in the volume of transaction of the treasury bill. The other lag of bitcoin price would further significantly cause decrease in the volume of transaction of the treasury bill, except for the third lag which is insignificant. The significance of one-month pasts in bitcoin prices, bitcoin volume and other macroeconomic economic imply that the effect of these fundamentals on the contemporaneous value of the treasury bills volume in Nigeria has not wane away.

Regarding the bitcoin traded volume, the outcome shows that bitcoin volume results in significant decrease in treasury bills transactions in line with expectation. More specifically, a 1% increase in bitcoin traded transaction will result in a 0.096% decrease in the money market treasury bill traded in Nigeria. Other macroeconomic variables also affect the volume of treasury bill. The outcome indicates that the all-share price index (an indication of capital market activities), oil prices, and their lags positively impact the money market instruments. For instance, a 1% increase in all share price index and oil price lead to a 0.279% increase in treasury bill transactions. Both inflation and exchange rates negatively affect treasury bills volume in Nigeria. Specifically, a 1% increase in inflation and exchange rates lead to approximately 0.123% and 0.380% decrease, respectively, in the treasury bill transactions.

Table 8 shows that the treasury bill rates, which is the 91day TB rate, is also explained by its own past (TBLR(-1)) as well as other considered variables. The treasury bill transaction amounts would increase by approximately 2.589% when other variables are not put into consideration. As expected, the first-three pasts of treasury bill rates have a significant positive effect on its contemporaneous value. Moreso, the results show that a 1% increase in bitcoin price (BTCP) would result in 0.059% decrease in the treasury bill rates. However, the effect of such change will translate into increase in the treasury bill rates in the lags periods. The significance of one-month pasts in bitcoin prices, bitcoin volume and other macroeconomic economic imply that the effect of these fundamentals on the contemporaneous value of the treasury bills volume in Nigeria has not wane away.

Regarding the bitcoin traded volume, the outcome shows that bitcoin volume results in significant decrease in treasury bills rates in line with expectation. More specifically, a 1% increase in bitcoin traded transaction will result in a 0.039% decrease in treasury bill rates in Nigeria. Other macroeconomic variables also affect the treasury bill rates. For instance, the outcome indicates that the all-share price index (an indication of capital market activities), oil prices, and their lags negative impact the treasury bill rates. For instance, a 1% increase in all share price index will cause decrease in treasury bill rates by 1.493%. While the exchange rates negatively affect treasury bills rates, inflation and positively affect it. A 1% increase exchange rates lead to approximately 0.004% decrease in the treasury bill rates, while a 1% increase inflation rates lead to approximately 0. 635% increase in the treasury bill rates.

The overall model is highly significant at 1% as shown by the $F$-test (26) and predictive power, as indicted by $\bar{R}^2$ of 87.2% is high. The overall model for the treasury bill rates is highly significant at 1% as shown by the $F$-test (48.11) and predictive power, as indicted by $\bar{R}^2$ of 90.36% is high. Because the purpose of study is to examine the responds of treasury bill transactions to bitcoin prices, bitcoin volume and other macroeconomic economic, hence, the high test of significance of the overall model is important rather than $\bar{R}^2$ which aims at predicting the treasury bill transactions.

Regarding the diagnostic examination, which confirms the adequacy of the treasury bill transactions and treasury bill rate models, the result shows that absence of autocorrelation of the errors. The Durbin Watson statistics (of 2.105 and 1.9675) test reject the null of serially correlation for the residuals of model of treasury bill transactions and treasury bill rates, respectively. The errors terms are white noise and normally distributed. All models' coefficients fall inside the critical bands (red lines) of the CUSUM and CUSUMSQ plots (Figure 3 and Figure 4") indicating stability of the coefficients. This is non-surprising since the short-run dynamic effects are sustained to the long-run, a significant $t$-test indicate that the long-run coefficients will be stable.

**Table 2: Sample Statistics**

| Variable | $\mu$ | $med$ | $max$ | $min$ | $\sigma$ | $\tilde{\mu}_1$ | $\tilde{\mu}_3$ | $jb$ | $p(jb)$ |
|---|---|---|---|---|---|---|---|---|---|
| TBLA | 3832.1 | 3642.7 | 9941.7 | 654.5 | 2302.0 | 0.527 | 2.255 | 7.489 | 0.024 |
| TBLR | 7.968 | 9.950 | 14.930 | 0.030 | 4.457 | -0.324 | 1.624 | 10.42 | 0.005 |
| BTCP | 11928.1 | 6641.2 | 60855.6 | 234.8 | 15909.7 | 1.602 | 4.437 | 55.49 | 0.000 |
| BTCV | 15.984 | 9.585 | 90.420 | 0.360 | 19.577 | 1.742 | 5.897 | 92.38 | 0.000 |
| ASPI | 34648.0 | 33883.6 | 52990.3 | 21300.5 | 7710.3 | 0.453 | 2.289 | 5.978 | 0.050 |
| INFL | 13.525 | 12.795 | 21.470 | 7.710 | 3.796 | 0.149 | 1.931 | 5.544 | 0.063 |
| EXCR | 301.0 | 306.3 | 448.9 | 157.3 | 86.61 | -0.229 | 1.999 | 5.452 | 0.065 |
| OILP | 66.380 | 63.020 | 120.080 | 23.340 | 22.086 | 0.639 | 2.699 | 7.761 | 0.021 |

