

## Volatility of bitcoin prices and the volatility of exchange rates in oil-producing countries

### **Abstract**

*The study examined the relations between the volatility of Bitcoin prices and the volatility of exchange rates of oil-producing countries. The study used ARIMA, GARCH estimators for analysis. The study found ARCH effects in the data (heteroskedasticity test;  $p < .05$ ). The GARCH results laid credence to a confirmation of adjustments in the Bitcoin market having significant volatility influence on local currencies. 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 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. 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. Countries should ensure adequate regulation of the foreign exchange markets so as to curtail the wave of risks and 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 (Drehmann & Sushko, 2022), 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.

Bitcoin currently occupies a powerful position in the market for currency exchange (Ganti, 2023). In spite of the homogeneity that characterized both the digital and forex markets, an investor would always seek to maximize returns and reduce risk. 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. 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 (2023), Jin, Li & Li (2022), Attarzadeh & Balcilar (2022), Conlon & McGee (2020), Youssef & Mokni (2019) 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. 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 theories that can be used to situate the relationship between Bitcoin price and exchange rate return. However, we have chosen to focus the theoretical review to 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 for 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. 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 the local currency terms. This potential for increased return boosts the demand for Bitcoin as a diversification tool, leading to increased demand (Bouri *et al.*, 2020). 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. 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 (Cheung *et al.*, 2020).

### 2.2. Empirical review

Several researches have their focus on the connection of 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 a 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 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 (2024) 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 (2024) 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 responding 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 (2024) 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 (2023) 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. Analyzing 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. 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 (2023) 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 influence 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 behavior 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-Quantilogram 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. 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 was 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)]:  $y_t = \mu_1 y_{t-1} + \mu_2 y_{t-2} + \dots + \mu_p y_{t-p} + v_t$  (1)

Moving average of order q [MA(q)]:  $y_t = e_t - \phi_1 e_{t-1} - \phi_2 e_{t-2} - \dots - \phi_q e_{t-q}$  (2)

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

ARMA(p,d,q):  $y_t = c + \mu_1 y_{t-1} + \mu_2 y_{t-2} + \dots + \mu_p y_{t-p} + e_t - \phi_1 e_{t-1} - \phi_2 e_{t-2} - \dots - \phi_q e_{t-q}$  (3)

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

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

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,  $\alpha_1, \dots, \alpha_4$  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,  $\theta_1, \dots, \theta_4$ , 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:

$$EXR_{it} = E(EXR_{it}|I_{t-1}) + e \quad (9)$$

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

$$\sigma_{EXRt}^2 = \beta_0 + \sum_{i=1}^1 \beta_i e_{t-i}^2 + \sum_{j=1}^1 \gamma_j \sigma_{EXRt-j}^2 \quad (10)$$

where:  $\sum_{j=1}^1 \gamma_j \sigma_{EXRt-j}^2$  is the GARCH term,  $\sum_{i=1}^1 \beta_i e_{t-i}^2$  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 of 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) variance and exchange rate volatility are shown in Figure 1. The trend of Bitcoin prices was relatively stable from early days of 2022. Thereafter, the prices trended upwards and became highly unstable.

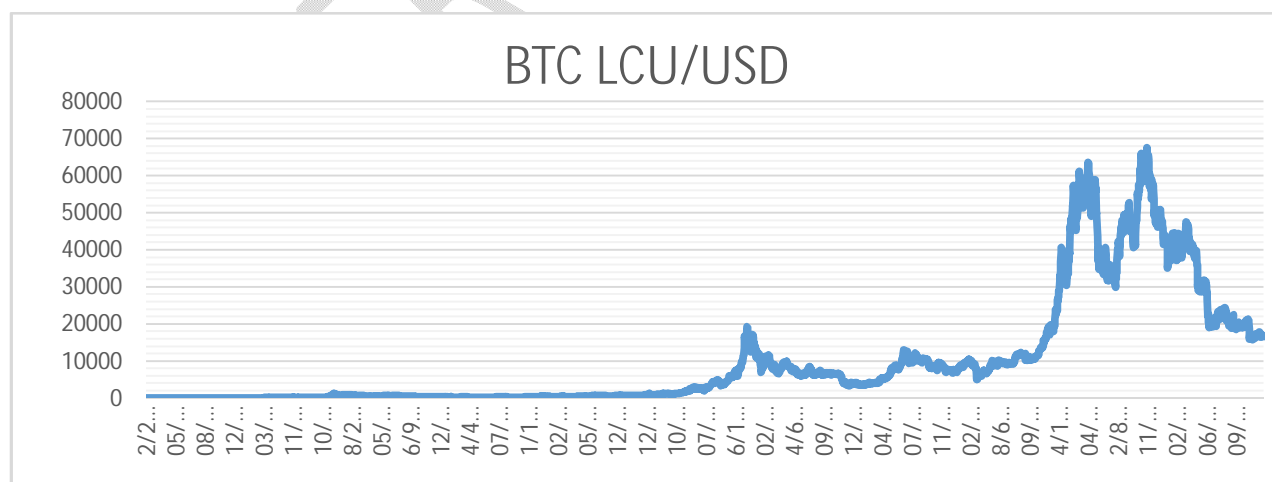


Figure 1: Bitcoin trend

Source: Authors' estimation 2024 with Eviews 13

The Brazilian real to US dollar exchange rate was shown in Figure 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 volatily 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. 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.

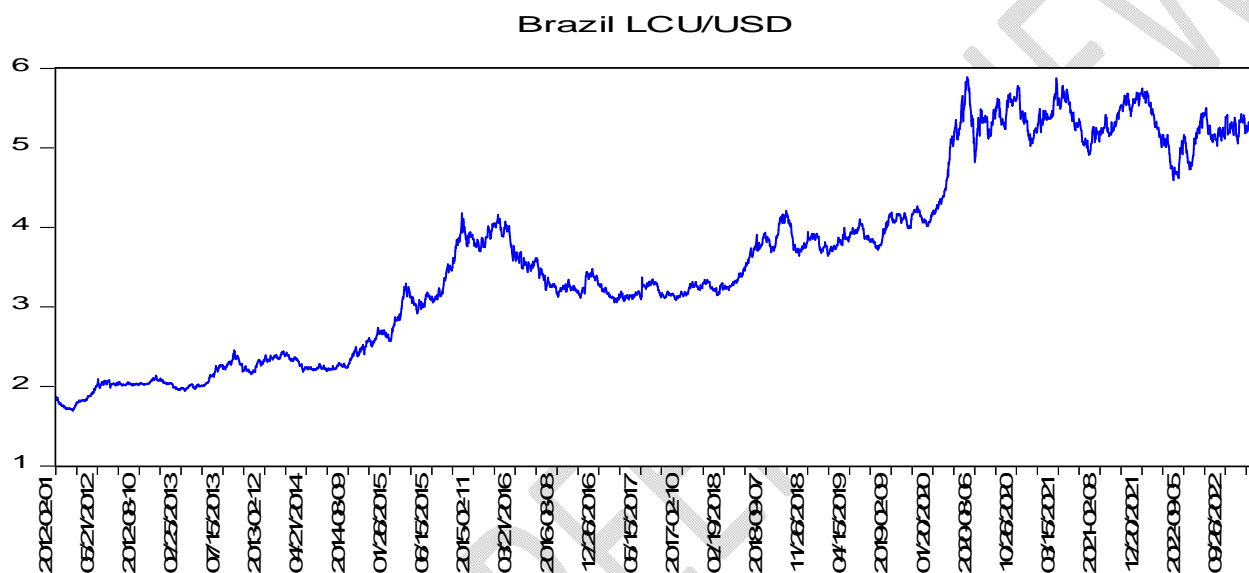


Figure 2: Trend Analysis of Brazil exchange rate

**Source:** Authors' estimation 2024 with Eviews 13

The volatility of the Canadian currency rate was illustrated in Figure 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.

