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Dynamics of Foreign Exchange Rates and Bitcoin Trading Prices

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Authors' contributions

This work was carried out in collaboration among all authors. The conception, methodology, validation, data issues, and software were handled by author DU, while the literature and formal analysis was done by authors BI, IAS, and MAO. All authors read and approved the final manuscript.

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ABSTRACT

The study examined the volatility of Bitcoin prices and volatility of exchange rates of oil-producing countries. The study used ARIMA, GARCH estimators for analysis. The study found ARCH effects in the data (heterskedasticity test; p<.05). The GARCH results laid credence to a confirmation of adjustments in the Bitcoin market having significant volatility influence on local currencies. Persistent volatility and volatility clustering found in some of the sampled countries denote increased risk and uncertainty in foreign exchange markets that stimulates increased borrowing costs and reduced liquidity. The actual and forecast values based on the ARIMA method match with an Out-of-Sample period plotted for forecast (27/12/2022 to 27/12/2024) except for Nigeria. The ARIMA models for UAE and Kuwait stand out with excellent fit and prediction accuracy. The poor ARIMA model for Nigeria was ascribed to the hyper-inflation in the economy and extremely volatile money market. In line with the efficient market hypothesis, significant interactions are

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pegged on available information being already reflected in the current value of the currencies. In effect, past currency rates and Bitcoin trading prices are useful predictors of future prices having factored in the relevant information that could influence currency's value. In addition, future values of local currencies can be forecasted from past values at a significant level of accuracy. Countries should ensure adequate regulation of the foreign exchange markets so as to curtail the wave of volatility risks on returns associated with Bitcoin trading and exchange rates.

Keywords: ARIMA; local currency rates; bitcoin prices; out-of-sample forecast; persist volatility; risk and uncertainty.

JEL Classification: D19, B42, C20.

1. INTRODUCTION

This study is embraced by two currency markets (Bitcoin, and foreign exchange). The common qualities of these markets include risks and returns that could be influenced by internal forces within and outside the domains. Bitcoin is digital money which is circulated, and traded via a decentralized system known as block chain for the payment of transactions across the borders of the stock market. Bitcoin is not governed like the regulation of fiat or paper money such as the US Dollar, Euro, and Japanese Yen by the central monetary authorities. Rather, it is safeguarded by its proof of work (POW) agreement which otherwise is known to as the mining process that brings fresh Bitcoin into the system. Given that the total value of all Bitcoin stocks is the number of Bitcoin stocks outstanding multiplied by the market value of a Bitcoin, the market valuation of Bitcoin is the largest amongst other crypto currencies. Though, volatility is a shock from prices of commodities [1], the financial market is known to be volatile. By this extension, the variation in the exchange rate persistently disrupt the stability of prices and consequently make the general economy sensitive to volatility of returns and risks. This puts financial markets to diverse risks and returns which consequently either raises the value of Bitcoin or the US dollar throughout the globe [2-7].

Bitcoin currently occupies a powerful position in the market for currency exchange [8]. In spite of the homogeneity that characterized both the digital and forex markets, an investor would always seek to maximize returns and reduce risk [9-15]. Hence, the degree of risks and returns connected with any investments and other criteria determine a great deal of the decision taken by the investors. Investors endeavor to get the entire knowledge of the market, whether digital currency market (Bitcoin) or traditional foreign exchange (forex) market, yet the nature of information available to the market participants needs to be examined empirically [16-18]. Accordingly, investigating the interactions between foreign exchange rates and Bitcoin trading values for countries with diversity of economic and regional structures is timely and relevant in line with the following hypothesis tested in this study: H_{01}*: Adjustments in the Bitcoin market do not have significant influence on volatility of local currencies.* H_{02}*: Previous currency values are not significant predictors of future currency values in selected countries.*

Empirically, while appreciating the contributions of Bensaida [19], Jin, Li & Li [20], Attarzadeh & Balcilar [21], Conlon & McGee [22],Youssef & Mokni [23] and those mentioned above, this study further contributes to the empirical literature on the interaction dynamics between volatility of Bitcoin, and exchange rates of Brazil, Canada, China, Egypt, Libya, Nigeria, Norway, United Arab Emirates, Kuwait, and Mexico. While some researchers like Gomez & Patel (2022) have begun to explore Bitcoin's impact on emerging market currencies, their analyses is not mostly recent.

This research cut across several fields, including data science, finance, and economics. By demonstrating how contemporary market instruments, like Bitcoin, react to and interact with conventional financial markets in the economies of ten oil-producing countries with diverse economic structures, this study offers empirical insights to the scientific community [24-28]. The correlation and possible hazards of digital currencies are brought to light by the examination of Bitcoin's volatility in relation to other currencies [29-34]. The scientific community can benefit from the research findings. The study adds empirical information about the volatility of Bitcoin and exchange rates across national boundaries. Empirically, the study explores the nexus between Bitcoin volatility and the volatility of exchange rates in various countries and validates Bitcoin as a decentralized digital currency that is highly priced and volatile, impacting price stability and, by extension, the sensitivity of the economy. This research is highly significant for the investment and business world as it addresses the complex interplay between exchange rate volatility and the volatility of Bitcoin trading values, particularly in economically unstable countries like Nigeria. Utilizing sophisticated econometric models like GARCH and ARIMA and incorporating graphical trend analysis, the study offers valuable insights into the predictive challenges and economic impacts of currency fluctuations and the financial effects of exchange rate swings. Furthermore, the graphical trend analysis strengthens the research's overall robustness by supplementing the quantitative findings [35-39]. Hence, the analytical rigour offers valuable insights about the interrelationships and volatility of financial markets. The results highlight the need for more flexible forecasting models and better foreign currency market management, which can help investors and governments navigate volatility and reduce related risks. In the field of financial stability in the context of digital currency and currency forecasting, the study provides a thorough approach to a critical research problem and has the potential to direct future research and policy development [40-44]. The next section is a review of relevant literature. In section three, the methodology of the study was discussed. Section four provides the empirical estimations and discussion of results while section five provides the conclusion.

2. LITERATURE REVIEW

2.1 Theoretical Review

There are a host of other theories that can be used to situate the relationship between the Bitcoin price and exchange rate return. However, we have chosen to focus the theoretical review on only three of them. These include safe haven asset theory (SHAT), portfolio diversification theory (PDT), and currency substitution theory (CST). According to the SHAT, investors tend to seek out safe-haven assets during times of economic uncertainty or financial crisis. These assets are thought to either maintain or increase their value during market downturns, providing a form of protection or insurance against losses. The PDT is a financial and investment theory presented by Markowitz (1952). This theory is a cornerstone of modern portfolio theory (MPT), which posits that investors can optimize their portfolios based on expected return and risk. The PDT suggests that by diversifying their investments across a variety of assets, investors can maximize their expected return at a given level of risk. This is because different assets often have different risk-return profiles and are not perfectly correlated. By holding a diversified portfolio, investors can reduce their exposure to individual asset risk and take advantage of potential gains across different asset classes. Bitcoin, with its unique properties and relatively low association with traditional assets, can serve as a diversification tool in an investment portfolio [45-50]. In emerging economies where exchange rate movements can be significant, Bitcoin may be seen as a way to hedge against currency risk. When a domestic currency devalues, the value of Bitcoin, classically denominated in U.S. dollars, rises in local currency terms. This potential for increased return boosts the demand for Bitcoin as a diversification tool, leading to increased demand [51]. The CST, also known as dollarization, is a theory in finance that describes a situation where individuals prefer using a foreign currency over the domestic currency. Currency substitution typically occurs when a domestic currency loses its credibility due to factors such as high inflation, economic instability, or significant depreciation [52-56]. In such situations, individuals might prefer to use a more stable foreign currency for transactions, savings, and as a store of value. Bitcoin, with its decentralized nature and global accessibility, can serve as a form of currency substitution. Moreover, the CST also encompasses the concept of risk, and Bitcoin is known for its high price volatility, which represents a level of risk [57].

2.2 Empirical Review

Several studies have focused on the connection between the Bitcoin market and foreign exchange market volatility risks and rewards among the oil-producing nations in developing countries. Gomez & Chiang (2024) investigated the link between Bitcoin returns and the exchange rate movements of the New Taiwan Dollar (TWD/USD). They used the Structural Breaks GARCH model to analyze the impact of Bitcoin market dynamics on the TWD from 2022 to 2024, particularly focusing on periods marked by significant technological advancements in the block chain and regulatory shifts in Taiwan. Their findings indicate that Bitcoin exerts a stabilizing influence on the TWD during periods of technological innovation but introduces volatility during regulatory upheavals, suggesting a dual role for Bitcoin dependent on external economic and political factors. Patel & Morris [58] focused on the spillover effects between Bitcoin trading returns and the Euro (EUR/USD) during periods of European banking stress. Employing a spillover index approach, they analyzed data from 2022 to 2024, particularly focusing on how crises in the banking sector influence the correlation between Bitcoin and the Euro. Their findings indicate that during banking crises, Bitcoin trading returns tend to correlate negatively with EUR/USD movements, suggesting that investors might turn to Bitcoin as a hedge against traditional banking risks. This relationship highlights the growing role of cryptocurrencies as alternative financial assets during times of traditional financial system instability. Patel & Kim [59] explored the returns on Bitcoin trading in relation to the movements in emerging market currencies, focusing specifically on the Brazilian Real (BRL) and the Indian Rupee (INR). Using a Vector Error Correction Model (VECM) to account for the long-term equilibrium relationships and short-term dynamics, they analyzed transaction data from 2022 to 2024. The study revealed that Bitcoin exhibits significant lead-lag relationships with these currencies, particularly in response to their economic indicators and policy changes. Interestingly, the research found that returns on Bitcoin trading often anticipate adverse macroeconomic events in these economies, potentially serving as an early warning system for forex traders. Thompson & Zhao [60] focused on the interrelationship between Bitcoin trading returns and the exchange rate movements of the British Pound (GBP) against the US Dollar (USD). Utilizing a multivariate GARCH model, they sought to capture the volatility spillover effects between these markets, analyzing data from 2022 to 2024. Their findings suggest that increased volatility in Bitcoin returns significantly influences the GBP/USD exchange rate, particularly in light of Brexit-related economic uncertainties. The study also noted that the influence of Bitcoin on the GBP tends to be more pronounced during times of political or economic news that directly impacts the UK economy, suggesting that Bitcoin's market dynamics are closely intertwined with local economic events in the UK. Ivanova & Schmidt [61] analyzed the relationship between Bitcoin returns and the exchange rate movements of the Swiss Franc (CHF) against the Euro (EUR). They used a Bayesian Vector Autoregression (BVAR) model, which allowed for incorporating prior information and uncertainty in model specifications. The study covered data from 2021 to 2023, highlighting that during periods of financial instability in the Eurozone, Bitcoin returns exhibited a predictive relationship with CHF/EUR movements. This correlation suggests that investors may perceive Bitcoin as a safer asset compared to the Euro, influencing the CHF's strength as a safe haven. Kim & Park (2024) studied the effects of Bitcoin returns on the exchange rate movements of the South Korean Won (KRW) against the US Dollar (USD). They utilized an asymmetric BEKK-GARCH model to capture the conditional heteroskedasticity and the potential asymmetry in the volatility spillover between the two markets. Analysing data from 2022 to 2024, they discovered that positive shocks in Bitcoin returns tend to have a more pronounced effect on the KRW/USD exchange rate than negative shocks [62-65]. This asymmetry indicates that while positive developments in Bitcoin are seen as beneficial for the KRW, adverse movements in Bitcoin may not necessarily harm the KRW to the same extent, possibly due to the hedging actions of market participants. Gupta & Lee [66] focused on the volatility spillovers between Bitcoin trading returns and the South African Rand (ZAR) against the US Dollar (USD). Using the spillover index approach developed by Diebold and Yilmaz, they analyzed how innovations in Bitcoin's market affect ZAR/USD exchange rate fluctuations. Covering the period from 2019 to 2022, their results showed significant spillovers during times of political uncertainty in South Africa and regulatory changes in cryptocurrency markets globally. This study highlights the growing influence of digital currencies on emerging market currencies, particularly in contexts of national and global uncertainties. Baxter & Singh (2023) focused on the volatility transmission between Bitcoin returns and the Swiss Franc (CHF/USD). Employing a Dynamic Conditional Score (DCS) model, they explored how innovations in Bitcoin’s price influenced CHF/USD exchange rates from 2019 to 2022. The study revealed that Bitcoin has become an increasingly significant factor in forex volatility, particularly for currencies like the Swiss Franc, which are considered safe havens during global financial turmoil. The findings suggest that Bitcoin may be starting to parallel the behaviour of traditional safe havens in times of economic stress. Thompson and Raj (2023) explored the spillover effects between Bitcoin trading returns and the South African Rand (ZAR/USD), focusing on how changes in Bitcoin's market dynamics influence the ZAR during commodity price fluctuations, especially in the gold and diamond sectors. Employing a cross-quantitative analysis, they examined data from 2021 to 2023. Their results revealed that the ZAR is particularly sensitive to Bitcoin's fluctuations, with stronger effects observed during periods when the prices of key commodities are volatile [67-71]. This study highlights the growing interconnection between digital currencies and commodity-dependent traditional currencies.