**Note:** Table 2 shows the statistics ($\mu, med, max, min, \sigma, \tilde{q}_1, \tilde{q}_3, jb$) of the considered variables. Where $\mu$ ≡ mean, $med$ ≡ median, $max \equiv maximum, min\ minimum$, $\sigma$ ≡Standard deviation, $\tilde{\mu}_1$ ≡ skewness coefficient $\tilde{\mu}_3$ ≡ $k$urtosis coefficient, Jarque-Bera (JB) and its probability value [$p(jb)$].

**Source:** Authors

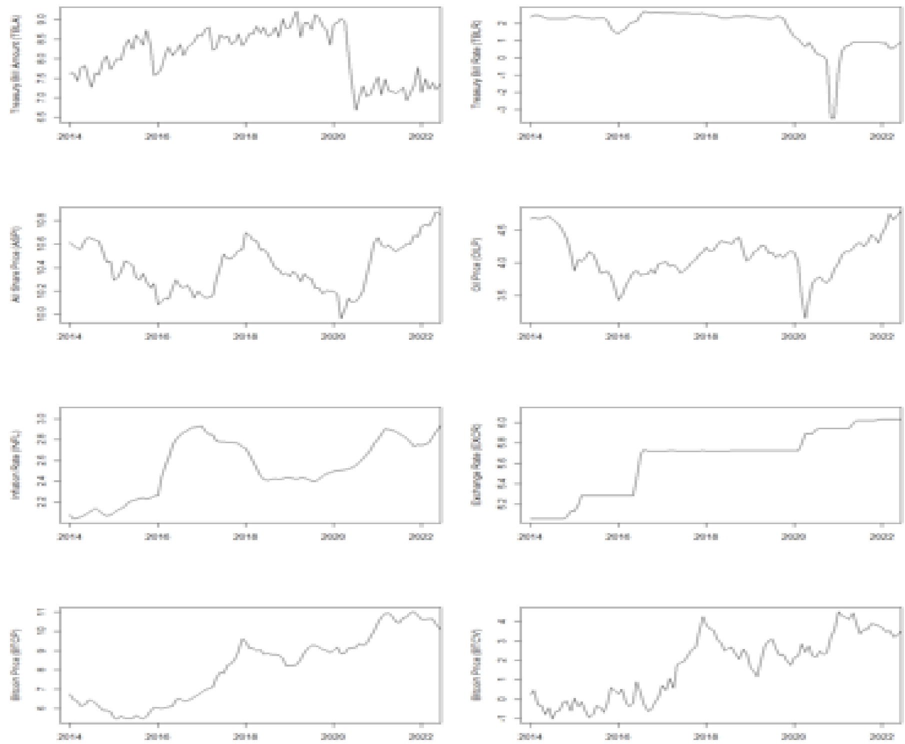
**Table 3: Sample Correlations**

| Variable | TBLA | TBLR | BTCP | BTCV | ASPI | INFL | EXCR | OILP |
|---|---|---|---|---|---|---|---|---|
| TBLA | 1.000 | | | | | | | |
| TBLR | **0.520** | 1.000 | | | | | | |
| BTCP | **-0.545** | **-0.670** | 1.000 | | | | | |
| BTCV | **-0.304** | **-0.491** | **0.831** | 1.000 | | | | |
| ASPI | **-0.494** | **-0.230** | **0.543** | **0.499** | 1.000 | | | |
| INFL | **-0.260** | **-0.227** | **0.510** | **0.484** | **0.305** | 1.000 | | |
| EXCR | **-0.187** | **-0.535** | **0.721** | **0.629** | **0.349** | **0.788** | 1.000 | |
| OILP | **-0.331** | -0.042 | **0.301** | **0.163** | **0.796** | -0.003 | 0.066 | 1.000 |

**Note:** Table 4 shows the Pearson correlation coefficients, $r_{x_1x_2}$, defined for linear correlation of a pair, $x_i$and $x_j$, having $n$-set $[(x_{1,1}, x_{2,1}),\ (x_{1,2}, x_{2,2}),\ ...,\ (x_{1,n}, x_{2,n})]$ with $r_{x_1x_2} = \sum_i^n (x_{1,t} - \bar{x}_1)(x_{2,t} - \bar{x}_2)\left[\sqrt{(x_{1,t} - \bar{x}_1)^2}\sqrt{(x_{2,t} - \bar{x}_2)^2}\right]^{-1}$, and the value lies between −1 and +1. A value of 0 means no correlation exists.