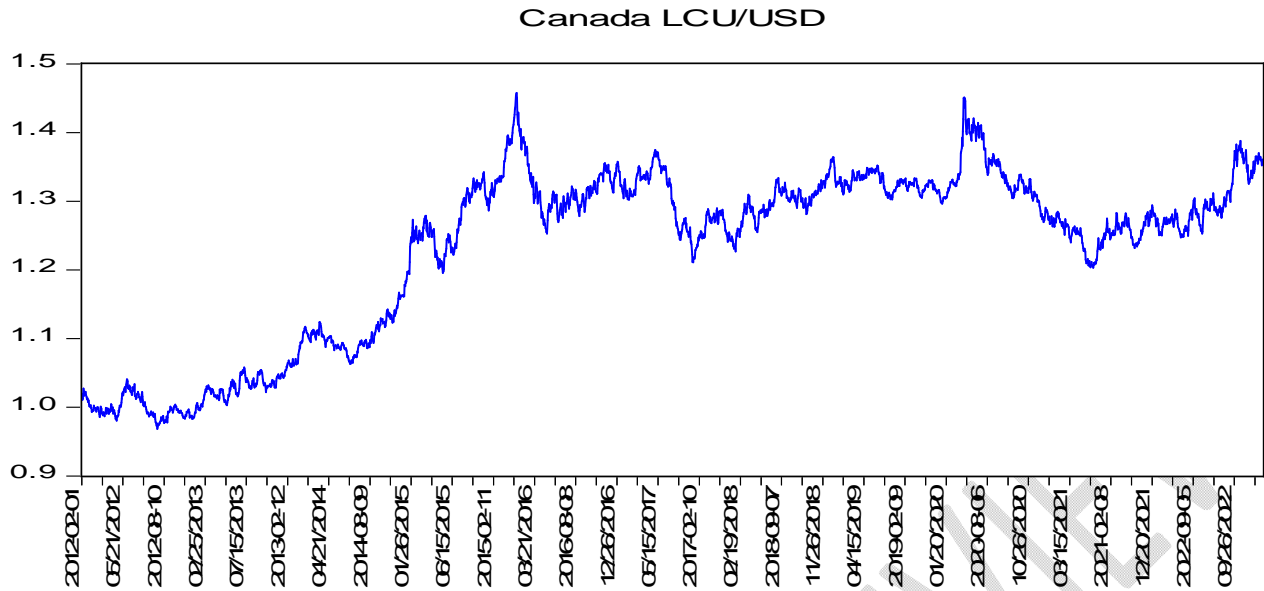


Figure 3: Volatility Trend Analysis of Canada Exchange Rate  
**Source:** Authors' estimation 2024 with Eviews 10

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 Figure 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 Yuan.

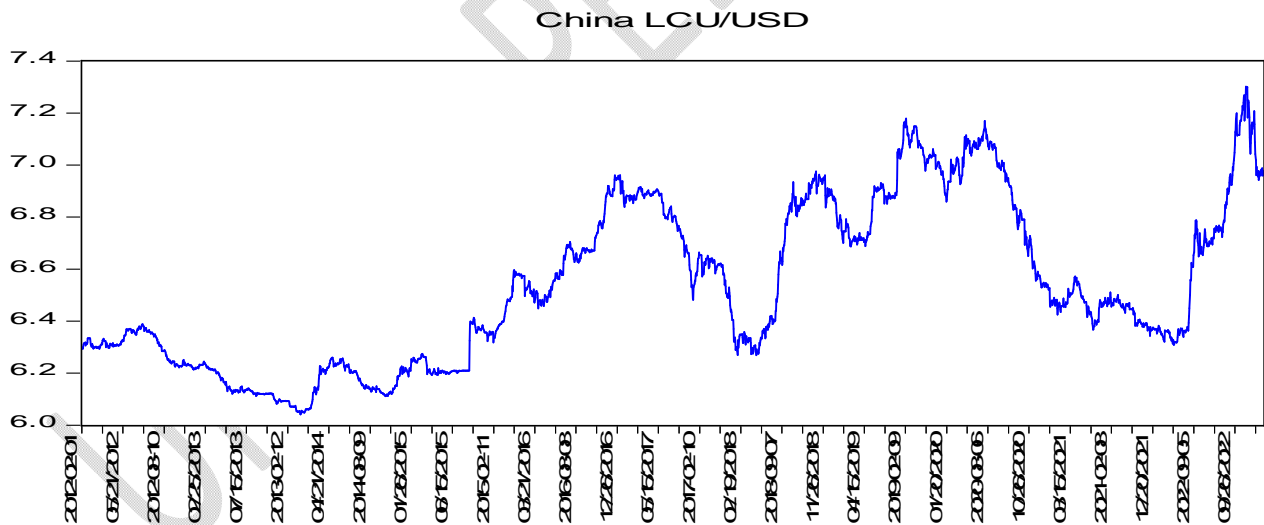


Figure 4: Volatility Trend Analysis of China Exchange Rate  
**Source:** Authors' estimation 2024 with Eviews 10

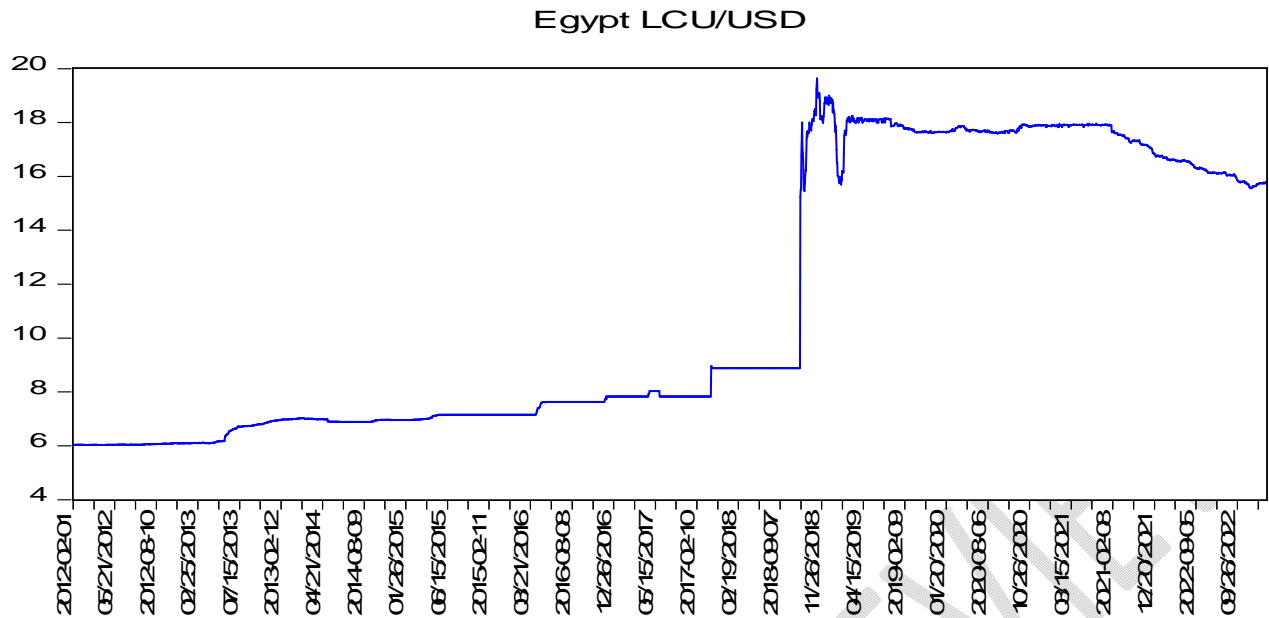


Figure 5: Volatility Trend Analysis of Egypt Exchange Rate  
**Source:** Authors' estimation 2024 with Eviews 10

The volatility tendency of Egypt's currency's exchange rate to the US dollar on the world oil markets is depicted in Figure 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 Figure 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.