2.3 Closing the Research Gap

The gap in the reviewed literature can be explained as follows: None of the studies reviewed above on the relationship between Bitcoin and exchange rate movement were specifically done for countries that import and export oil simultaneously. Also, none of the studies estimated the ARIMA estimation methodology. This therefore forms the research gap the present study fills.

3. METHODOLOGY

The research makes use of the ARIMA and GARCH methods. The ARIMA technique was used to test the hypothesis that previous currency values are not significant predictors of future currency values in selected countries. Moreover, the ARIMA method is predominantly useful for non-stationary datasets, which is common in financial time series such as Bitcoin price fluctuations and exchange rate movements. Using ARIMA in the frequency domain allows the researchers to capture both short-term fluctuations and long-term trends in exchange rate relative to Bitcoin price fluctuation, and the lags of exchange rate. We specified the ARIMA model for the exchange rate variable in relations to its lagged values and each country's Bitcoin price. Since ARIMA is generalization of ARMA,

we thus specified the ARMA(p,q) model by specifying AR(p) and MA(q) equations independently and later combine them as follows:

Autoregressive order p[AR(p)] : $yt = \mu_1 y_{t-1} + \mu_2 y_{t-2} + . . . + \mu_p y_{t-p} + v_t$ (1)

Moving average of order q[MA(q)]: $yt = e_t - C_1 e_{t-1} - C_2 e_{t-2} - . . . - Cq e_t\text{-}q$ (2)

The combined ARMA(p,d,q) model is specified thus:

ARMA(p,d,q): $yt = c + \mu_1 y_{t-1} + \mu_2 y_{t-2} + . . . + \mu_p y_{t-p} + e_t - C_1 e_{t-1} - C_2 e_{t-2} - . . . - Cq e_t\text{-}q$ (3)

Using the relevant study variables, the ARIMA model specification becomes:

ARIMA (4,1,4) $EXR_t = c + \alpha_1 d(EXR)_{,t-1} + \alpha_2 d(EXR)_{,t-2} + \alpha_3 d(EXR)_{,t-3} + \alpha_4 d(EXR)_{,t-4} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \theta_3 e_{t-3} + \theta_4 e_{t-4}$ (4)

where the dependent variable is y*t*, which represents exchange rate variable at time *t*, and our set of exogenous variables which includes the lagged values of effective exchange rate, and the prices of Bitcoin. Where *c* is a constant term, α_1 ,..., α_4 are the coefficients for the autoregressive terms, *p* is the number of autoregressive terms (lags of the dependent variable), *q* is the number of moving average terms, θ_1 ,..., θ_4 , are the coefficients for the moving average terms, *d* is the degree of differencing required to make the time series stationary. To test volatility, the study employed GARCH models. In particular, the GARCH estimation was conducted to test the hypothesis that adjustments in the Bitcoin market do not have significant influence on volatility of local currencies. The typical GARCH (1,1) model has a conditional mean equation specified as:

$$EXR_{it} = E(EXR_{it} \,|I_{t-1}) + \, e \quad (5)$$

where: $\mathrm{E(EXR_{it}\,|I_{t-1})}$ is the conditional expected exchange rate returns; e is conditional heteroscedastic error. The GARCH (1,1) conditional variance equation is given as:

$$\sigma^2_{EXRt} = \beta_0 + \sum_{i=1}^{1} \beta_i e^2_{t-i} + \sum_{j=1}^{1} \gamma_j \, \sigma^2_{EXRt-j} \quad (6)$$

where: $\sum_{j=1}^{1} \gamma_1 \sigma^2_{EXRt-j}$ is the GARCH term, $\sum_{i=1}^{1} \beta_i e^2_{t-i}$ is the ARCH term. For the years 2020 to 2023, the research uses daily historical data on the prices of Bitcoin, and exchange rates from ten (10) nations that import and export oil, namely: Brazil, Canada, China, Egypt, Libya, Nigeria, Norway, United Arab Emirates, Kuwait and Mexico. The choice of these countries was borne out of the diversity of economic and regional structures that they represent with a mix of advanced economies (Canada, Norway), emerging markets (Brazil, China, Mexico), and developing economies (Nigeria, Libya); and a diversification or regions; North America (Canada, Mexico), South America (Brazil), Africa (Egypt, Nigeria, Libya), Europe (Norway) and Middle East (UAE, Kuwait). The study used exchange rates and Bitcoin market prices as the variables of study. The cost of one currency in terms of the currency of another nation is known as the exchange rate. It displays the value of one currency in relation to another. For exchange rates, descriptive statistics were compute using direct rates, which are local currency units per USD. However, for inferential analysis and diagnostic tests, exchange rates used was the indirect form, which is USD per local currency unit to ensure uniformity in country data. The two sources of data were the World Bank database and the Google Finance. According to Google Finance, the price of one Bitcoin is equal to 29,183.20 USD as of August 15, 2023.

4. RESULTS

The research employed several statistical techniques, including GARCH and ARIMA model estimators, to examine and compare the relationship between Bitcoin price fluctuation and foreign exchange volatility in a subset of oil-producing nations. The description of Bitcoin (BTC) trading price and its volatility behaviour of Bitcoin is shown in Fig. 1. The graph showed that there was a relative stability in the behaviour of the Bitcoin movement. It reached its high for the first time in November, 2021, after which there was a rather quiet decrease that was marked by extreme volatility between February to June 2022. In October 2022, there were wildly fluctuating peaks and valleys. This indicates that the period from 2020 to 2021 had significant fluctuation in the value of Bitcoin in relation to the US dollar, which had a ripple impact on the economy. By the latter half of 2022, the volatility of both the US currency and Bitcoin has been shown to be plummeting. The trend of Bitcoin prices was relatively stable from early days of 2022. Thereafter, the prices trended upwards and became highly unstable.

The Brazilian real to US dollar exchange rate was shown in Fig. 2. The table showed that there is a startling wave movement in the value of the Brazilian real relative to the US dollar, which is what caused the exchange to behave volatilely over the course of the inquiry. The study's initial year, which ran from 2012 to 2015, had very modest volatility with a range of peaks. The movement of the exchange rate increased to a greater peak in the year 2015, and from 2016 to 2017, there was a relative fall in the exchange rate, indicating the appreciation of the Brazilian real during that time. Subsequently, there was another surge in the exchange rate over the examined period of 2020 to 2022. Brazil had previously unheard-of levels of currency rate volatility during this time. This illustrates how much the US dollar has an impact on Brazil's currency by looking at the price of oil on the international market [72-77]. Nevertheless, despite the shocks to the global oil and Bitcoin markets, Brazil's exchange rate is still a digit number that shows robust buying power parity of Brazilian real to US dollar.

The volatility of the Canadian currency rate was illustrated in Fig. 3. This displays the Canadian dollar's parity with the US dollar throughout the time period under consideration. During that time, there was a noticeable increase in the volatility of the Canadian dollar relative to the US dollar. From 2012 onward, the exchange rate increased on its own with very little volatility, reaching a high in 2015. In 2016, there was a sharp decrease in the exchange rate, which was quickly followed by increases and decreases in 2017 and 2019. The Canadian dollar saw unusually high volatility during this time. 2020 saw yet another high, which was swiftly followed by a sharply slowed down decrease in the latter half of 2020 through 2021, when it encountered yet another floor, until the latter part of 2021 saw the start of yet another wave of exchange rate acceleration. The frequency of the exchange rate fluctuation showed that the Canadian currency is susceptible to shocks resulting from other variables such as the price of oil, bitcoin, and the influence of the US dollar on global markets.

The link between China local currency units and US dollars, which represents the rate at which the Chinese unit currency is exchanged for a dollar between 2011 and 2022, is depicted in Fig. 4. The graph showed the pattern of China's exchange rate volatility. The trend shows that throughout the time under examination, there was significant volatility in the exchange rate between the Chinese Yuan and the US dollar, with several peaks and floors that typified the currency's conduct. This showed that the dollar's interaction effects with other market indices, such as Bitcoin, and oil prices, will greatly affect China's Yean.

The volatility tendency of Egypt's currency's exchange rate to the US dollar on the world oil markets is depicted in Fig. 5. Between 2011 and 2018, Egypt's currency remained reasonably stable in relation to the US dollar. But late in 2018, there was a spike in Egypt's currency that could have been related to the shock of rising oil prices. The exchange rate peaked in 2019 and then began to decrease somewhat, although it still remained high compared to its pre-2018 shock trend. Although there wasn't much fluctuation, Egypt's exchange behaviour pattern showed a persistently high exchange rate. The volatility pattern of the Kuwaiti dollar exchange rate is seen in Fig. 6. The graph indicates that in 2021, the Kuwaiti dinar to US dollar exchange rate peaked at a value of 0.31. Although the exchange rate varied between 0.278 and 0.289 from 2011 to 2014, it fell to 0.279 in the early months of 2015, and then it started to grow with little variations until 2021, when it reaches its high. Throughout 2021 and 2022, the Kuwaiti dinar to US dollar exchange rate fluctuated downward, despite other market instability such as the volatility of Bitcoin and oil prices. It was discovered that Kuwait's exchange rate was robust compared to the US dollar and fluctuated less than a digit, suggesting that shocks to the global Bitcoin market and oil prices had less of an influence.