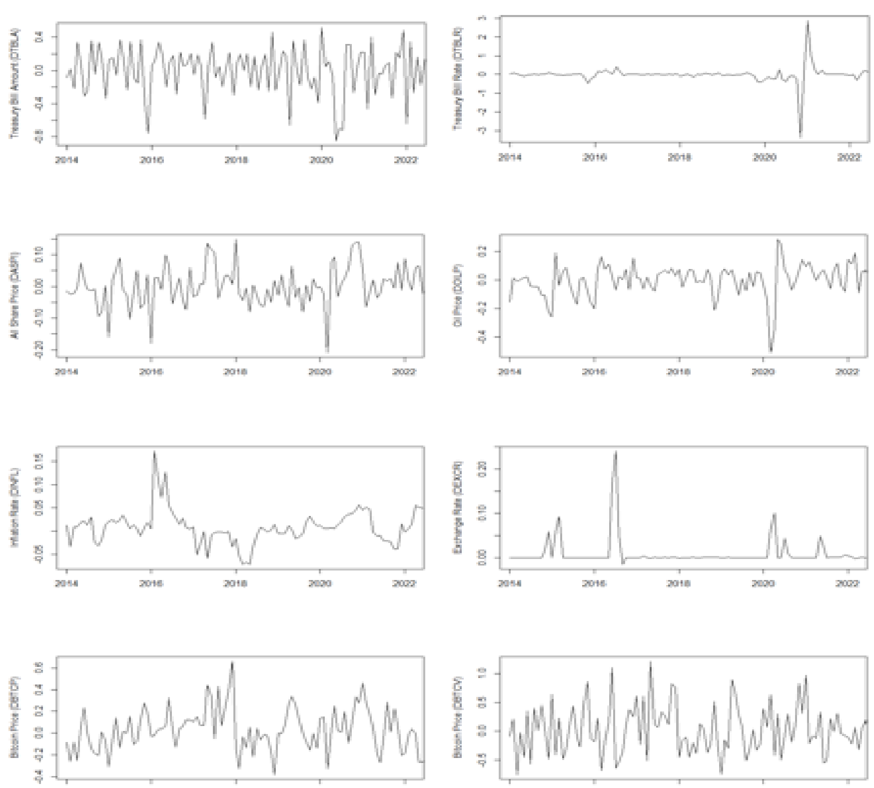
**Bold** value is significant coefficient using probability, $p|t| = 0$.

**Source:** Authors



**Note: Figure 1 shows the time plots for the variables in levels form.**

**Source: Authors (2024)**



**Note: Figure 2 shows the time plots for the variables in levels form.**

**Source: Authors (2024)**

**Table 4: Stationary Test**

| | Level Forms | | | | | | First Difference [Δ] | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | $\tau_\mu$ | 1% | 5% | 10% | $ADF_\alpha$ * | | $\tau_\mu$ | 1% | 5% | 10% | $ADF_\alpha$ * | | Remark |
| Test Includes Intercept without Time Trend | | | | | | | | | | | | | |
| TBLA | -2.29 | -3.49 | -2.89 | -2.58 | 0.176 | | -11.60 | -3.49 | -2.89 | -2.58 | 0.000 | | *I(1)* |
| TBLR | -1.93 | -3.49 | -2.89 | -2.58 | 0.316 | | -9.90 | -3.49 | -2.89 | -2.58 | 0.000 | | *I(1)* |
| BTCP | -0.98 | -3.49 | -2.89 | -2.58 | 0.758 | | -6.78 | -3.49 | -2.89 | -2.58 | 0.000 | | *I(1)* |
| BTCV | -1.45 | -3.49 | -2.89 | -2.58 | 0.557 | | -10.63 | -3.49 | -2.89 | -2.58 | 0.000 | | *I(1)* |
| ASPI | -1.59 | -4.05 | -3.45 | -3.15 | 0.791 | | -8.79 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| INFL | -1.41 | -3.50 | -2.89 | -2.58 | 0.577 | | -4.06 | -3.50 | -2.89 | -2.58 | 0.002 | | *I(1)* |
| EXCR | -1.54 | -3.50 | -2.89 | -2.58 | 0.510 | | -5.31 | -3.50 | -2.89 | -2.58 | 0.000 | | *I(1)* |
| OILP | -2.34 | -3.49 | -2.89 | -2.58 | 0.161 | | -7.56 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| Test Includes Intercept with Time Trend | | | | | | | | | | | | | |
| TBLA | -2.64 | -4.05 | -3.45 | -3.15 | 0.264 | | -11.58 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| TBLR | -2.19 | -4.05 | -3.45 | -3.15 | 0.489 | | -9.86 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| BTCP | -2.06 | -4.05 | -3.45 | -3.15 | 0.561 | | -6.75 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| BTCV | -2.48 | -4.05 | -3.45 | -3.15 | 0.338 | | -10.58 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| ASPI | -1.03 | -3.49 | -2.89 | -2.58 | 0.741 | | -8.66 | -3.49 | -2.89 | -2.58 | 0.000 | | *I(1)* |
| INFL | -1.92 | -4.05 | -3.45 | -3.15 | 0.640 | | -4.04 | -4.05 | -3.45 | -3.15 | 0.010 | | *I(1)* |
| EXCR | -2.08 | -4.05 | -3.45 | -3.15 | 0.553 | | -5.38 | -4.05 | -3.45 | -3.15 | 0.000 | | *I(1)* |
| OILP | -2.54 | -4.05 | -3.45 | -3.15 | 0.308 | | -7.48 | -3.49 | -2.89 | -2.58 | 0.000 | | *I(1)* |