Kuwait LCU/USD

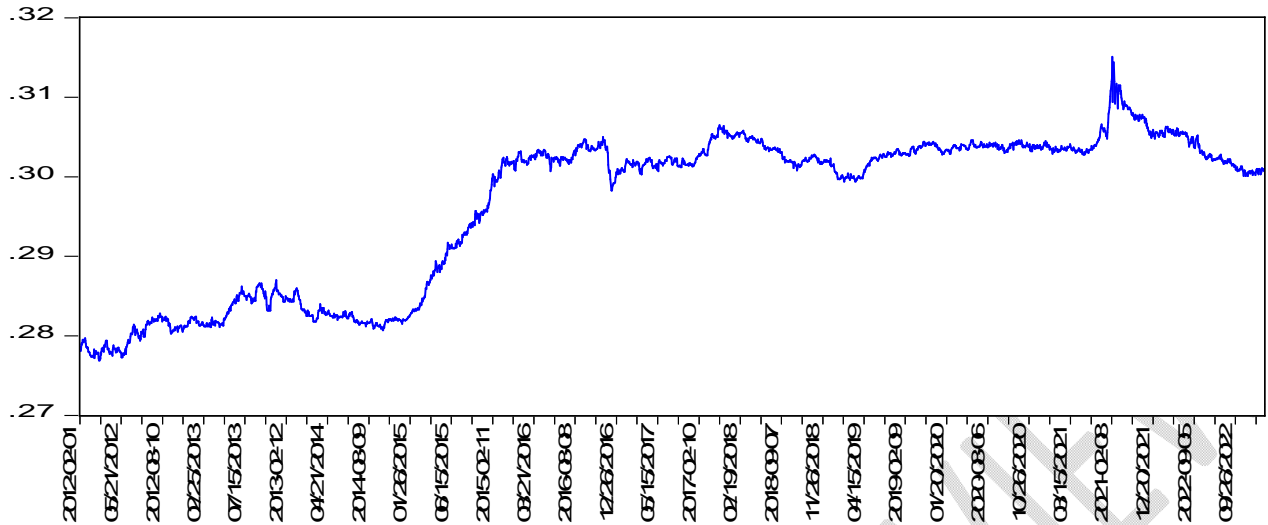


Figure 6: Volatility Trend Analysis of Kuwait Exchange Rate

Source: Authors' estimation 2024 with Eviews 10

Figure 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).

Libya LCU/USD

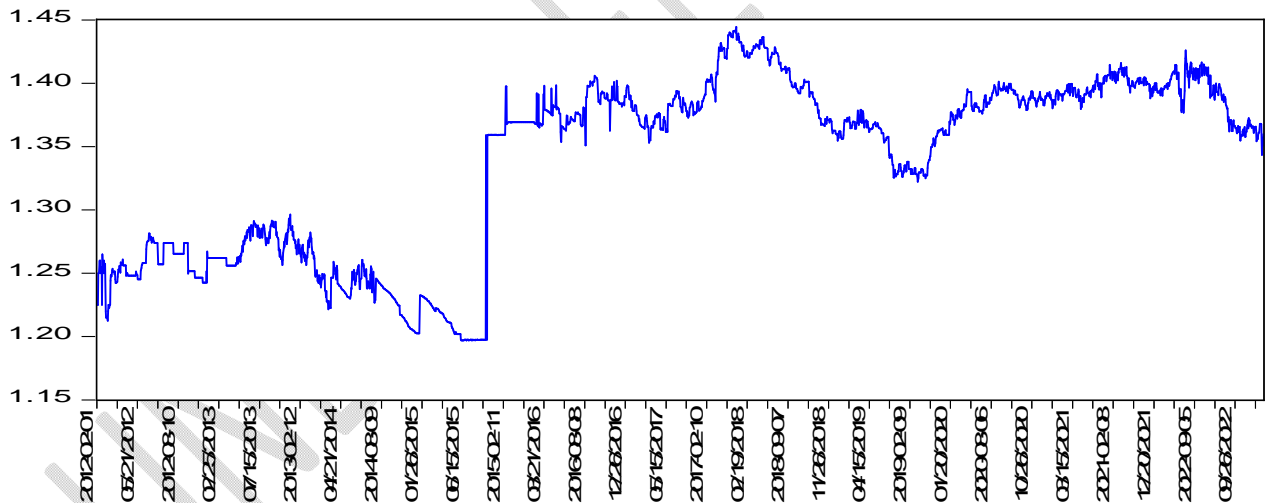


Figure 7: Volatility Trend Analysis of Libya Exchange Rate

Source: Authors' estimation 2024 with Eviews 10

The trend of the Mexican exchange rate liveliness was depicted in Figure 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.

### Mexico LCU/USD

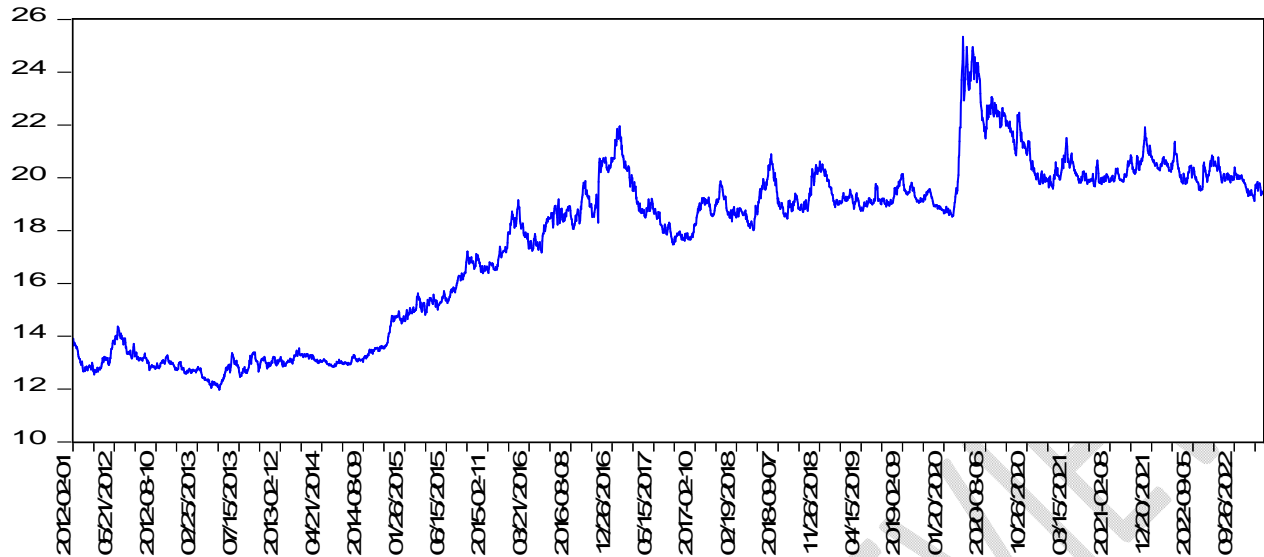


Figure 8: Volatility Trend Analysis of Mexico Exchange Rate

Source: Authors' estimation 2024 with Eviews 10

The development of volatility in the Nigerian exchange rate was illustrated in Figure 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).

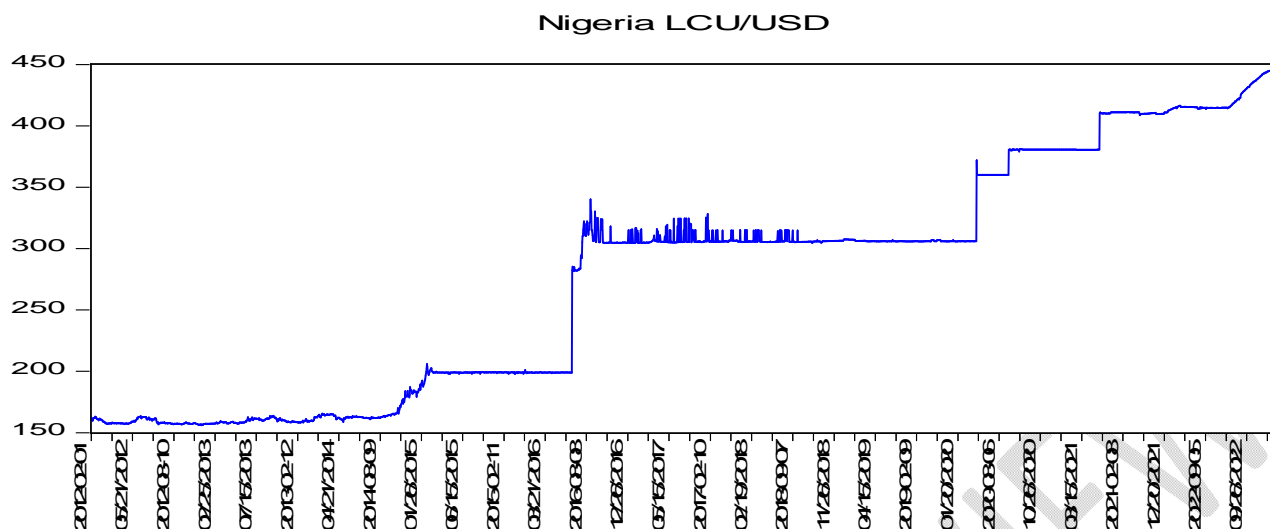


Figure 9: Volatility Trend Analysis of Nigeria Exchange Rate

Source: Authors' estimation 2024 with Eviews 10

The volatility pattern of the Norwegian currency rate relative to the US dollar is depicted in Figure 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.