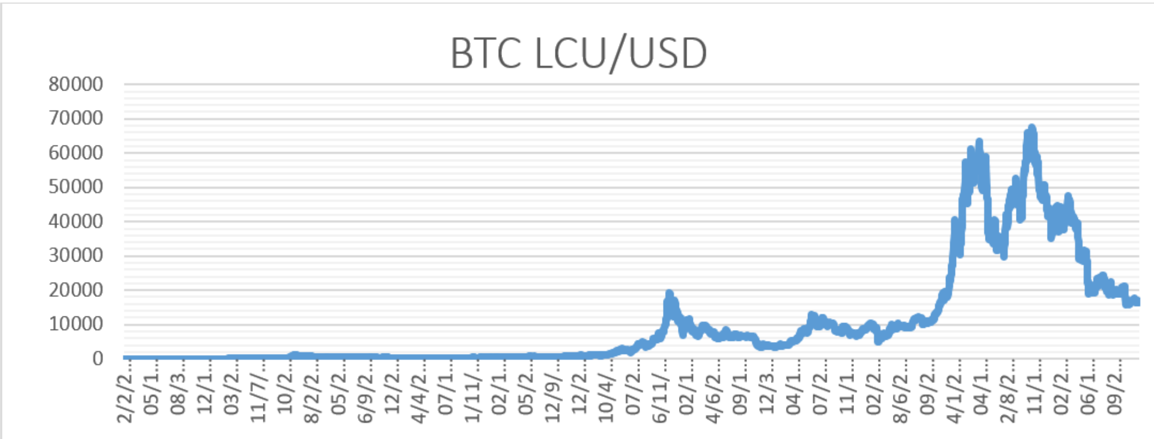

Fig. 1. Bitcoin trend
Source: Authors' estimation 2024 with Eviews 13

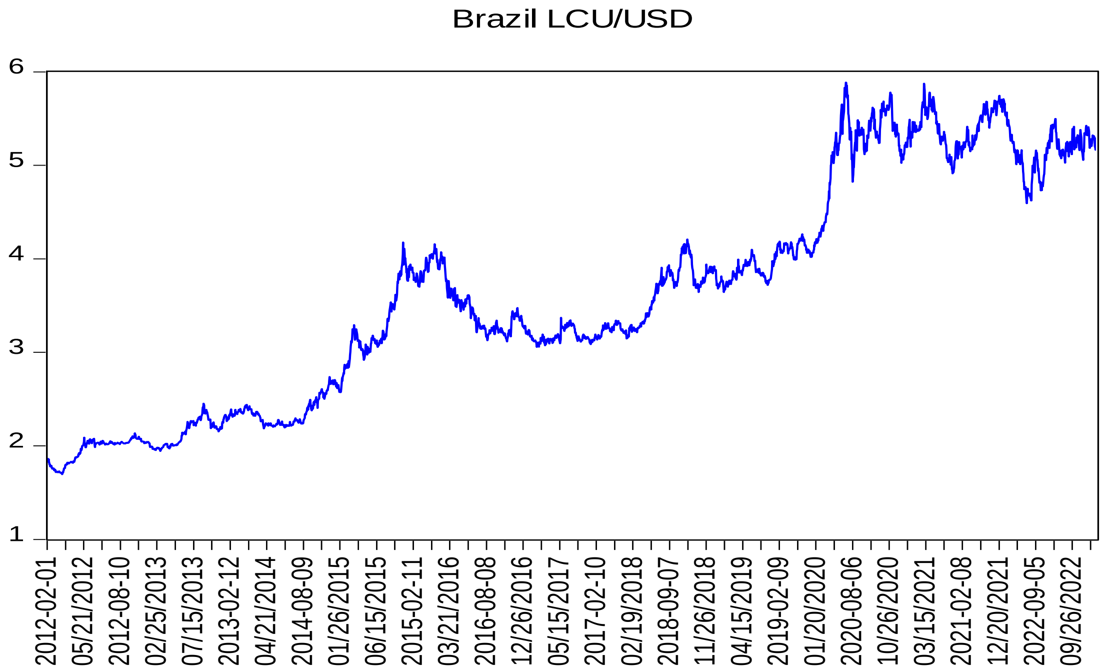

Fig. 2. Trend Analysis of Brazil exchange rate
Source: Authors' estimation 2024 with Eviews 13

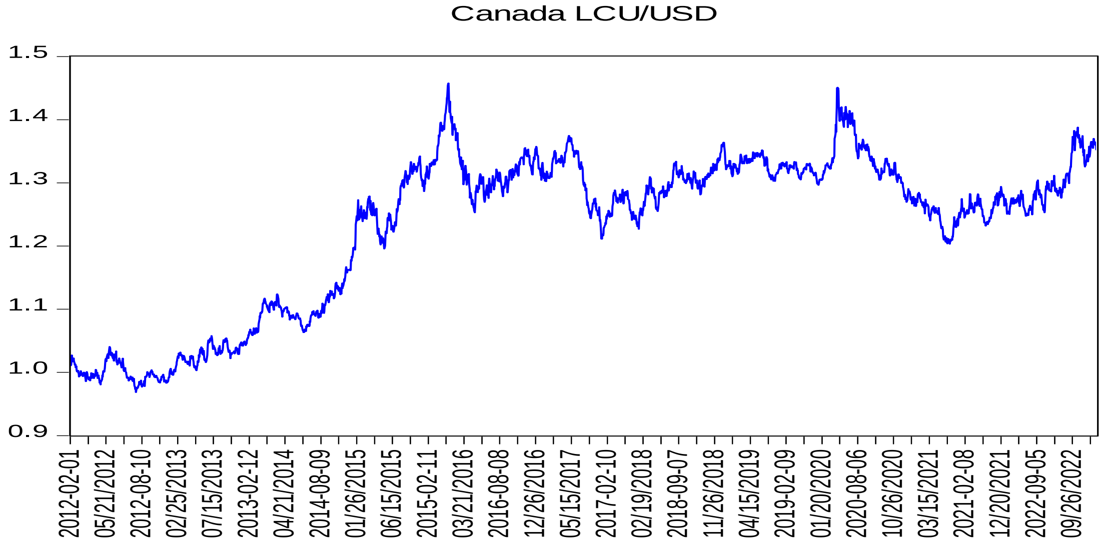

Fig. 3. Volatility trend analysis of canada exchange rate
Source: Authors' estimation 2024 with Eviews 10

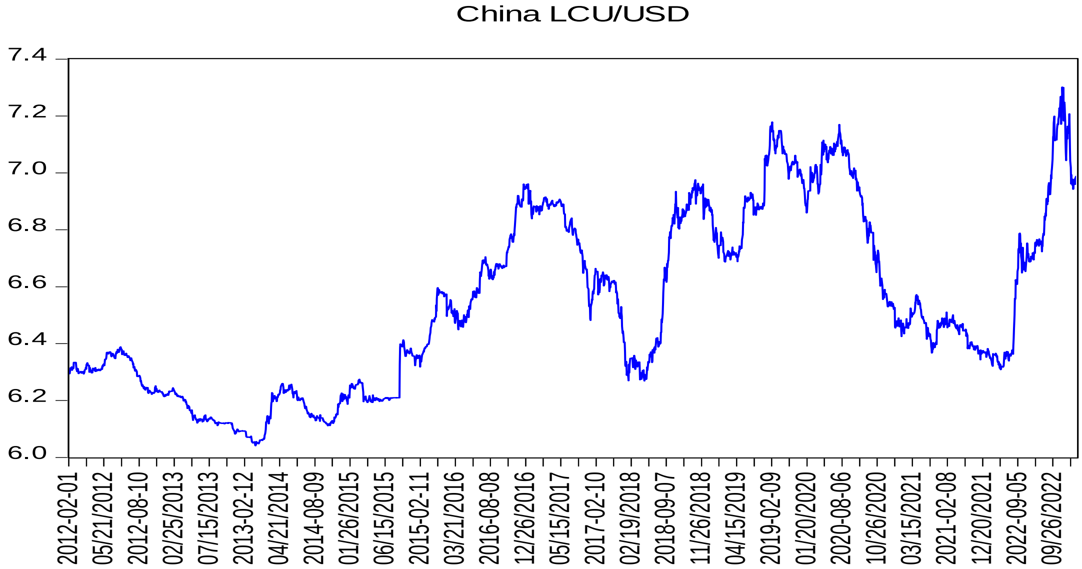

Fig. 4. Volatility trend analysis of china exchange rate
Source: Authors' estimation 2024 with Eviews 10

Fig. 7 showed the volatility pattern of the Libyan currency exchange rate to US dollar as a result of shocks to the global oil market's oil prices and Bitcoin. The volatility of the Libyan currency rate, which was discovered to be wildly behaved at the beginning of the review period (2011 to 2014), indicates a significant degree of vulnerability. A floor of 1.20 was encountered by the Libyan currency rate in 2015 and the latter half of that year. The exchange rate saw a significant spike to 1.40 in 2016, which was followed by high, continuous peaks and floors in the study's following years (2017 - 2022).

The trend of the Mexican exchange rate liveliness was depicted in Fig. 8. The graph showed that Mexico's exchange rate behaviour is characterized by a variety of peaks and floors. However, as the graph shows, the exchange rate was seen to have been rising despite the floors. The fluctuations in Mexico's currency exchange rate due to fluctuations in the price of oil and Bitcoin have had a significant impact on the purchasing power parity. The rate between Mexico's currency and the US dollar has been two digits, with a minimum of 12 and a maximum of 25.

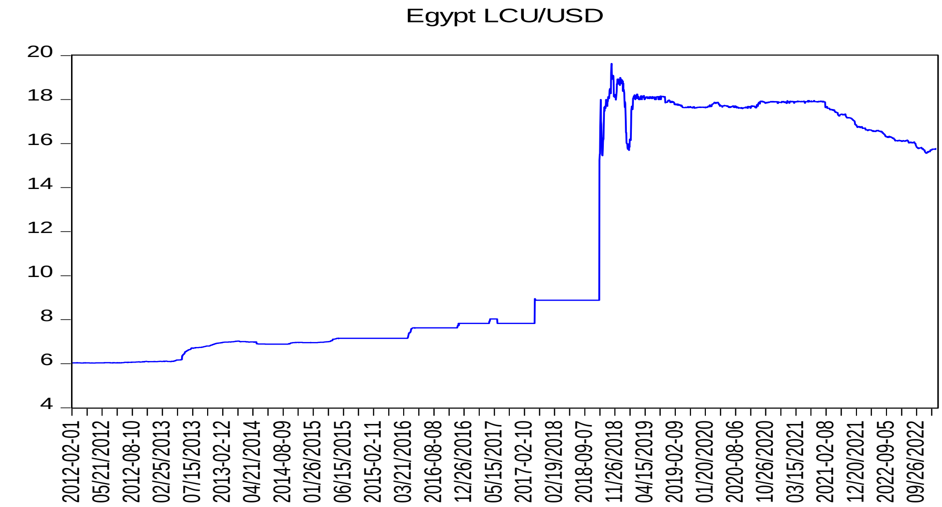

Fig. 5. Volatility trend analysis of egypt exchange rate
Source: Authors' estimation 2024 with Eviews 10