Note: Null ($H_0$): Non-stationary, and $ADF_\alpha$: MacKinnon (1996) one-sided p-values

**Table 5: Lag Selection**

| Variable | Model | AIC* | BIC | HQ | $\bar{R}^2$ | Specification |
|---|---|---|---|---|---|---|
| TBLA | 52 | -0.127 | 0.546 | 0.152 | 0.975 | ARDL(1, 4, 5, 2, 1, 0, 0)** |
| | 497 | -0.117 | 0.422 | 0.106 | 0.974 | ARDL(1, 3, 3, 3, 0, 2, 1) |
| | 593 | -0.116 | 0.522 | 0.149 | 0.975 | ARDL(1, 4, 3, 4, 3, 2, 2) |
| | 169 | -0.115 | 0.523 | 0.150 | 0.975 | ARDL(2, 4, 4, 2, 2, 1, 2) |
| | 288 | -0.114 | 0.491 | 0.137 | 0.975 | ARDL(1, 5, 3, 2, 3, 1, 2) |
| | | | | | | |
| TBLR | 68 | -0.131 | 0.648 | 0.180 | 0.980 | ARDL(3, 3, 2, 1, 0, 0, 0)** |
| | 105 | -0.118 | 0.501 | 0.126 | 0.979 | ARDL(1, 4, 3, 1, 2, 2, 2) |
| | 288 | -0.111 | 0.621 | 0.177 | 0.980 | ARDL(3, 2, 4, 2, 1, 1, 0) |
| | 522 | -0.109 | 0.622 | 0.178 | 0.980 | ARDL(2, 5, 3, 3, 0, 2, 1) |
| | 691 | -0.106 | 0.547 | 0.149 | 0.979 | ARDL(3, 4,2, 4, 3, 1, 0) |

**Table 6: Cointegration Bounds Test**

| C.B.V. (5%) | I0 Bound | I1 Bound | I0 Bound | I1 Bound |
|---|---|---|---|---|
| 10% | 2.704 | 3.142 | 2.991 | 3.865 |
| 5% | 3.218 | 4.120 | 3.492 | 4.403 |
| 2.50% | 3.484 | 4.288 | 3.968 | 4.930 |
| 1% | 4.119 | 5.127 | 4.566 | 5.556 |
| $F_m$ | 8.738 | $m$ = 4 | 9.569 | $m$ = 4 |

**Note:** Null ($H_0$): No long-run relationships exist

**Source:** Authors

**Table 7: ARDL Model for Treasury Bill Amounts**

| Variable | Coefficient | Std. Error | t-stat |
|---|---|---|---|
| C | 9.193 | 4.269 | 2.153 |
| TBLA(-1) | 0.748 | 0.064 | 11.735 |
| BTCP | -0.004 | 0.002 | -2.019 |
| BTCP(-1) | -0.468 | 0.132 | -3.533 |
| BTCP(-2) | -0.495 | 0.308 | -1.609 |
| BTCP(-3) | -0.252 | 0.140 | -1.803 |
| BTCP(-4) | -0.535 | 0.204 | -2.621 |
| BTCV | 0.096 | 0.024 | 4.003 |
| BTCV(-1) | 0.063 | 0.024 | 2.596 |

| | | | |
|---|---|---|---|
| BTCV(-2) | -0.051 | 0.101 | -0.502 |
| BTCV(-3) | 0.110 | 0.101 | 1.088 |
| BTCV(-4) | 0.022 | 0.101 | 0.216 |
| BTCV(-5) | 0.235 | 0.076 | 3.100 |
| ASPI | 0.279 | 0.050 | 5.630 |
| ASPI(-1) | 0.230 | 0.069 | 3.330 |
| ASPI(-2) | 0.848 | 0.442 | 1.917 |
| OILP | 0.180 | 0.051 | 3.551 |
| OILP(-1) | 0.924 | 0.325 | 2.840 |
| INFL | -0.123 | 0.035 | -3.495 |
| EXCR | -0.380 | 0.191 | -1.990 |
| Test | | | |
| $\bar{R}^2$ | 0.872 | | |
| F-stat. | 26.02 | | |
| Prob(F-stat.) | 0.000 | | |
| DW | 2.105 | | |