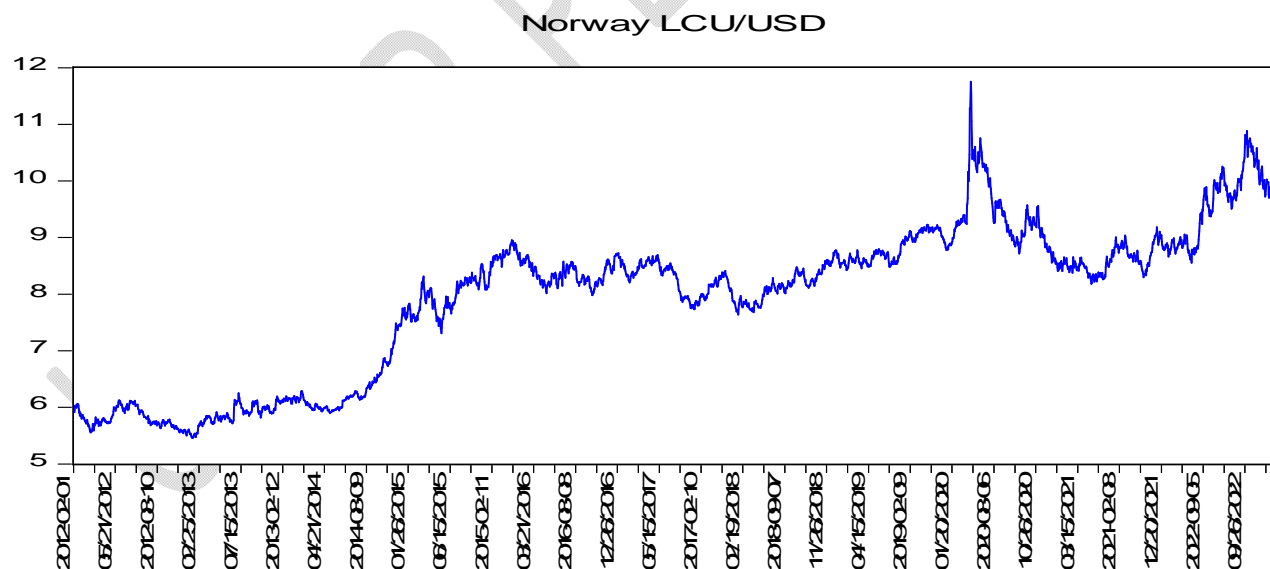


Figure 10: Volatility Trend Analysis of Norway Exchange Rate

Source: Authors' estimation 2024 with Eviews 10

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 Figure 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.

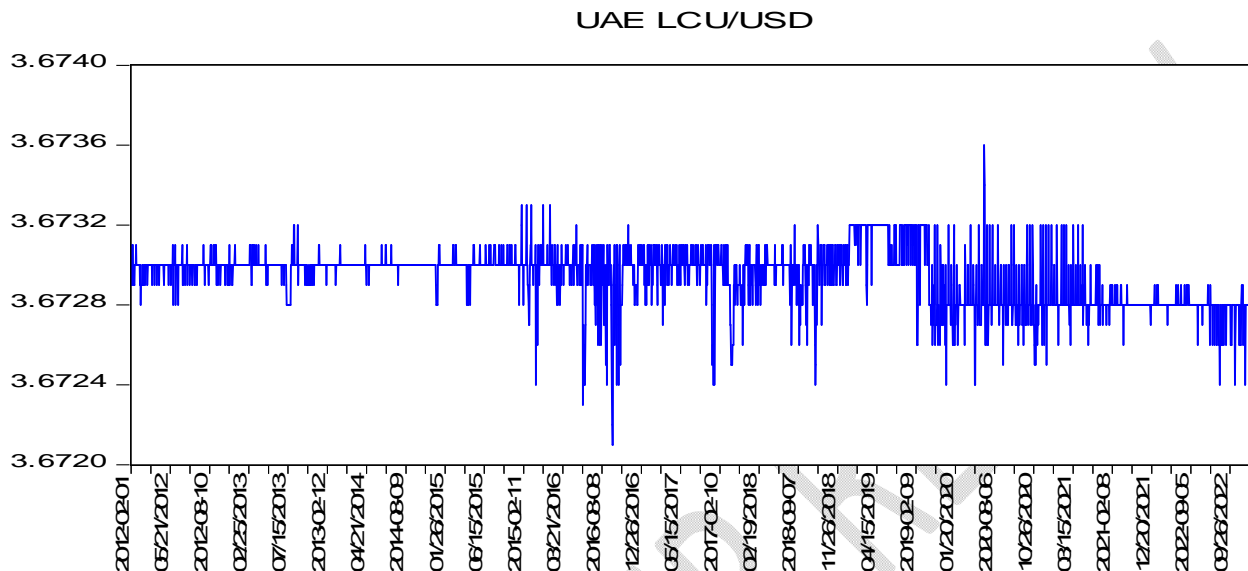


Figure 11: Volatility Trend Analysis of UAE Exchange Rate

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.

Table 1: Test for ARCH Effects

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

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.

**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

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.

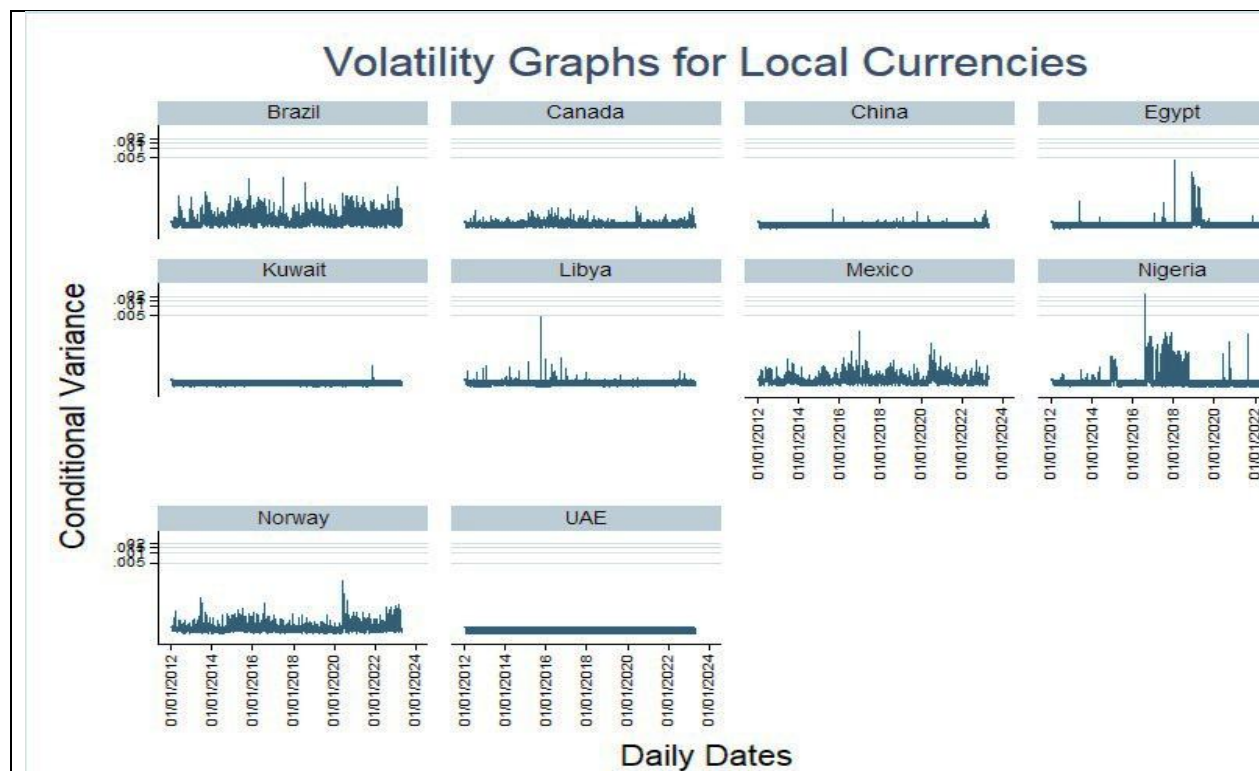
The significant leverage impact (TARCH term) is negative(-0.6712), indicating considerable evidence of asymmetry in the Bitcoin price reactions to exchange rate depreciation. In other words, the market participants would respond to both positive and negative news differently. All the market participants 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		

The volatility charts reported in Figure 12 below 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.