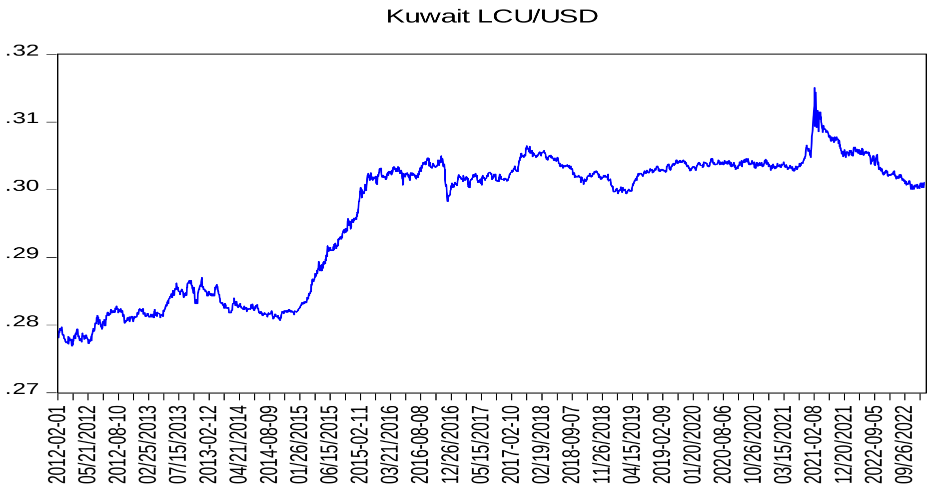

Fig. 6. Volatility trend analysis of kuwait exchange rate
Source: Authors' estimation 2024 with Eviews 10

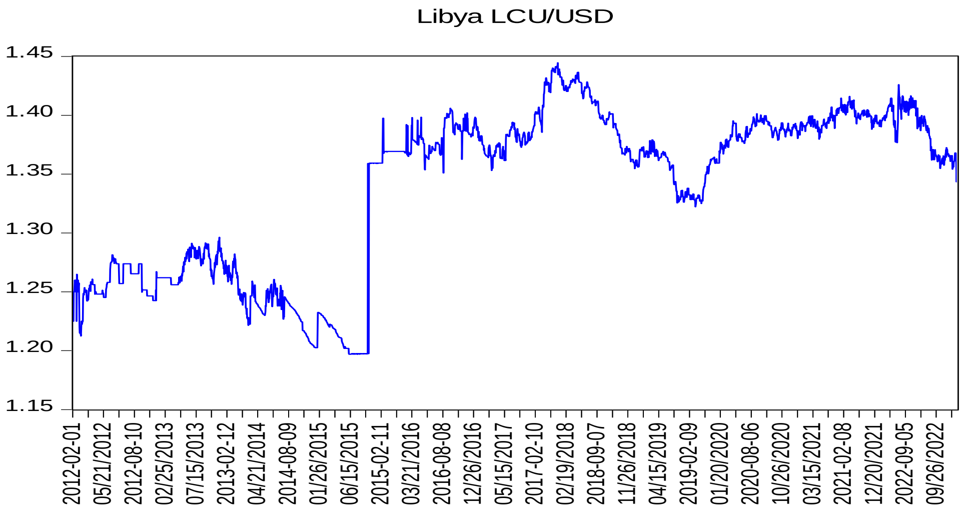

Fig. 7. Volatility trend analysis of libya exchange rate
Source: Authors' estimation 2024 with Eviews 10

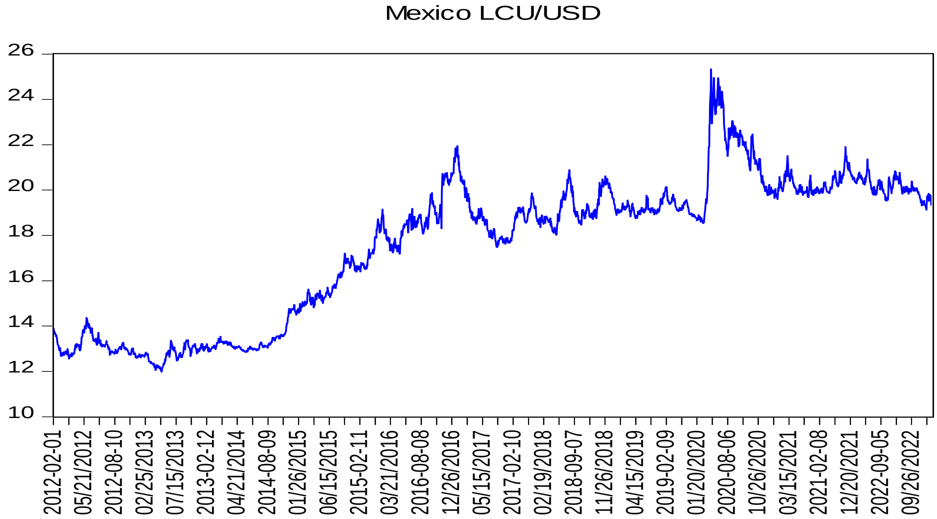

Fig. 8. Volatility trend analysis of mexico exchange rate
Source: Authors' estimation 2024 with Eviews 10

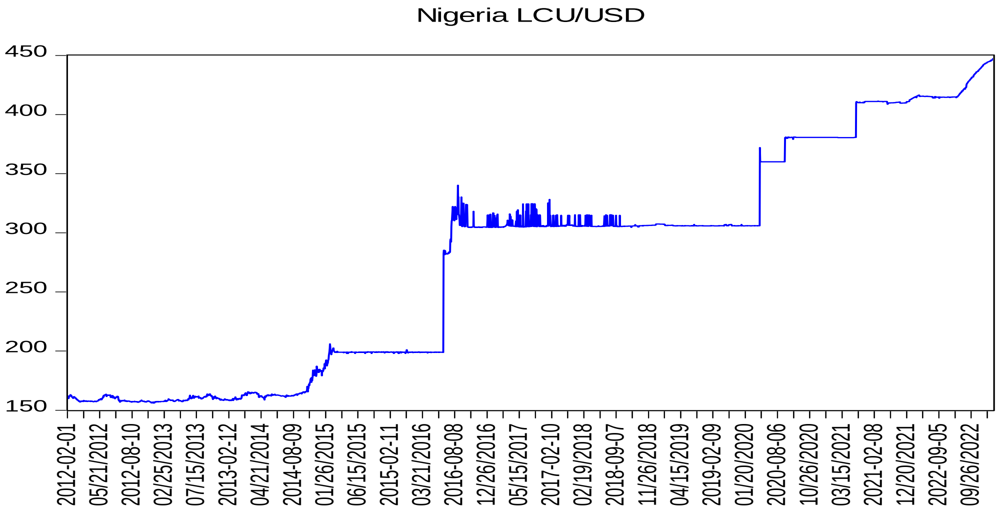

Fig. 9. Volatility trend analysis of nigeria exchange rate
Source: Authors' estimation 2024 with Eviews 10

The development of volatility in the Nigerian exchange rate was illustrated in Fig. 9. This illustrates the behaviour of the Nigerian currency's exchange rate in relation to the US dollar as a result of shocks to the global oil market and Bitcoin prices. The graph showed that, over the time under examination, Nigeria's exchange rate has maintained three digits to the US dollar, with a minimum rate of 150 in 2011 and a high rate of 450 in 2022. From 2011 to 2014, the minimum exchange rate remained a constant N150 to the US dollar. The naira to dollar exchange rate (N200/1$) increased in 2015 and continued to do so in 2016. This suggests that the naira would continue to weaken against the dollar as a result of shocks to the global oil markets caused by fluctuations in Bitcoin and oil prices. The value of the naira significantly declined in the latter half of 2016 when the exchange rate spiked to N350/1$. There was also evidence of regular fluctuation within the N320 to N340/1$ range from 2016 to 2018. On the other hand, relative stability was observed at N320/1$ from 2018 and 2020. A spark caused the currency rate to rise from N320 to N360/1$ in the latter half of 2020. The unanticipated depreciation of the naira against the US dollar as a result of the shocks to the global Bitcoin market and oil prices has led to a continuing increase in the naira's exchange rate against the US dollar. This has had a severe negative impact on Nigeria's economy and capacity to compete globally, particularly on its purchasing power parity (PPP).

The volatility pattern of the Norwegian currency rate relative to the US dollar is depicted in Fig. 10. The figure shows the rate of change in Norwegian currency from US dollars to units of that currency in reaction to shocks to the global market brought on by fluctuations in Bitcoin prices and oil prices. With a digit unit of exchange rate from 2011 to 2020, it was seen from the figure that the minimum exchange rate of Norway's currency to the dollar was 5.5, while the maximum was 11.9 throughout the period under consideration (2011 to 2022). Nonetheless, there was an increase in the exchange rate in the first half of 2020, reaching a peak of 11.8. The exchange rate fell in the latter half of 2020, reaching a low of 8.2, with several peaks and floors from 2021 to 2022. During the reviewed period, there was very little fluctuation in the currency rate of Norway, suggesting that purchasing power parity was still good.

The volatility pattern of the United Arab Emirate (UAE) exchange rate to the US dollar as a result of fluctuations in oil and Bitcoin prices due to market shocks was depicted in Fig. 11. The graph showed that there aren't many fluctuations in the UAE exchange rate, indicating relative stability. From early 2015 until the end of 2011, there was a period of relative stability with little variation in the exchange rate, which fluctuated between 3.672 and 3.673. From 2016 to 2022, a comparable pattern with little non-significant fluctuation was also noted. This suggests that the UAE's exchange rate is more robust to volatility shocks resulting from fluctuations in the price of oil and Bitcoin relative to the US currency.

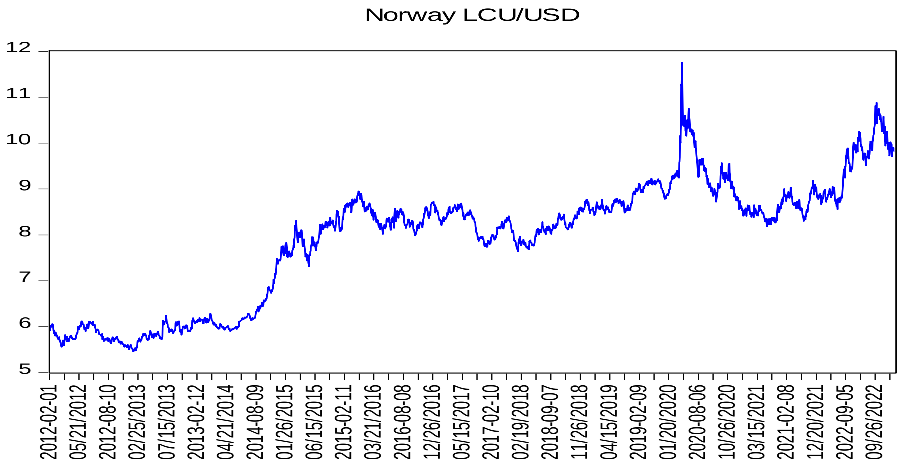

Fig. 10. Volatility trend analysis of norway exchange rate
Source: Authors' estimation 2024 with Eviews 10

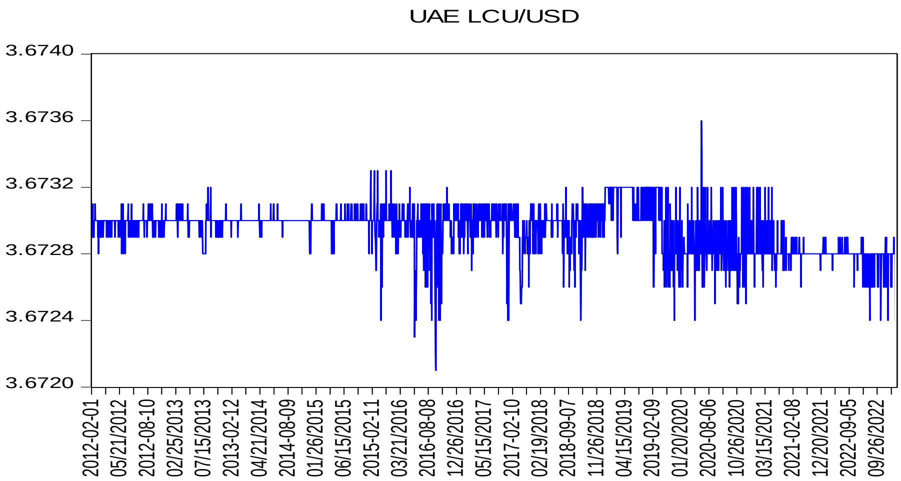

Fig. 11. Volatility trend analysis of uae exchange rate
Source: Authors' estimation 2024 with Eviews 10