**Source:** Authors

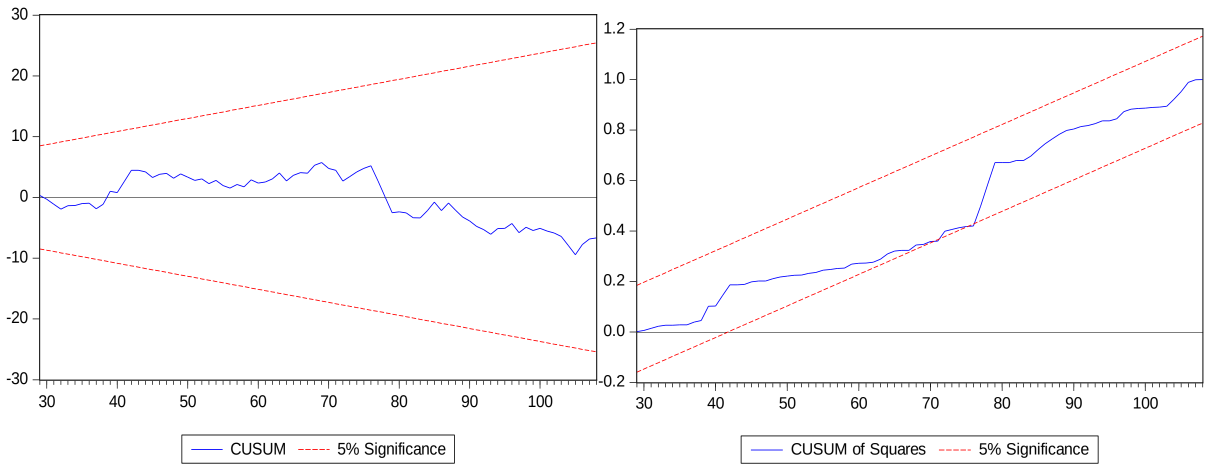
**Table 8: ARDL for Treasury Bill Rates (LTBLR)**

| Variable | Coefficient | Std. Error | t-stat |
|---|---|---|---|
| C | 2.589 | 4.603 | 0.562 |
| TBLR(-1) | 0.985 | 0.098 | 10.081 |
| TBLR(-2) | -0.667 | 0.129 | -5.155 |
| TBLR(-3) | 0.442 | 0.093 | 4.755 |
| BTCP | -0.059 | 0.279 | -0.211 |
| BTCP(-1) | 0.075 | 0.378 | 0.198 |
| BTCP(-2) | 0.003 | 0.376 | 0.007 |
| BTCP(-3) | -0.483 | 0.235 | -2.060 |
| BTCV | -0.039 | 0.122 | -0.316 |
| BTCV(-1) | 0.161 | 0.132 | 1.220 |
| BTCV(-2) | 0.243 | 0.112 | 2.167 |
| ASPI | -1.493 | 0.657 | -2.274 |
| ASPI(-1) | -0.443 | 0.913 | -0.485 |
| ASPI(-2) | 0.252 | 0.906 | 0.279 |
| ASPI(-3) | 1.235 | 0.652 | 1.895 |
| OILP | 0.980 | 0.336 | 2.922 |