**Figure 12:** Volatility Charts for local currency exchange rates in relation to the USD

Source: Authors’ estimation 2024 with Eviews 13

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.

**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

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  $3.87 \times 10^{-5}$ – $53.87 \times 10^{-5}$ . 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 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.

**Table 5: Results of ARIMA models for selected countries**

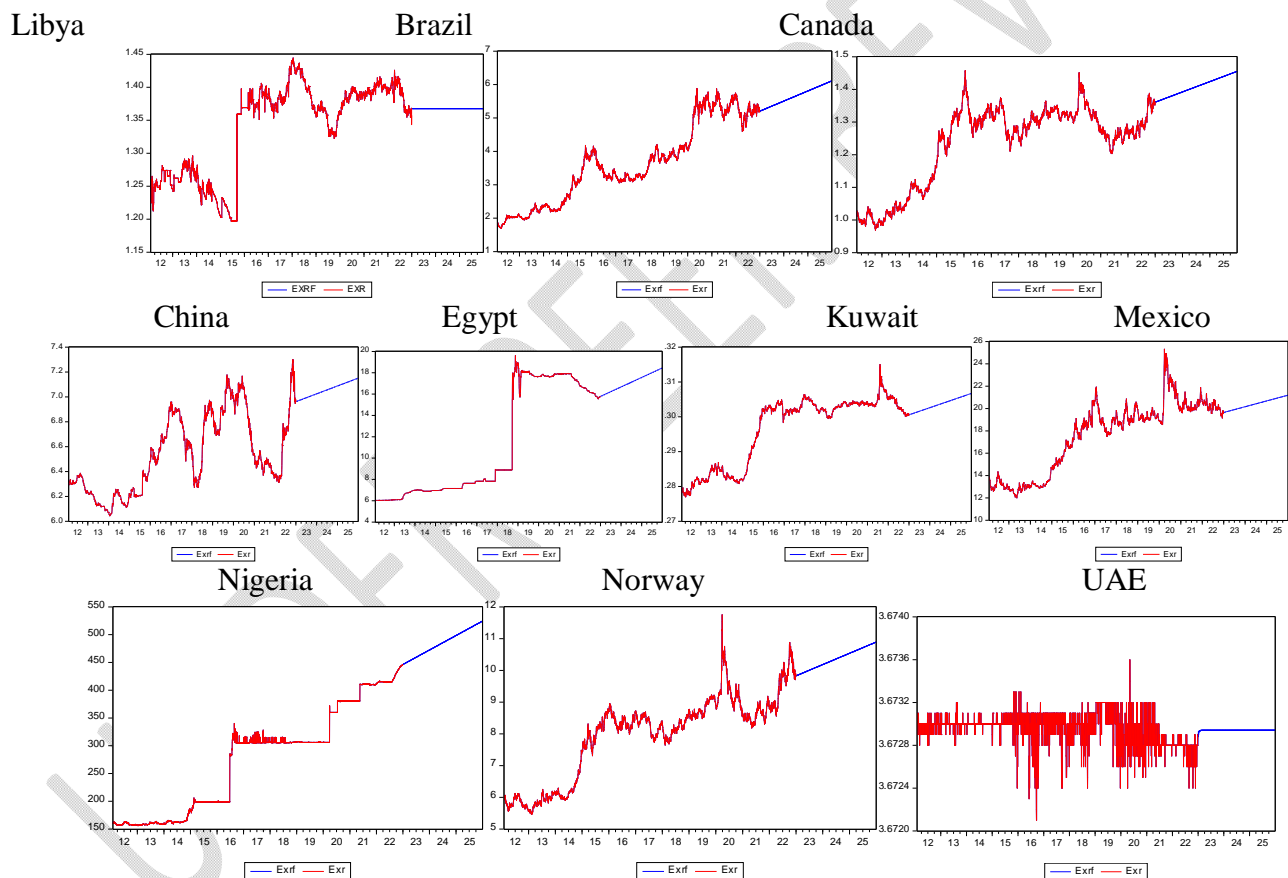
	Model (p,d,q)	C	AR	MA	SIGMASQ	AIC	RMSE
Libya	1,1,1	4.52E-05*	0.0769*	-0.4733*	3.87E-05*	-7.3185	0.0685
Brazil	1,1,0	0.0012*	-0.0519*	-	0.0017*	-3.5219	0.1087
Canada	1,1,0	0.00012*	-0.0208	-	3.43E-05	-7.4403	0.0045
China	4,1,4	0.0002*	-0.6598*	0.7071*	0.0002*	-5.5711	0.0097
Egypt	1,1,1	0.0034*	0.6947*	-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

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 Figure 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.



**Figure 13: ARIMA Forecast Charts for Selected Countries**

Source: Authors' estimation 2024 with Eviews 10

#### 4.1. 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 face 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.

## **5. Conclusion**

This study examined volatility in currencies of selected countries and their relationship with Bitcoin trading values. The GARCH and ARIMA estimators were used for analysis. Descriptive 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. 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 research found that past currency values jointly predict future values in most countries. 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 or 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. 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.

## References

- Attarzadeh, A., & Balcilar, M. (2022). On the dynamic returns and volatility connectedness of cryptocurrency, crude oil, clean energy, and stock markets: a time varying analysis. *National Center for Biotechnology Information/National library for Medicine, Environmental Science Pollution Research International*. 29(43), 65185-65196, doi. <https://doi.org/10.1007%2Fs11356-022-20115-2>
- Bensaida, A. (2023). The linkages between bitcoin and foreign exchange in developed and emerging markets, *Financial Innovation* 9(38), 3-27, <https://doi.org/10.1186/s40854/-023-00454-w>.
- Drehmann, M. & Sushko, V. (2022). The global foreign exchange market in a higher-volatility environment. *BIS Quarterly Review*, 5. The global foreign exchange market in a higher-volatility environment (bis.org)
- Ghazani, M. M. & Jafari, M.A. (2021). Cryptocurrencies, gold and WTI crude oil Market efficiency: A dynamic analysis based on the adaptive market hypothesis. *Finan. Innov* 7,29 (2021). <https://doi.org/10.1186/s40854-021-00246-0>.
- Gkillas, K., Bouri, E., Gupta, R., & Roubaud, D. (2022). Spillovers in higher-order moments of crude oil, gold and Bitcoin. *The Quarterly Review of Economics and Finance*, 84, May 2022. 398-406.
- Gomes, G. (2016). On the Impact of dollar movement on the oil Currencies. *CEPII Working Papers*, Research and Expertise on the world economy.
- Goodell, J.W. & Goutte S. (2020). Diversifying equities with Cryptocurrencies during covid-19, *International Review of Financial Analysis*. Volume 76(2021), <https://doi.org/10.1016/j.irfa.2021.101781>
- Guidci, P. & Abu-Hashish, I. (2019). What Determines Bitcoin Exchange Prices. A network VAR Approach. *Finance Research Letter*, 28(2019), 309-318. <https://doi.org/10.1016/j.frl.2018.05.013>
- Jin, F., Li, J., & Li, G. (2022). Modeling the linkages between bitcoin, gold, dollar, crude oil and stock markets: A GARCH-EVT-Copula Approach. *Discrete Dynamics in Nature and Society*
- Li, D., Hong, Y., Wang, L. Xu, P., & Pan, Z. (2022). Extreme Risks Transmission among Bitcoin and crude oil markets. *Resource Policy*, 77(2022),
- Lin, M.Y., & An, C. (2021). The relationship between bitcoin and resource commodity futures: evidence from NARDL approach. *Resource Policy*, 74(3415),
- Park, S., Jang, K., & Yang, J. (2021). Information flows between Bitcoin and other financial assets. *Physical A: Statistical Mechanics and its Application*, Vol.566 (2021), <https://doi.org/10.1016/j.physa.2020.125604>
-