Table 1. Test for ARCH effects

Variables	F-Stat	Obs*R-squared
BTC	757.68** 0.00	622.65** 0.00
EXR	143.08** 0.00	138.16** 0.00

Table 2. GARCH (1, 1) results

Variables	BTC	EXR
Mean Equation	Coefficients	Coefficients
BTC	0.22319** (0.0016)	1.7879*** (0.0000)
EXR	-0.1908*** (0.0000)	-0.0023*** (0.0000)
_cons	1.0615** (0.0014)	0.0124*** (0.0004)
Variance Equation	Coefficients	Coefficients
Constant	1.0089*** (0.0000)	0.0015*** (0.000)
ARCH Term	0.2556** (0.0014)	0.1027*** (0.000)
GARCH Term	0.3956*** (0.0000)	0.5699*** (0.0000)
Persistence	0.6512	0.6726
Log Likelihood	102177.8	123477.9

*Note: *(**) indicates significance at 1%(5%) levels*
Source: Authors' estimation 2024 with Eviews 10

Regarding the research hypothesis that "*adjustments in the Bitcoin market do not have significant influence on volatility of local currencies",* the study used the symmetric GARCH (1, 1) model to test for volatility effect. The reason was because the dataset were tested for the presence of ARCH effects to ascertain the appropriateness of GARCH estimation. In order to guarantee that the GARCH analysis would yield accurate findings having performed a pre-diagnostic test on the data; we further estimated the Threshold-GARCH (T-GARCH) model to determine the presence or otherwise of volatility. In order to provide a preliminary diagnostic, the test for arch effects looks at the panel series' heteroscedasticity component to identify whether or not GARCH estimations are suitable. Based on the results of Table 1, ARCH effects were confirmed (p<.05) for the models in our study.

From the GARCH estimates above as presented in Table 2, the constant of the mean equation, -0.12315 indicates the baseline value of currency returns when other variables affecting currency rates are zero. The negative value depicts that exchange rate returns fall or exchange rates will depreciate when other factors are absent. The coefficient of Bitcoin price fluctuations 0.22319 represents the effect of the lagged value of the Bitcoin on local currency exchange rates in relation to USD. In this case, it suggests that a one-unit increase in the lagged value of Bitcoin adjustments leads to a 0.22319 units increase in its current value, but this is found to be significant (p<.05), depicting that Bitcoin adjustments do not affect local currency fluctuations in the short term. Moving to the variance equation, the constant, 1.0089 indicates the baseline level of volatility in local currencies. It is also called the unconditional volatility, implying volatility that exists regardless of other factors. The ARCH Term, 0.2556 captures the impact of past currency returns squared on the present volatility of exchange rates. The GARCH coefficient, 0.3956, on the other hand captures the impact of past volatility on the current volatility. Together, these terms make up the measure for volatility persistence. Persistence is 0.6512 (< 1) confirming that current volatility in the exchange rates has significant impact unconditional volatility of local currencies' exchange rates for a long time before the effect dissipates. The presence of persistence in the midst of Bitcoin effects confirms the long term impact of Bitcoin as spelt out in the ARDL results. The log likelihood value (102177.8) measures the overall fit of the GARCH model to the data. Higher log likelihood values indicate better model fit. Given the significant p values for both ARCH and GARCH terms (p<.05), the study denounces the null hypothesis and accepts the alternate hypothesis that adjustments in the Bitcoin market have significant influence on local currency volatility.

The estimates Threshold GARCH model of Table 3 contain mean and variance equations with terms for GARCH, T-GARCH, and ARCH. Sum of the arch and GARCH terms indicates sustained volatility in the exchange rate (persistence=0.7370). This implies that little variations in exchange rates likely to be followed by other small fluctuations in prices, and big fluctuations in exchange rates tend to be followed by other major changes in prices. This confirms the participating nations' capacity to predict exchange rate depreciation using previous data. The effect is measured by the exchange rate devaluation T-GARCH term, which is greater than 0 and thus positive. The phrase's lack of meaning suggests that there is no imbalance in the global market. The research of stock markets in oil-importing nations revealed no indication of volatility persistence (persistence= 1.746>1). The Arch and GARCH nomenclature provides significant confirmation of exchange rate volatility.

The significant leverage impact (TARCH term) is negative (-0.6712), indicating considerable evidence of asymmetry in the Bitcoin price reactions to exchange rate depreciation. In other words, the market participants would respond to both positive and negative news differently. All the market participants of the emerging countries researched exhibit persistent volatility in their Bitcoin demand responses to exchange rate depreciation (persistence = 0.8605<1). Same results of a significant negative TARCH coefficient (-0.4289***) and persistence (-0.4289***) were obtained for the exchange rate equation. Additionally, the evidence of a leveraging effect was found, indicating that dynamic interaction between the variation in Bitcoin trading prices and exchange rate depreciation are stronger in response to bad news than to good news. The depreciation of the currency rate was further reinforced by a significant TARCH coefficient in exchange rate equation. With a TARCH term bigger than zero, and also statistically significant, it implies that leverage effects in connection with Bitcoin values are responsible for some of the currency instability in emerging nations. When news of a decline in exchange rates is received, investors and other market players react more forcefully than when news of an increase in currency values is received.

Table 3. T-GARCH estimations

Variables	**BTC**	**EXR**
Mean Equation	Coefficients	Coefficients
Constant	1.0357 (0.7828)	0.0812** (0.0014)
AR(1)	0.1050*** (0.000)	0.1683*** (0.000)
BTC	-	-0.1057*** (0.000)
EXR	-0.0197*** (0.000)	-
Variance Equation	Coefficients	Coefficients
Constant	1.1450*** (0.000)	0.0315** (0.0014)
ARCH	0.1467*** (0.000)	0.1350*** (0.000)
LEVERAGE	-0.6712** (0.0015)	-0.4289*** (0.000)
GARCH	0.7138*** (0.000)	0.6271** (0.0016)
Persistence	0.8605	0.7621
Likelihood	15538.50	3002.804

Wald	17.28	67.24

****(**) indicates significance at 1(5) percent levels respectively*

Table 4. ARIMA Parameters- Derivation of (p, d, q)

Country	I(0)	I(1)	PACF (AR)	ACF (MA)
	d		p	q
Brazil	-2.7331	-56.1618*	1, 2	1, 2, 4
Canada	-1.9439	-54.4256*	1, 2	1, 2
China	-1.6524	-53.8612*	3, 4, 5, 7	3, 4, 5, 7
Egypt	-1.8144	-13.7858*	1, 3, 4, 5	3, 4, 5
Kuwait	-0.7518	-67.6852	1, 6	1, 6, 7
Libya	-1.8335	-59.667*	1, 2, 3	1, 2
Mexico	-2.3779	-51.9248*	4, 8	4, 8
Nigeria	-2.7136	-45.9275*	1	1, 2
Norway	-2.6822	-53.3517*	2, 6	2, 6
UAE	-6.0619*	-	1-∞	1-7

Source: Authors' estimation 2024 with Eviews 13

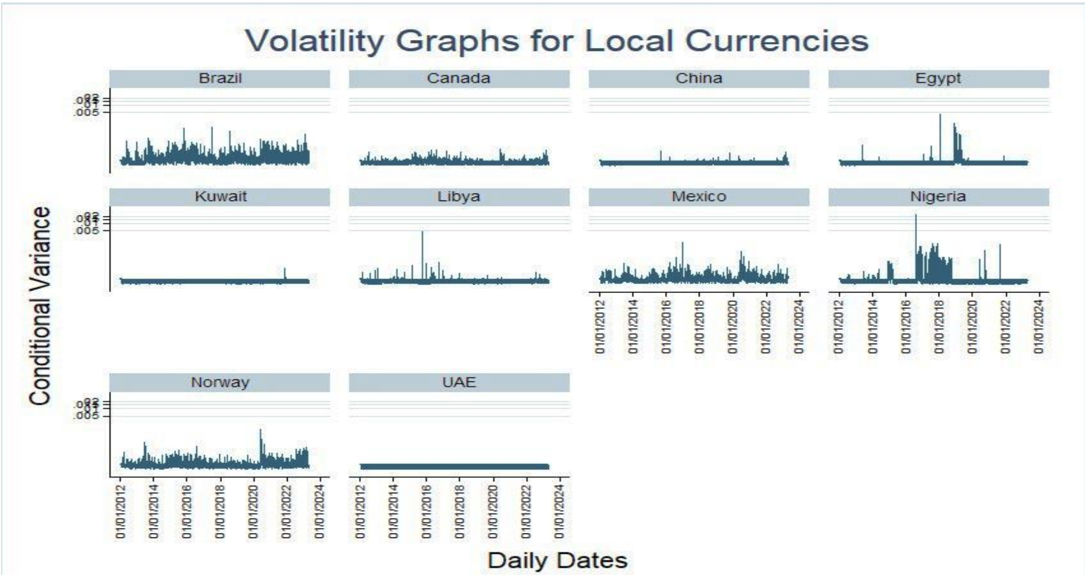

Fig. 12. Volatility Charts for local currency exchange rates in relation to the USD

Source: Authors' estimation 2024 with Eviews 13

The volatility charts reported in Fig. 12 above measured by the conditional variance series derived from estimation show volatility clustering in Libya, Mexico, Nigeria, Norway and Brazil. The UAE dirham and Kuwait dinar had the most stable volatility patterns with minimal spikes across periods. By volatility clustering, the study implies that similar volatility patterns follow one another consecutively. In other words, small fluctuations occur within the same period and large fluctuations occur within the same period as well.

To make a decision on research hypothesis that "*previous currency values are not significant predictors of future currency values in selected countries",* the ARIMA or ARMA model was used. ARMA (ARIMA) models' outputs for each of the sampled countries are displayed in Table 4 below. The use of previous values of the dependent variable to forecast future values is referred to as the AR component of the model. The model's MA component describes how future values are predicted using historical prediction mistakes. ARIMA forecasting model is strictly on time series, hence the requirement to conduct analysis per country as opposed to, on panel basis as other analytical tools used. The nations are listed in the first column, and the calculated model coefficients are shown in the remaining columns. A statistical model for analyzing time series data is the ARMA model. It combines two terms: the moving average (MA) model and the autoregressive (AR) model. To attain the AR label (p) to be used, the partial autocorrelation (PACF) portion of the correlogram of the exchange rates were examined while the MA label (q) was determined by the autocorrelation factor (ACF) portion of the correlogram. The d value of the model identifier represents the differencing that occurred in the variable where 0 implies the variable was stationary at level and 1 represents stationarity at first differencing.