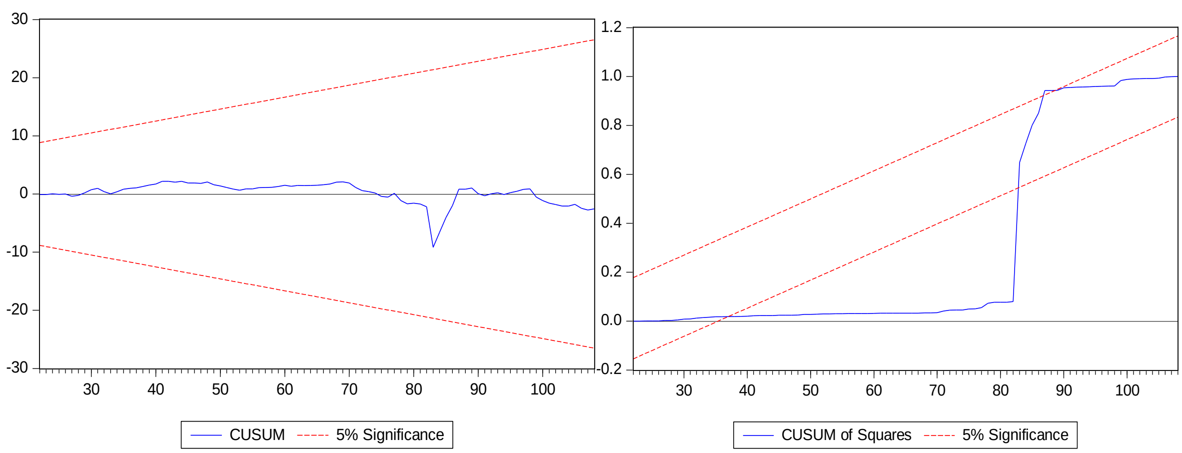
| | | | |
|---|---|---|---|
| INFL | 0.635 | 0.299 | 2.123 |
| EXCR | -0.004 | 0.507 | -0.007 |
| Test | | | |
| $\bar{R}^2$ | 0.904 | | |
| F-stat. | 48.11 | | |
| Prob(F-stat.) | 0.000 | | |
| DW | 1.967 | | |

**Source:** Authors

A: CUSUM B: CUSUM Square




**Note:** Figure 3 is the CUSUM [Panel A] and the CUSUM Square [Panel B] for the ARDL Model for Treasury Bill Amounts Equation Estimation.




**Source:** Authors

**Note:** Figure 4 is the CUSUM [Panel A] and the CUSUM Square [Panel B] for the ARDL Model for Treasury Bill Rates Equation Estimation.

**Source:** Authors

## 5. CONCLUSIONS

During the last decade, a wide range of digital currencies have emerged. The study reviews the benefits and challenges of cryptocurrencies in Nigeria. We apply the linear Transfer Function and ARDL model to examine the effects of selected cryptocurrencies on the financial system with specific focus on the money market in Nigeria. The outcome shows the variables are non-stationary at levels and integrated. The bound tests reject the null of no cointegration at 5% significance for the treasury bill amounts and treasury bill rates equations, thus established equilibrium relationship between treasury bill amounts and the regressors.

The result shows that the treasury bill transaction amount is explained by its own past, as well as other considered variables. A 1% increase in bitcoin price would result in 0.004% decrease in the volume of transaction of the treasury bill. Also, a 1% increase in bitcoin traded transaction will result in a 0.096% decrease in the money market treasury bill. Regarding the treasury bill rates, the result identified that the treasury bill rate is also explain by own past and other considered variables. A 1% t increase in bitcoin price would result in 0.059% decrease in the treasury bill rates. Lastly, bitcoin volume would result in significant decrease in treasury bills rates in line with expectation. A 1% increase in bitcoin traded transaction will result in a 0.039% decrease in treasury bill rates. Thus, the study contributes to the existing literature by providing how the financial transactions in the cryptocurrency market are drives price discovering in the financial markets in Nigeria. The findings open room for future research since the study is limited to only few financial markets in Nigeria.

## REFERENCES

Aalborg H. A., Molnar, P., & Erik de Vries, J. (2018). What can explain the price, volatility and trading volume of Bitcoin? *Finance Research Letters.* doi: https://doi.org/10.1016/j.frl.2018.08.010.

Matkovskyy, R. *&* Jalan, A. (2019). From financial markets to bitcoin markets: A fresh look at the contagion effect. *Finance Research Letters* 31, 93–97.

Mikhaylov, A., (2020). Cryptocurrency market analysis from the open innovation perspective. *Journal of Open Innovative Technology Mark. Complex.* 6 (4): 197. https://doi.org/10.3390/joitmc6040197.

Gbadebo, A. D., Adekunle, A.O., Adedokun, W., Lukman, A. A., & Akande, J. O. (2021) BTC price volatility: Fundamentals versus information, Cogent Business & Management, 8:1, DOI: 10.1080/23311975.2021.1984624

Ciaian, P., Rajcaniova, M., and Kancs, D. A. (2016). The economics of Bitcoin price formation. Applied Economics 48 (19): 1799–1815.

Dyhrberg, A.H., Foley, S., Svec, J., 2018. How investible is Bitcoin? Analyzing the liquidity and transaction costs of bitcoin markets. Econ. Lett. 171, 140–143.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? Journal of International Financial Markets, Institutions and Money, 54, 177–189.

Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). Bitcoin: Safe haven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation—A stochastic volatility approach. Physica A: Statistical Mechanics and Its Applications, 524, 246–257.