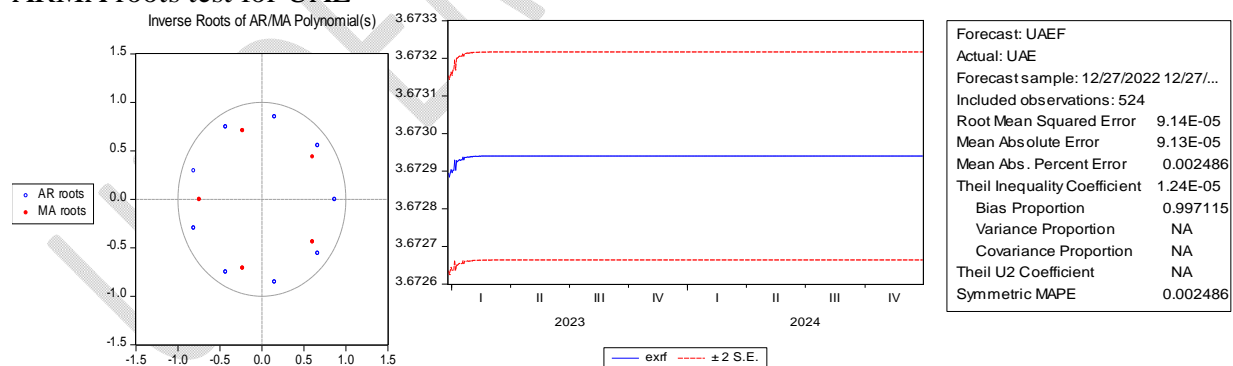
- Ren, S., Wang, R., Duan, K., & Chen, J. (2022). Dynamics of the Sheltering role of bitcoin against crude oil market crash with severity of the COVID-19: A comparison with Gold. *Res.Int Bus Finance*, 62, <https://doi.org/10.1016%2Fj.ribaf.2022.101672>.
- Pallazzi, R.B., Raimundo-Junior, G.S., & Klotzle, M.C. (2021). The dynamic of Bitcoin and Foreign Exchange Market: A Nonlinear Approach to test causality between Bitcoin currencies. *Finance Research Letters*. Vol.42, October 2021,
- Barber, S., Boyen, X., Shi, E., & Uzun, E. (2022). Bitcoin and Financial Inclusion: A Case Study of Emerging Economies. *IEEE Transactions on Information Forensics and Security*, 17(2), 361-374.
- Baur, D. G., & Dimpfl, T. (2020). Cryptocurrency Return Distributions and Market Factors: A Panel VAR Approach. *Journal of International Financial Markets, Institutions and Money*, 67, 101203.
- Baur, D. G., & Hoang, T. C. (2020). Bitcoin as a Hedge against Local Currency Depreciation and Economic Instability: Evidence from Emerging Economies. *Emerging Markets Finance and Trade*, 56(11), 2581-2596.
- Baur, D. G., & Lucey, B. M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. *Financial Review*, 45(2), 217-229.
- Baur, D. G., Dimpfl, T., & Kuck, K. (2020). Bitcoin as a Digital Investment Asset: Insights from Emerging Markets. *Emerging Markets Finance and Trade*, 56(10), 2358-2372.
- Bodie, Z., Kane, A., & Marcus, A. J. (2021). *Investments*. McGraw-Hill Education.
- Bonneau, J., Narayanan, A., Miller, A., Clark, J., Kroll, J. A., & Felten, E. W. (2020). Research Perspectives and Challenges for Bitcoin and Cryptocurrencies. *Communications of the ACM*, 62(2), 92-101.
- Cheah, E. T., & Fry, J. (2020). Bitcoin in Emerging Economies: Understanding the Dynamics of Bitcoin Demand in Response to Exchange Rate Movements. *Emerging Markets Finance and Trade*, 56(9), 2119-2133.
- Cong, L. W., Li, Z., & Wang, J. (2020). Blockchain Disruption and Smart Contracts. *Review of Financial Studies*, 33(1), 193-229.
- Corbet, S., Larkin, C., Lucey, B., & Yarovaya, L. (2020). The Impact of Regulatory News on Cryptocurrency Returns. *Finance Research Letters*, 35, 101554.
- Demirgüç-Kunt, A., Klapper, L., Singer, D., & Van Oudheusden, P. (2022). Financial Inclusion in Emerging Economies: The Role of Bitcoin. *Emerging Markets Finance and Trade*, 58(9), 2089-2103.
- Eichengreen, B., & Rose, A. K. (2023). Bitcoin and Capital Controls: Evidence from Emerging Economies. *Emerging Markets Finance and Trade*, 59(4), 783-797.
- Eiteman, D. K., Stonehill, A. I., & Moffett, M. H. (2020). *Multinational Business Finance*. Pearson.
- Fenwick, M., Kaal, W., & Vermeulen, E. P. (2020). Legal Education in the Blockchain Revolution. *University of Illinois Law Review*, 2020(1), 101-142.
- Fernandes, G., & Malik, S. (2024). The effects of monetary policy on stock market volatility and returns in the European Union. *European Financial Review*, 40(3), 320-340.
- Fischer, D., & Schwartz, G. (2023). Liquidity risk and dividend-paying stocks in European markets. *Finance Research Letters*, 39, 85-98.
- Green, D., & Carter, J. (2022). Market volatility and stock returns post-Brexit. *British Journal of Finance*, 31(4), 202-223.
- Hansen, S., & Kumar, P. (2022). Technological innovation, stock market volatility, and returns: A multifactor GARCH analysis. *American Economic Review*, 112(5), 1504-1527.
- Harper, C., & Lim, R. (2022). Stock market volatility and returns in developed economies: An analysis using FIGARCH. *Journal of Financial Stability*, 54, 47-63.
-

- Hayes, A. S. (2023). Bitcoin's Role in the Financial System: Opportunities and Challenges. *Journal of Financial Planning*, 36(4), 56-69.
- Hillier, F. S., & Lieberman, G. J. (2022). *Introduction to Operations Research*. McGraw-Hill Education.
- Hoang, T. C., Wilson, P., & Pham, N. (2020). Bitcoin's Role as a Contributor to Returns and Volatility Spillovers Among Cryptocurrencies: Evidence from Emerging Economies. *Emerging Markets Finance and Trade*, 56(1), 87-106.
- Ibikunle, G., & Akutson, J. (2022). Volatility spillover effects of cryptocurrency prices on foreign exchange markets: evidence from emerging economies. *Emerging Markets Finance and Trade*, 58(5), 1036-1053.
- Ibrahim, A., & Clark, E. (2022). Liquidity risk and stock returns in sub-Saharan African markets. *African Journal of Economic and Management Studies*, 13(2), 234-251.
- Ivanov, D., & Petrova, E. (2023). Geopolitical risks and stock market dynamics in Eastern Europe. *Emerging Markets Review*, 39, 100-115.
- Karau, S. (2023). Monetary policy and Bitcoin: Evidence from historical data. *Finance Research Letters*, 36, 101691.
- Kim, T., Song, B., & Kim, D. (2022). Bitcoin Trading Volumes in Emerging Economies during Economic Crisis: The Case of Venezuela. *Journal of Economic Development*, 47(3), 97-112.
- Kostika, E., & Laopodis, N. T. (2020). Dynamic linkages of cryptocurrencies with other asset classes: A study on their interaction with equities, commodities, and currencies. *International Review of Financial Analysis*, 71, 101514.
- Kristoufek, L. (2015). What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis. *PLOS ONE*, 10(4), e0123923.
- Kristoufek, L. (2020). On Bitcoin Markets (in) Efficiency and (in) Stability. *Finance Research Letters*, 35, 101580.
- Lee, D., & Chen, F. (2024). Liquidity risk and stock returns in the technology sector. *Journal of Financial Markets*, 37, 45-62.
- Letho, V., Luoma, A., & Suvas, A. (2022). Diversification Benefits of Cryptocurrencies in Emerging Market Economies. *Emerging Markets Finance and Trade*, 58(3), 572-589.
- Liu, Y., & Tsyvinski, A. (2021). Bitcoin's Diversification Potential: Evidence from Emerging Economies. *Emerging Markets Finance and Trade*, 57(8), 1843-1857.
- Lukeman, M. (2015). Impact of inflation on investment in Nigeria: Evidence from time series analysis. *Journal of Economics and Sustainable Development*, 6(22), 142-156.
- Luther, W. J., & Salter, A. W. (2020). Bitcoin: A Hedge Against Currency Volatility in Emerging Markets. *Journal of Financial Stability*, 49, 100785.
- Mallick, B., & Mallik, G. (2023). Cryptocurrency and exchange rate: Empirical evidence from India. *Management Dynamics in the Knowledge Economy*, 11(2), 187-207.
- Narayanan, A., Bonneau, J., Felten, E., Miller, A., & Goldfeder, S. (2016). *Bitcoin and Cryptocurrency Technologies: A Comprehensive Introduction*. Princeton University Press.
- Nkosi, B., & Adesina, K. (2024). Volatility-return dynamics in African stock markets. *Journal of African Economies*, 33(4), 410-430.
- Patel, H., & Lee, S. (2023). Liquidity risk and stock returns in the fintech industry in Asia. *Journal of Financial Technology*, 5(1), 58-74.
- Polat, O., & Günay, S. (2021). Volatility Spillovers from Cryptocurrencies during the COVID-19 Pandemic: Evidence from Emerging and Developed Markets. *Emerging Markets Finance and Trade*, 57(14), 3428-3443.
- Qarni, M. A., & Gulzar, S. (2021). Dynamics of volatility spillover from bitcoin to foreign exchange pairs: evidence from major trading currencies. *Emerging Markets Finance and Trade*, 57(13), 3217-3234.
-