Only UAE had exchange rates stationary at level, implying that only UAE estimation had zero as the integrated value (d). Others had 1 as the order of integration. The PACF and ACF columns show different available choices as displayed by the correlogram that were available to run the ARIMA models. Models were run with different mix and the Akaike Information Criterion (AIC) and ARMA Roots graph used to choose the best model. The model used and estimated values of the model's parameters are shown by the coefficients on Table 5. The ARIMA (1, 1, 1) model for Libya includes one autoregressive term and one moving average term. The AR coefficient (0.0769) and the MA coefficient (-0.4733) are significant, indicating both short-term dependencies and corrections for past forecast errors. SIGMASQ coefficient was $3.87\times10^{-5}3.87\times10^{-5}$. Akaike Information Criteria was -7.3185 and Root Mean Square Error (RMSE) a value of 0.0685. The low value of SIGMASQ and a negative AIC suggest a good model fit. The RMSE is also relatively low, indicating the model's predictions are close to the actual values. For Brazil, the ARIMA (1, 1, 0) model includes one autoregressive term. The significant AR coefficient (-0.0519) indicates a short-term dependency. The higher value of SIGMASQ compared to Libya suggests higher variance in the residuals. The AIC value is also negative (-3.5219), indicating an optimal fit of model for forecasting of current values of the Brazilian reel. The RMSE is low, but higher than Libya’s suggesting less accurate predictions. The ARIMA (1, 1, 0) model for Canada model includes one autoregressive term. The AR coefficient (-0.0208) is not significant, indicating weak short-term dependencies. Low SIGMASQ (0.000034) and a negative AIC suggest a good model fit while the RMSE is very low, indicating highly accurate predictions. Other countries except Nigeria had models of good fit as shown by the negative AIC value and RMSE. Like Brazil and Canada, Norway also had no MA term as depicted from the correlogram. The AR coefficient (0.0469) is not significant, indicating weak short-term dependencies. Low SIGMASQ (0.0039) and a negative AIC of -2.6829 suggest a good model fit while the RMSE is very low (0.0532), indicating highly accurate predictions.
The ARIMA (4, 1, 4) model for China contains four autoregressive terms and moving average component. The AR coefficient ((-0.6598) and MA coefficient (0.7071) are substantial, demonstrating both short-term dependence and corrections for previous forecast mistakes. The SIGMASQ coefficient is 0.0002 and AIC, -5.5711 with a RMSE of 0.0097. A low value of SIGMASQ and a negative AIC indicate a strong model fit. The RMSE is likewise reasonably low, showing that the model's projections are near to the true values, confirming the strength of our model in predicting future values of currency values. The ARIMA (1, 1, 1) model for Egypt consists of one autoregressive term and a moving average component. The AR coefficient (-0.6947) and the MA coefficient (-0.6294) are significant, indicating both short-term reliance and corrections for earlier forecast errors. The SIGMASQ coefficient is 0.0195, and the AIC are -1.0962, with a RMSE of 0.0185. A low SIGMASQ score and a negative AIC suggest a high model fit. The RMSE is also rather low, indicating that the model's forecasts are close to real values and verifying our model's ability to predict future currency values.

For Kuwait, The ARIMA (1,1,1) model had the AR coefficient (-0.7714) and the MA coefficient (-0.1654) are significant, indicating both short-term reliance and corrections for earlier forecast errors. The SIGMASQ coefficient is 1.04E-07, and the AIC are -13.239, with a RMSE of 0.0003. A low SIGMASQ score and a negative AIC suggest a high model fit. The RMSE is also rather low, indicating that the model’s forecasts are close to real values and verifying our model’s ability to predict future currency values. The ARIMA (1, 1, 1) model for Mexico has four autoregressive terms and a moving average component. The AR coefficient (-0.4721) and MA coefficient (0.4202) are significant, indicating both short-term reliance and corrections for past forecast errors. The SIGMASQ coefficient is 0.0212, and the AIC are -1.0032, with a Root Mean Square Error of 0.1646. A low SIGMASQ and a negative AIC suggest a high model fit. The RMSE is also relatively low, indicating that the model’s forecasts are close to real values and verifying our model’s ability to predict future currency values. Nigeria had slightly different results. The ARIMA (2, 1, 1) model was applicable for Nigeria and as denoted by the p,d,q estimates, it includes two autoregressive and one moving average term. The AR coefficient (0.0176) is not significant, while the MA coefficient (-0.3098) is significant, indicating

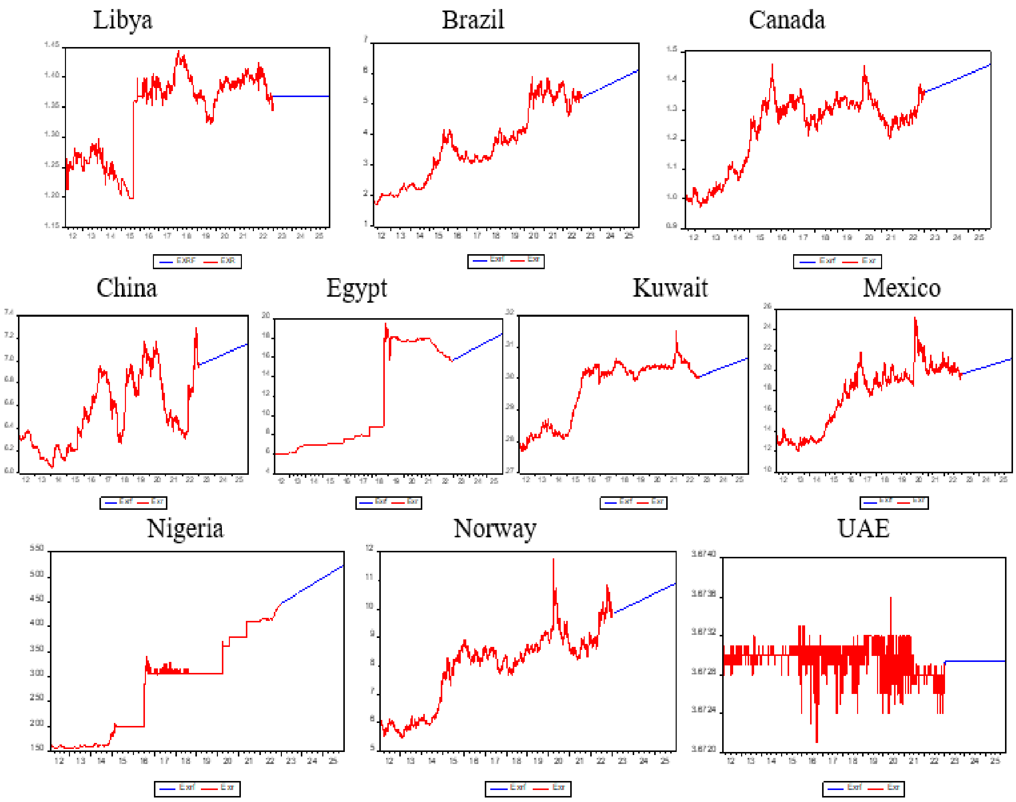

Fig. 13. ARIMA forecast charts for selected countries

Source: Authors' estimation 2024 with Eviews 10

Table 5. Results of ARIMA models for selected countries

	Model (p,d,q)	C	AR	MA	SIGMASQ	AIC	RMSE
Libya	1,1,1	4.52E-05*	0.0769*	-0.4733*	3.87E-05*	-7.3185	0.0685
Brazil	1,1,0	0.0012*	-0.0519*	-	0.0017*	-3.5219	0.1087
Canada	1,1,0	0.00012*	-0.0208	-	3.43E-05	-7.4403	0.0045
China	4,1,4	0.0002*	-0.6598*	0.7071*	0.0002*	-5.5711	0.0097
Egypt	1,1,1	0.0034*	0.6947*	-0.6294*	0.0195*	-1.0962	0.0185
Kuwait	1,1,1	7.85E-06*	-0.7714*	-0.1654*	1.04E-07*	-13.239	0.0003
Mexico	4,1,4	0.001982*	-0.4721*	0.4202*	0.0212*	-1.0032	0.1646
Nigeria	2,1,1	0.0999	0.0176	-0.3098*	10.409*	5.1834	0.4534
Norway	2,1,0	0.0013*	0.0469*	-	0.0039*	-2.6829	0.0532
UAE	9,0,5	3.6729*	0.2698*	0.2308*	1.68E-08*	-15.062	9.14E-06

Source: Authors' estimation 2024 with Eviews 10

some short-term error corrections. The output also had a very high SIGMASQ (10.409) and a positive AIC (5.1834) indicating poor model fit. The RMSE (0.4534) was also high, suggesting inaccurate predictions.

The ARIMA (9, 0, 5) model for predicting UAE's Dirham had nine autoregressive terms and five moving average components. UAE did not need differencing as the level values were found to be stationary; hence the d value is zero (0). The AR coefficient (0.2698) and MA coefficient (0.2308) are significant, indicating temporary reliance and adjustments for earlier forecast errors. The SIGMASQ coefficient is 1.68E-08, and the AIC is -15.062, with a Root Mean Square Error of 9.14E-06. A low SIGMASQ and a negative AIC imply a well-fitted

model. The RMSE is also rather low, indicating that the model's forecasts are close to real values, establishing our model's ability to predict future currency values.
Overall, all models passed ARMA roots test as all ARMA points lay within the circle as shown in the figures in appendix section. The ARIMA models for UAE and Kuwait stand out with excellent fit and prediction accuracy, while the model for Nigeria was poor in forecasting. The poor model for Nigeria can be attributed to the hyper-inflation in the economy and extremely volatile money market. The decision is to accept the hypothesis if p values of AR, MA and SIGMASQ coefficients are significant (p<.05). Given the significant p-values in nine countries out of ten (p<.05), the null hypothesis that previous currency values are not significant predictors of future currency values in selected countries is rejected and alternate hypothesis accepted that future values of local currencies can be forecasted from past values to a significant level of accuracy. The plots of actual values and forecast values derived through ARIMA models on exchange rates per country are reported in Fig. 13. Actual and forecast values are found to match with an Out-of-Sample period plotted for forecast (27/12/2022 to 27/12/2024) as marked by the extended blue line.

5. DISCUSSION OF FINDINGS

The significance in the interactions of Bitcoin prices and exchange rates of local currencies of selected countries in the short run confirm that currency markets are quite efficient on information availability to market participants. Thus, in line with the efficient market hypothesis, significant interactions in the short run are pegged on available information being already reflected in the current value of the currency. In other words, past currency rates and Bitcoin trading prices can be used to predict future prices having factored in the relevant information that could influence currency's value. Volatility and risk management techniques, such as derivatives like futures and options used by investors can also be responsible for the absence of short run interactions between currency rates and Bitcoin. The weak adjustment of short term dynamics to long-term equilibrium implies that slow adjustment of currency rates stimulates delayed pass-through effects of exchange rate movements on import prices that affect inflation dynamics. Investors faces greater short-term volatility and need robust diversification and hedging strategies. Businesses involved in international trade are not left out. Accordingly, businesses also face greater uncertainty in their financial planning and pricing strategies due to unpredictable currency movements. Policy implications include that short-term traders may find currency rates influenced by immediate events and market sentiment, leading to speculative profits but increasing risk due to high volatility. Long-term investors should base their strategies on mean reversion principles, which may be less effective in the short term. Diversification and hedging are important strategies to mitigate risks, especially for multinational corporations and investors with significant foreign exposure. Hedging against currency risk becomes crucial, especially for multinational corporations and those with significant foreign exposure, due to the unpredictable nature of short-term currency fluctuations. Policymakers need to closely monitor and manage these effects to ensure price stability. Policymakers might need to closely monitor and employ more proactive and coordinated approaches to manage exchange rate stability. For the economy, this can lead to increased uncertainty for businesses, potential impacts on trade and investment, and challenges in maintaining price stability and fostering economic growth.