*Pagliery, J. (2014). Bitcoin: And the Future of Money. Triumph Books. ISBN 978-1629370361. Archived from the original on 21 January 2018. Retrieved 20 January 2018.*

*Milutinović, M. (2018). Cryptocurrency. Ekonomika.* ***64*** *(1): 105–122. doi:10.5937/ekonomika1801105M. ISSN 0350-137X. Archived from the original on 16 April 2022. Retrieved 18 April 2022.*

Bech M, R Garratt (2017) 'Central Bank Cryptocurrencies', BIS Quarterly Review September 2017, Bank for International settlements

Bartoletti, M., Carta, S., Cimoli, T., & Saia, R. (2017). Dissecting Ponzi schemes on Ethereum: identification, analysis, and impact. Retrieved from: https://arxiv.org

Financial Stability Board (2024). Crypto-assets and Global Stablecoins. Retrieved from: https://www.fsb.org/work-of-the-fsb/financial-innovation-and-structural-change/crypto-assets-and-global-stablecoins/

Aalborg H. A., Molnar, P., & Erik de Vries, J. (2018). What can explain the price, volatility and trading volume of Bitcoin? *Finance Research Letters.* doi: https://doi.org/10.1016/j.frl.2018.08.010.

Acharya, S., Thomas, A., & Pani, B. (2018). Volatility of Bitcoin and its implication to be a currency. *International Journal of Engineering Technology Science and Research* 5 (1): 1017–1024.

Adkins, T. (2019). Calculating volatility: A simplified approach. www.investopedia.com/.

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economic Letters* 161,1-4.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189.

Baur, D., Cahill, D., Godfrey, K., & Liu, Z., (2019). Bitcoin time-of-day, day-of-week and month-of-year effects in returns and trading volume. *Finance Research Letters.* 31, 78–92.

Bitcoinwiki, 2014, Bitcoin History, https://en.bitcoinwiki.org/wiki/Bitcoin_history.

Böhme, R., Christin, N., Edelman, E., & Moore, T. (2015). Bitcoin: economics, technology, and governance. *Journal of Economic Perspectives*. 29 (2): 213–238. doi:10.1257/jep.29.2.213.

Borensztein, E., J. De Gregorio and J.-W. Lee, 1998. How does FDI affect economic growth. *Journal of International Economics,* 45(1): 115-135.

Bouoiyour, J., & Selmi, R. (2015). What does Bitcoin look like? *Annals of Economics and Finance,* 16(2), 449-492.

Bouri, E., Gupta, R., Lau, C.K.M., Roubaud, D., Wang, S. (2018). Bitcoin and global financial stress: A copula-based approach to dependence and causality in the quantiles. *Quarterly Review of Economics and Finance* 69, 297–307.

Boyte-White, C. 2020 What Is the Best Measure of Stock Price Volatility?, www.investopedia.com.

Cheah, E.T., *&* Fry, J. (2015). Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. *Economics Letters* 130, 32–36.

Chowdhury, A. (2014). Is Bitcoin the 'Paris Hilton' of the Currency World? Or are the early investors onto something that will make them rich? Department of Economics, College of Business Administration, Marquette University.

Clement, J. (2020). Market shares of search engines 2010 – 2020. Statista.

Corbet, S., Lucey, B. *&* Yarovaya, L. (2018). Datestamping the bitcoin and ethereum bubbles. Finance Research. Letters 26, 81–88.

Dufour, A., & Engle, R. F., 2000. Time and the price impact of a trade. J. of Finance 55, 2467–2498

Dwyer, G. P. (2015). The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability* 17: 81–91.

Eross, A., McGroarty, F., Urquhart, A., Wolfe, S. (2019). The intraday dynamics of bitcoin. Res. Int. Bus. Finance 49, 71–81.

Finance.yahoo.com (2021), quote/BTC-USD, https://finance.yahoo.com/quote/BTC-USD/.

Goutte, S., Guesmi, K., & Saadi, S., (2019). Crypto finance and mechanisms of exchange: The Making of Virtual Currency. Springer Edition. ISBN 978-3-030-30738-7.

Guizani, S. *&* Nafti I. K. (2019). The determinants of bitcoin price volatility: an investigation with ardl model. *Procedia Computer Science,* 164 (2019) 233–238.

Hughes, A, Park A, Kietzmann, J *&* Archer-Brown, C (2019). Beyond bitcoin: What blockchain and distributed ledger technologies mean for firms, Kelley School of Business, Indiana University , Business Horizons (2019) 62, 273—281.

Hung, J., Liu, H. *&* Yang, J.J. (2020). Improving the realized GARCH's volatility forecast for Bitcoin with jump-robust estimators, *North American Journal of Economics and Finance* 52 (2020) 10116.

Jain, P., Jiang, C., 2014. Predicting future price volatility: Empirical evidence from an emerging limit order market. Pacific-Basin Finance Journal 27, 72–93.

Jeon, Y, Samarbakhsh, L *&* Hewitt, K. (2020). Fragmentation in the Bitcoin market: Evidence from multiple coexisting order books. *Finance Research Letters*. doi: https://doi.org/10.1016/j.frl.2020.101654.