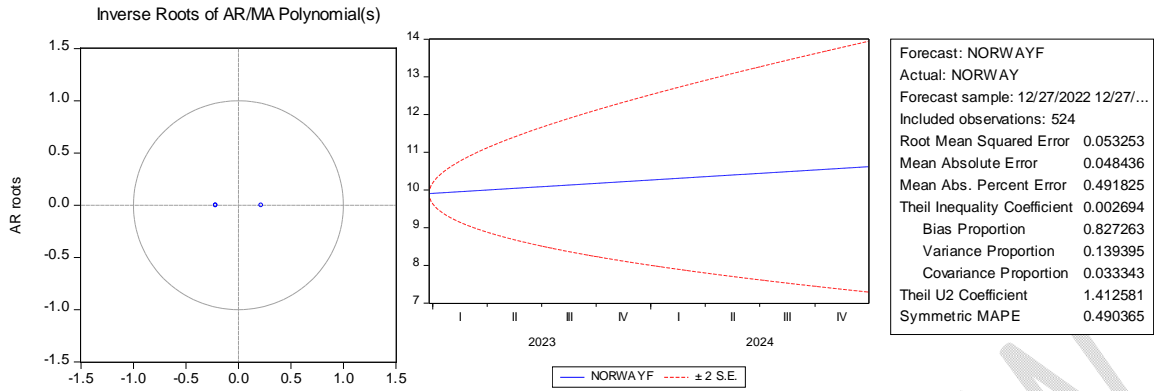
- Sahar, A., et al. (2024). Dynamic interactions among fintech, digital currencies, exchange rates, oil price volatility, and financial risk. *Finance Research Letters*, 44, 102267.
- Shaik, M. (2023). Dynamic volatility connectedness of FinTech, innovative technology communication, and cryptocurrency indices. *Finance Research Letters*, 40, 101931.
- Siauwijaya, M., & Sanjung, J. (2022). Bitcoin and the Cryptocurrency Market: Evolution, Dominance, and Impact on Global Financial Markets. *Journal of Economic Behavior & Organization*, 195, 95-114.
- Smales, L. A. (2022). Bitcoin as a Hedge against Political Instability and Economic Policy Uncertainty: Evidence from Emerging Economies. *Emerging Markets Finance and Trade*, 58(7), 1545-1560.
- Tang, K., Lee, H., Huang, Y., & Liu, H. (2024). E-mini S&P 500 futures crash risk and Bitcoin futures returns and volatility: Evidence from 2017 to 2021. *Finance Research Letters*, 42, 101886.
- Tapscott, D., & Tapscott, A. (2016). *Blockchain Revolution: How the Technology Behind Bitcoin is Changing Money, Business, and the World*. Penguin.
- Tapscott, D., & Tapscott, A. (2023). Blockchain Technology and Its Implications for Various Industries. *Harvard Business Review*, 101(2), 162-177.
- Thompson, S., & Raj, V. (2021). The impact of volatility shocks on stock returns in North American markets. *North American Journal of Economics and Finance*, 55, 101233.
- Tobin, J. (1958). Liquidity Preference as Behavior Towards Risk. *Review of Economic Studies*, 25(2), 65-86.
- Urquhart, A., & Zhang, H. (2020). Is Bitcoin a Hedge or Safe Haven for Currencies? An Intraday Analysis. *International Review of Financial Analysis*, 63, 105-116.
- Urquhart, A., & Zhang, H. (2023). Exchange Rate Volatility and Bitcoin Demand in Emerging Economies. *Emerging Markets Finance and Trade*, 59(2), 314-329.
- Zitis, G., et al. (2023). Changes in the multifractal characteristics of Bitcoin and Euro returns before and after the COVID-19 outbreak. *Physica A: Statistical Mechanics and its Applications*, 588, 125643.