The significant impact of Bitcoin trading price on the value of the local currencies of nations can be viewed through the potential of Bitcoin trading to attract significant foreign direct investment (FDI) in the fintech sector, which can stimulate economic growth and increase productivity, increasing the value of the local currency. Incorporating Bitcoin into the financial system can provide diversification benefits, reducing systemic risks, and enhancing the efficiency and competitiveness of the financial sector. Bitcoin trading provides a hedge against local currency devaluation and stabilizing the exchange rate. Thus, Bitcoin trading facilitates international trade by reducing transaction costs and time, increases trade volumes and improving the trade balance by boosting exports and strengthening the local currency.

The study also found that past values of currency rates for an extended period can predict future values as observed in ARIMA models except for Nigeria. Exchange rate forecasts play a crucial role in various aspects of economic policy, including foreign exchange interventions, fiscal policy, trade and economic policy, investment climate, financial regulation and supervision, economic stability, and international policy coordination. Central banks can use exchange rate forecasts to stabilize currencies, manage reserves, and enhance fiscal policy. Governments can better predict the impact of exchange rate fluctuations on revenues and expenditures, and manage foreign-denominated debt. Financial regulators are also able to better monitor the industry and currency markets by better monitoring and managing risks related to exchange rate fluctuations in the banking sector. Improved forecasting can help identify and mitigate systemic risks arising from currency volatility, contributing to overall financial market stability. Trade and economic policies can also benefit from accurate predictions, as they can inform trade agreements and help attract foreign direct investment (FDI). Predictable exchange rates reduce risks for foreign investors and improve local business planning, ultimately promoting economic growth. The capability to obtain accurate exchange rate forecasts will aid central banks in coordinating interest rate decisions, allowing them to anticipate future movements and adjust their strategies accordingly. They also aid in inflation targeting, as exchange rates influence import prices and inflation. Accurate forecasts help central banks manage inflation expectations and achieve their targets by anticipating the pass-through effects of exchange rate fluctuations. In general, reliable exchange rate forecasts promote economic stability, which can also aid in crisis prevention. Early warning systems can be developed to anticipate and mitigate potential currency crises, protecting the economy from severe disruptions.

For a country like Nigeria where future values of exchange rates cannot be predicted accurately from historical records, forecasted currency rates overvalue the domestic currency (due to currency depreciation), leading to a loss of competitiveness for domestic exporters and reduced export revenue. Rising import costs also contribute to inflation, affecting consumer purchasing power and real wages. Uncertainty among foreign investors can lead to capital flight risks, leading to volatile capital flows and potential economic instability. Central banks rely on accurate currency rate forecasts to formulate and implement effective monetary policies, but inaccurate forecasts can hinder their ability to achieve policy objectives and potentially exacerbate macroeconomic imbalances. Inconsistent forecasts may also lead to misalignment between actual economic conditions and policy responses, potentially exacerbating macroeconomic imbalances. Business planning and investment decisions are also affected by currency rate forecasts, as increased risks can deter businesses from making long-term investments, affecting economic growth and employment. Consumer confidence and spending can be undermined by fluctuating exchange rate volatility, potentially dampening economic activity and growth. Government budgets and debt servicing can also face challenges due to revenue shortfalls or increased expenditures, resulting in budget deficits and debt servicing costs. External imbalances in the current account can make the economy vulnerable to external shocks and speculative attacks, posing risks to economic stability.

Persistent volatility and volatility clustering found in some of the sampled countries denote increased risk and uncertainty in foreign exchange markets, leading to increased borrowing costs and reduced liquidity. This can affect investment, consumer confidence, international trade, and competitiveness. This can also result in increased hedging costs for businesses, which can impact profit margins. High volatility also affect consumer confidence and spending patterns, leading to fluctuating prices for imported goods and reducing consumption. Inflation uncertainty can also be exacerbated by volatile currency rates, making it difficult for consumers and businesses to plan for the future. Prolonged periods of volatility may attract speculative trading, further escalating volatility and leading to short-term market distortions. High exchange rate volatility can complicate budget planning and fiscal policy, as governments may face unpredictable revenue from trade taxes and fluctuating costs for foreign-denominated debt Budget planning can be complicated by persistent volatility, especially for countries heavily reliant on imports or with significant foreign-denominated debt. Debt management becomes more challenging due to persistent volatility, which can lead to higher debt servicing costs if the local currency depreciates significantly. Policies are to be focus on market stability, which can be achieved by improving market transparency and reducing speculative behaviour. Other strategies to mitigate negative impacts of persistence and clustering include hedging, diversifying investment portfolios across different currencies and asset classes, and building economic resilience by strengthening domestic financial markets, improving fiscal discipline, and enhancing the regulatory framework. Central banks may also intervene in the foreign exchange market to stabilize the currency, using foreign reserves, although this is a very temporary solution.

6. CONCLUSION

This study examined volatility in currencies of selected countries and their interactions with Bitcoin trading values. The GARCH and ARIMA estimators were used for analysis. Graphical trend analysis was also utilized as an additional means of data analysis to show the movement patterns of the values of Bitcoin and currencies of sampled nations but the descriptive statistics were not reported to keep the research report concise. The research findings are as follows: Volatility of exchange rates is persistent in foreign exchange markets amidst Bitcoin dynamics although intensity of volatility clustering may vary across markets in different geographical regions. The Bitcoin market has significantly changed, affecting local currencies, according to the results. While Nigeria's bad ARIMA model is a result of hyperinflation and unstable money markets, the models for the United Arab Emirates and Kuwait are accurate. Future prices of Bitcoin can be predicted using historical exchange rates and trade prices, but sustained volatility in some nations points to more risk and unpredictability in the foreign exchange markets. Due to its meticulous application of econometric methodologies, such as GARCH and ARIMA models, which are well-suited for analyzing volatility in currency and Bitcoin markets, the study is both technically and scientifically sound. The approach employed in the paper enables a comprehensive analysis of volatility clustering and the dynamic relationship between Bitcoin trading prices and currency exchange rates. However for highly unstable economies like Nigeria, the propensity of predicting future values is low due to extreme volatility and economic downturns. Also, we found significant Bitcoin trading prices among the nations that impose negative shocks on exchange rates the price of Bitcoin, with both upward and downward swings. The negative impact of Bitcoin prices on exchange rates indicates danger or loss due to fluctuations in the market, whilst the positive impact represents gains in exchange rates as a result of Bitcoin trading values. Based on the study's summary of findings and conclusion, countries should ensure foreign exchange markets are adequately managed and regulated in order to stem the tide of frequent volatility of risks and returns related to the country's exchange rates. This will help to mitigate the negative impacts or risks of associated with exchange rates movements and Bitcoin trading values. Future studies ought to take into account several forecasting windows. By doing this, policymakers, business owners, and investors may also obtain additional insights into the ways in which Bitcoin influences the exchange rate at different times, thereby strengthening the findings' robustness. Regardless of the predictive power of ARIMA models in forecasting local currency values, policymakers and researchers alike should recognize the limitations of forecasting models and continuously adapt their models and approaches to incorporate new historical information and emerging trends. In order to close this gap, the study suggests that future research concentrate on the relationships between frequency and volatility of risk and return utilizing the daily Bitcoin prices and exchange rates of the global market, as well as additional countries.

DISCLAIMER (ARTIFICIAL INTELLIGENCE)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc) and text-to-image generators have been used during writing or editing of manuscripts.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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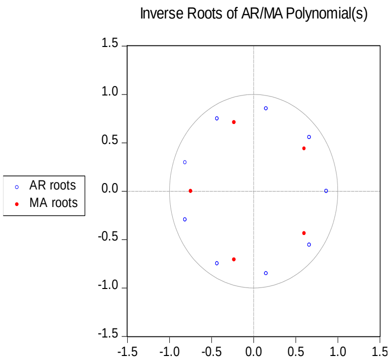
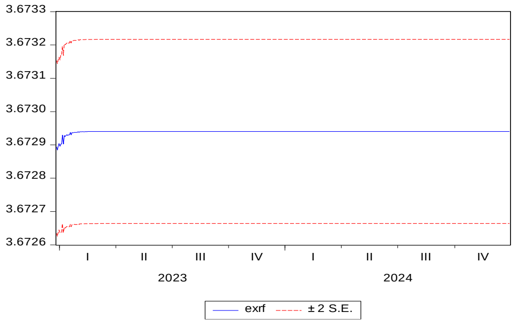
APPENDIX

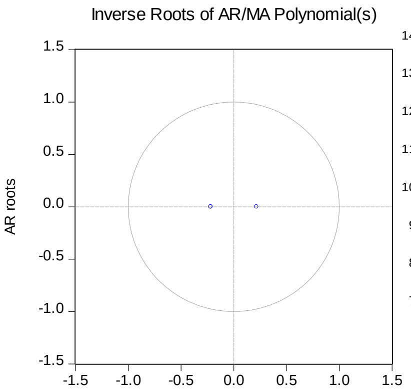
ARMA roots test for UAE

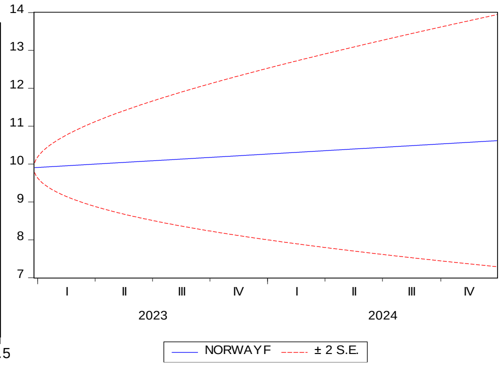




Forecast: UAEF	
Actual: UAE	
Forecast sample: 12/27/2022 12/27/...	
Included observations: 524	
Root Mean Squared Error	9.14E-05
Mean Absolute Error	9.13E-05
Mean Abs. Percent Error	0.002486
Theil Inequality Coefficient	1.24E-05
Bias Proportion	0.997115
Variance Proportion	NA
Covariance Proportion	NA
Theil U2 Coefficient	NA
Symmetric MAPE	0.002486

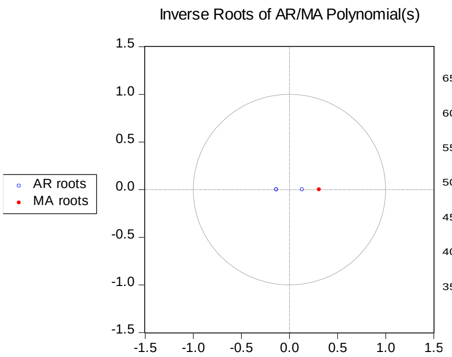
ARMA roots test for Norway

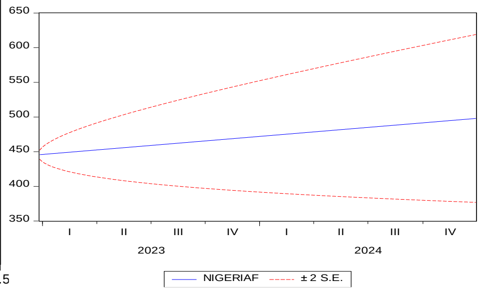




Forecast: NORWAYF	
Actual: NORWAY	
Forecast sample: 12/27/2022 12/27/...	
Included observations: 524	
Root Mean Squared Error	0.053253
Mean Absolute Error	0.048436
Mean Abs. Percent Error	0.491825
Theil Inequality Coefficient	0.002694
Bias Proportion	0.827263
Variance Proportion	0.139395
Covariance Proportion	0.033343
Theil U2 Coefficient	1.412581
Symmetric MAPE	0.490365