Jiang, Y., Cao, Y., Liu, X., & Zhai, J. (2019). Volatility modelling and prediction: the role of price impact.

Ji, Q, Bouri, E., Kristoufek, L *&* Lucey, B (2019). Realised volatility connectedness among Bitcoin exchange markets. *Finance Research Letters.* doi: https://doi.org/10.1016/j.frl.2019.101391.

Julio C.S. (2017). Analyzing Bitcoin Price Volatility. University of California, Berkeley, https://www.econ.berkeley.edu/sites/default/files/Thesis_Julio_Soldevilla.pdf.

Kennedy, P. (2008). A Guide to Econometrics. 6th Edition, Wiley-Blackwell.

Kevin H. (2019). 23 Central banks divulge their digital currency requirements. https://news.bitcoin.com/23-central-banks-divulge-their-digital-currency-requirements/.

Kharpal, A, (2020). In a world where central banks issue digital currencies, bitcoin and Libra may find a place, *Consumer News and Business Channel*, https://www.cnbc.com/2020/08/20/.

Kjærland, F., Khazal, A., Krogstad, E. A., Nordstrøm, F. B. G & Oust, A. (2018). An Analysis of Bitcoin's Price Dynamics. *Journal of Risk and Financial Management.*

Koopman, S.J., Jungbacker, B. & Hol, E. (2005). Forecasting daily variability of the S&P 100 stock index using historical, realised and implied volatility measurements. *Journal of Empirical Finance* 12 (3), 445–475.

Kristoufek, L. (2018). On Bitcoin markets (in) efficiency and its evolution. Physica A: Statistical Mechanics and its Applications 503: 257– 262.

Kurka, J., (2019). Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters* 31, 38–46.

Lahmiri, S., S. Bekiros & A. Salvi. (2018) Long-range memory, distributional variation and randomness of bitcoin volatility. *Chaos, Solitons and Fractals* 107,43-48.

Laszlo, H. (2014), https://en.bitcoin.it/wiki/Laszlo_Hanyecz.

Li, X., & Wang, C. A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. *Decision Support Systems* 95: 49–60.

Matkovskyy, R. & Jalan, A. (2019). From financial markets to bitcoin markets: A fresh look at the contagion effect. *Finance Research Letters* 31, 93–97.

Mikhaylov, A., (2020). Cryptocurrency market analysis from the open innovation perspective. *Journal of Open Innovative Technology Mark. Complex.* 6 (4): 197. https://doi.org/10.3390/joitmc6040197.

Nadarajah, S. & Chu, J., 2017. On the inefficiency of bitcoin. *Economics Letters.* 150, 6–9.

Nathan R. (2019). 20% of all bitcoin price is lost and unrecovered. *Investopidia*, June 25, 2019.

O'Hara, M. (2015). High frequency market microstructure. *J. Financial Economics* 116(2),257–270.

Pesaran, M. & Shin, Y. (1999), An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis. in S. Strom, (ed) Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch centennial Symposium, Cambridge University Press.

Pesaran, M., Shin, Y. & Smith, R.J. (2001) Bounds testing approaches to the analysis of level relationship. *Journal of Applied Economics* 16: 289-326.

Poyser, O. (2017). Exploring the determinants of Bitcoin's price: an application of Bayesian Structural Time Series. Monograph.

Pyo, S. & Lee, J. (2019). Do FOMC and macroeconomic announcements affect Bitcoin prices? *Finance Research Letters* doi: https://doi.org/10.1016/j.frl.2019.101386.

Sam, C.Y., Mcnown, R. & Goh, S.K. (2018). An augmented Autoregressive Distributed Lag bounds test for cointegration, *Economic Modelling*. doi: https://doi.org/10.1016/.

Selgin, G., (2015). Synthetic commodity money. *Journal of Financial Stability*. 17, 92–99.

Silva, P., Klotzle, M., Pinto, A. & Gomes, L. (2019) Herding behavior and contagion in the cryptocurrency market. *Journal of Behavioural Finance* 22, 41–50.

Smales, L.A. (2019). Bitcoin as a safe haven: Is it even worth considering? *Finance Research Letters* 30, 385–393.

Taylor, B. M. (2017). The evolution of bitcoin hardware. *Computer* 50 (9) 58–66, https://doi.org/10.1109/MC.2017.3571056.

Terence C. M. (2019), Applied Time Series Analysis: A Practical Guide to Modeling and Forecasting, Loughborough University, Loughborough, United Kingdom, Academic Press

Troster, V., Tiwari, A.K., Shahbaz, M. & Macedo, D.N. (2018). Bitcoin returns and risk: a general GARCH and GAS analysis. Finance Res. Lett Article in Press.