## Appendix

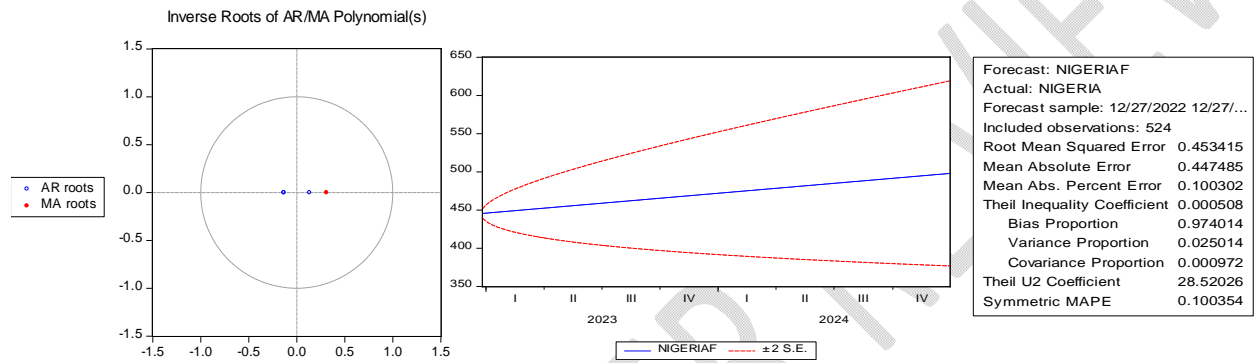
### ARMA roots test for UAE



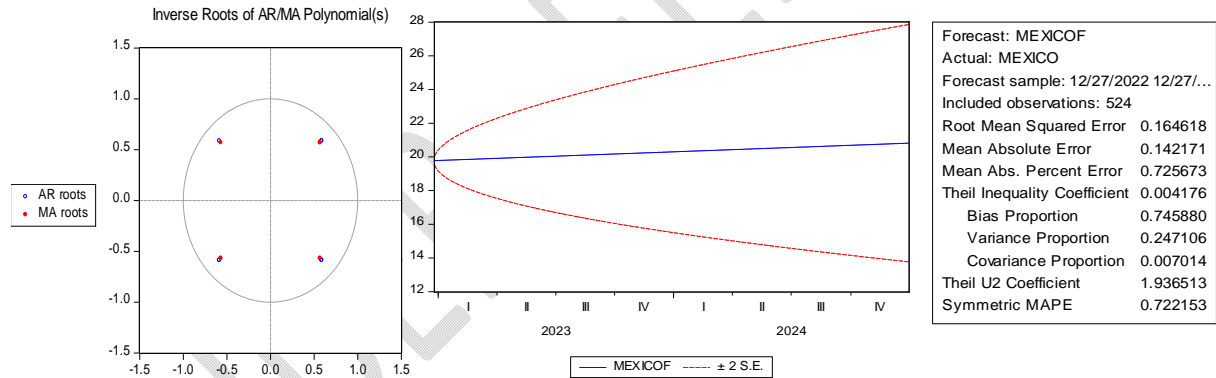
### ARMA roots test for Norway



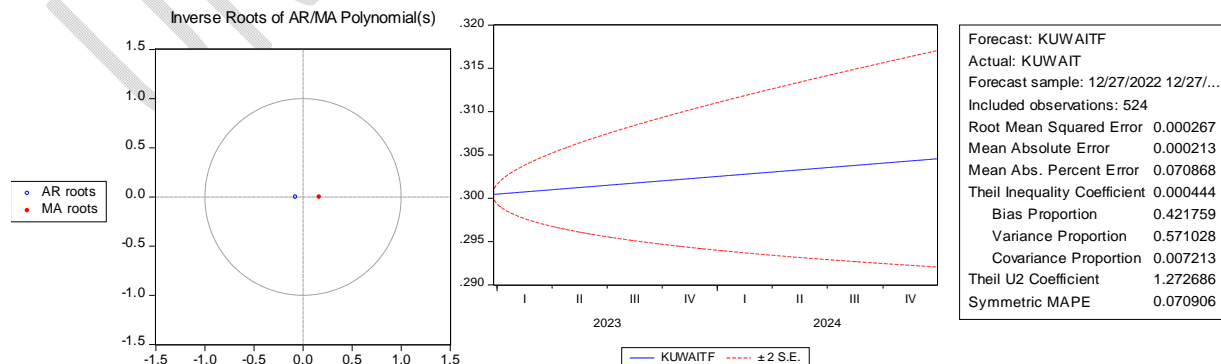
### ARMA roots test for Nigeria



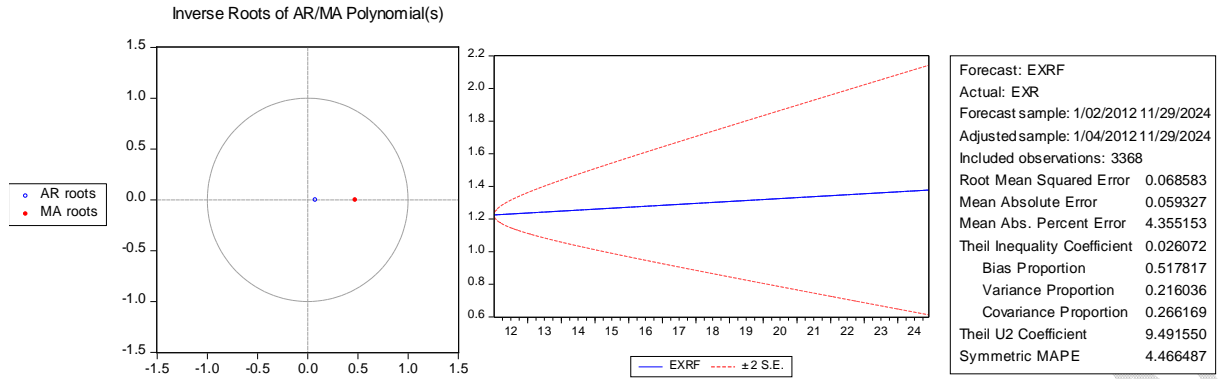
### ARMA roots test for Mexico



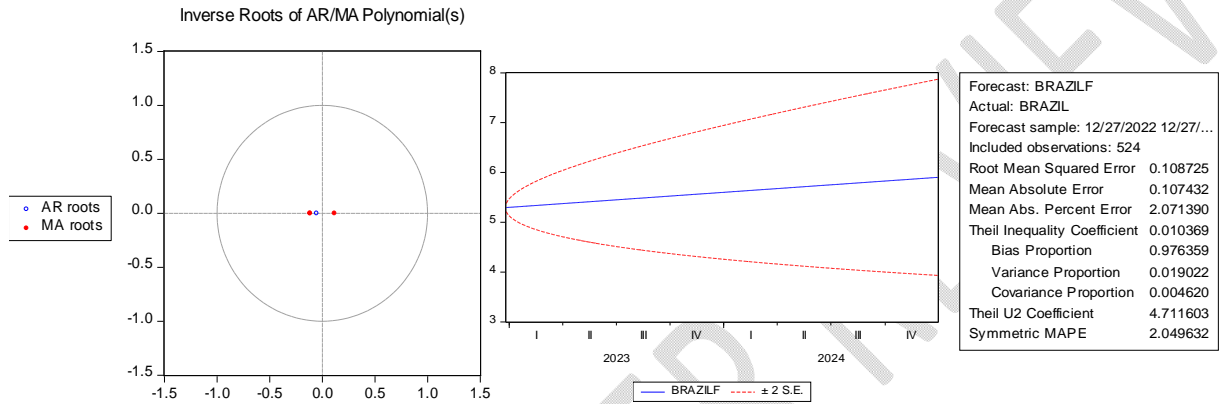
### ARMA roots test for Kuwait



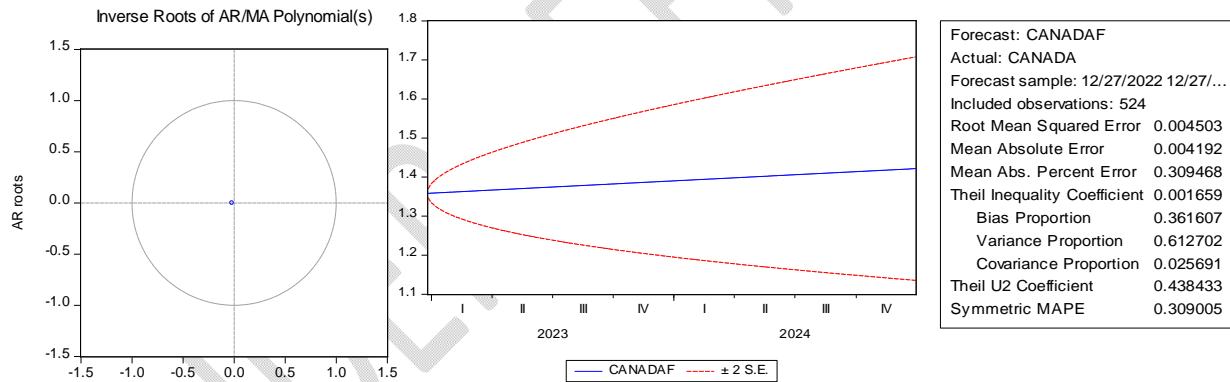
### ARMA roots test for Libya



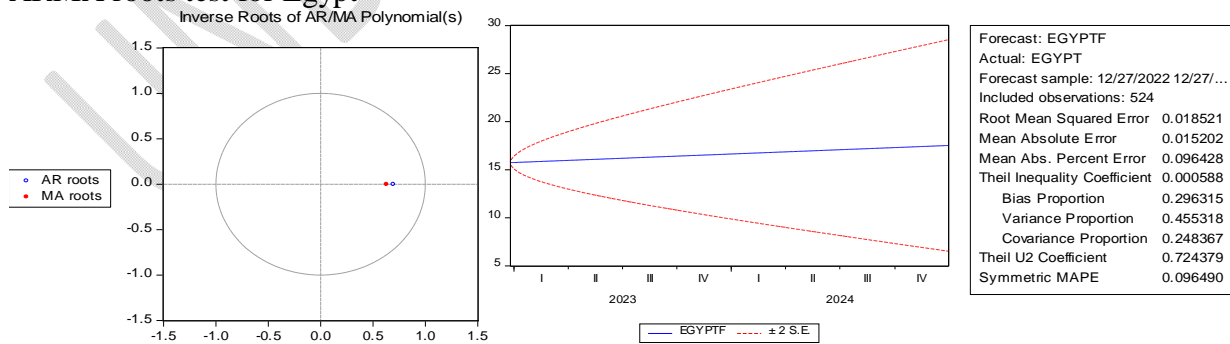
### ARMA roots test for Brazil



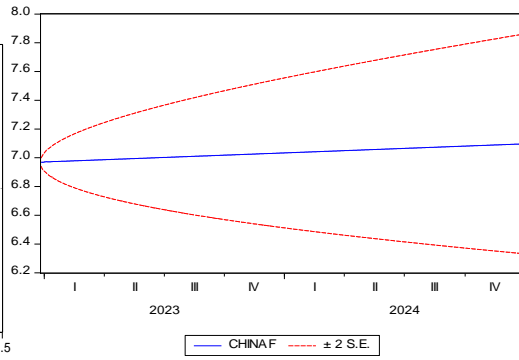
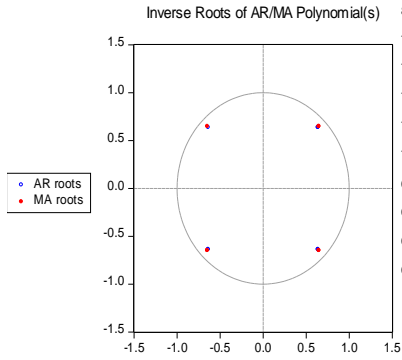
### ARMA roots test for Canada



### ARMA roots test for Egypt



### ARMA roots test for China



Forecast:	CHINAF
Actual:	CHINA
Forecast sample:	12/27/2022 12/27/...
Included observations:	524
Root Mean Squared Error	0.009682
Mean Absolute Error	0.009494
Mean Abs. Percent Error	0.136140
Theil Inequality Coefficient	0.000694
Bias Proportion	0.142685
Variance Proportion	0.822461
Covariance Proportion	0.034853
Theil U2 Coefficient	0.550251
Symmetric MAPE	0.136183

UNDER PEER REVIEW