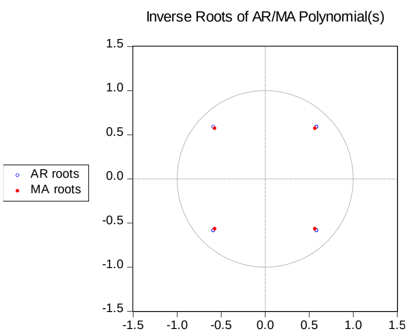
ARMA roots test for Nigeria

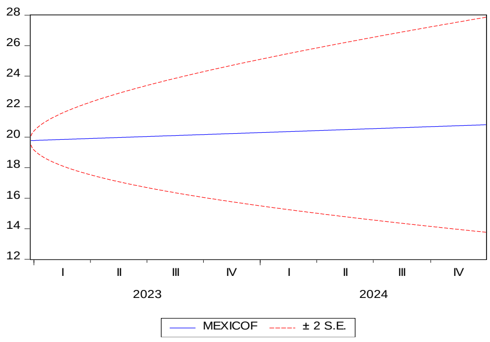




Forecast: NIGERIAF	
Actual: NIGERIA	
Forecast sample: 12/27/2022 12/27/...	
Included observations: 524	
Root Mean Squared Error	0.453415
Mean Absolute Error	0.447485
Mean Abs. Percent Error	0.100302
Theil Inequality Coefficient	0.000508
Bias Proportion	0.974014
Variance Proportion	0.025014
Covariance Proportion	0.000972
Theil U2 Coefficient	28.52026
Symmetric MAPE	0.100354

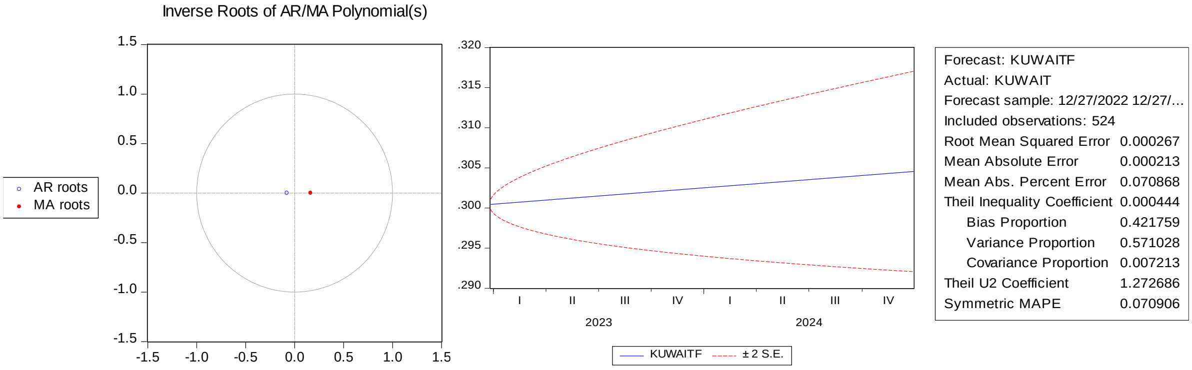
ARMA roots test for Mexico



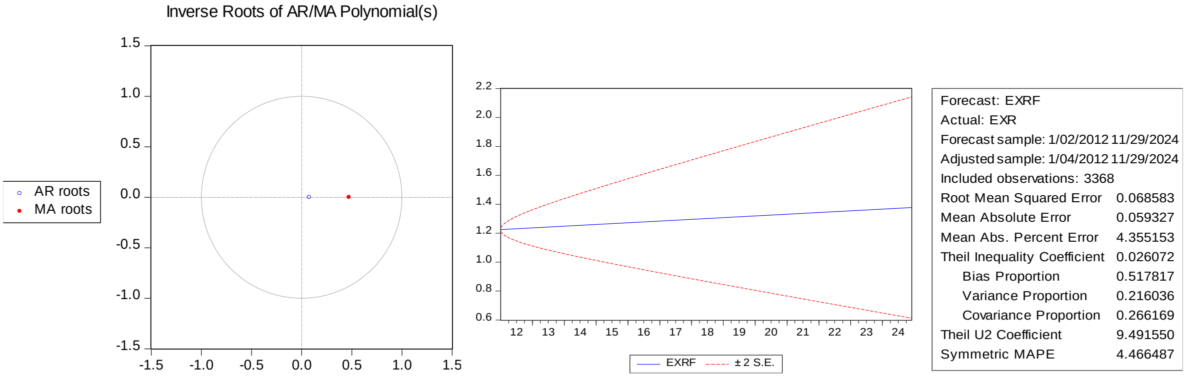


Forecast: MEXICOF	
Actual: MEXICO	
Forecast sample: 12/27/2022 12/27/...	
Included observations: 524	
Root Mean Squared Error	0.164618
Mean Absolute Error	0.142171
Mean Abs. Percent Error	0.725673
Theil Inequality Coefficient	0.004176
Bias Proportion	0.745880
Variance Proportion	0.247106
Covariance Proportion	0.007014
Theil U2 Coefficient	1.936513
Symmetric MAPE	0.722153

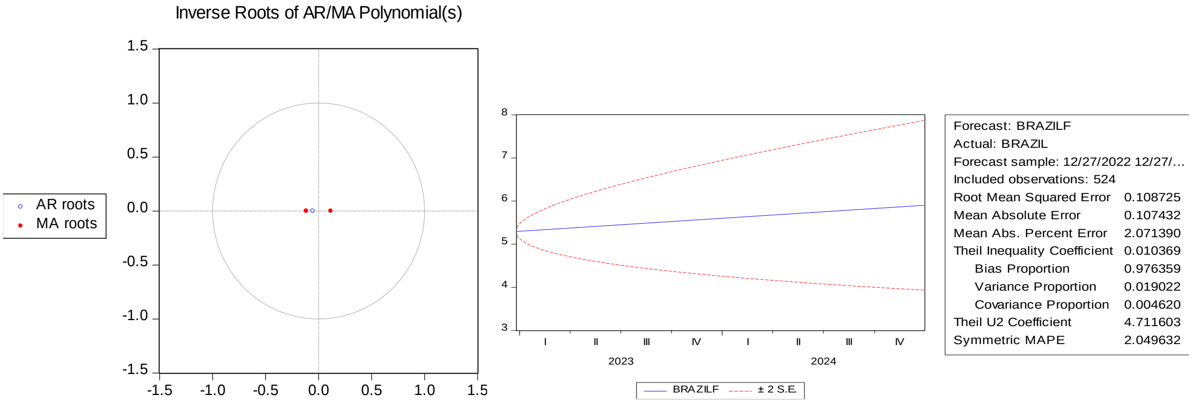
ARMA roots test for Kuwait



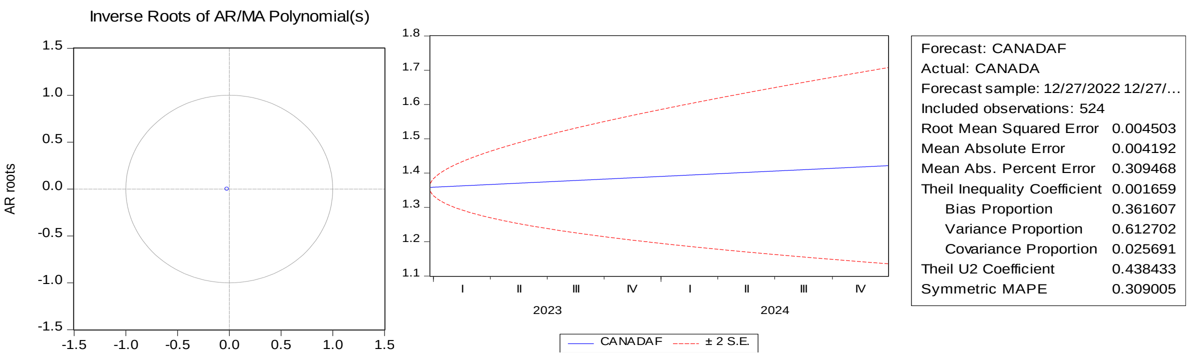
ARMA roots test for Libya



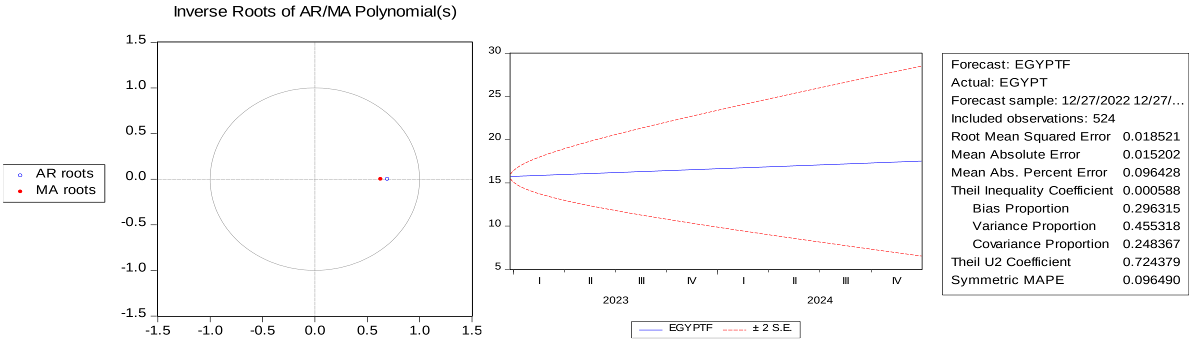
ARMA roots test for Brazil



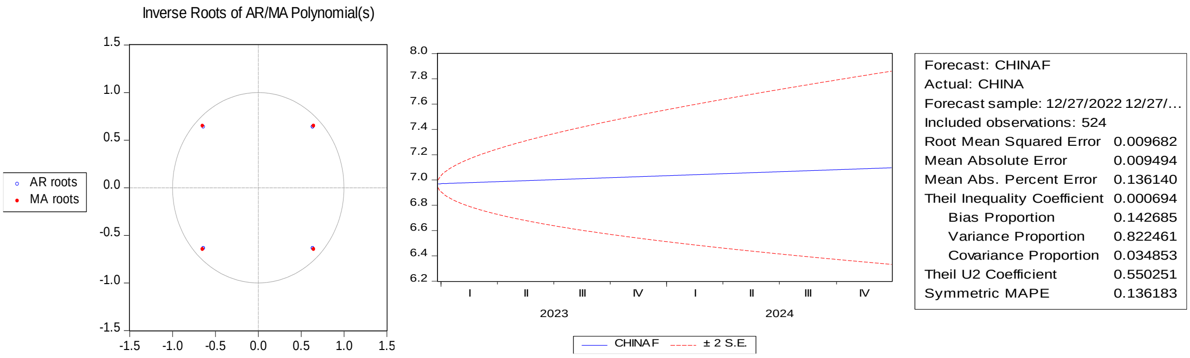
ARMA roots test for Canada



ARMA roots test for Egypt



ARMA roots test for China



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