Volatility behaviour of currency exchange rates in selected countries: Long Memory Effect

Abstract

In financial econometrics, models of long memory, such as ARFIMA models, are compared to short memory models, such as ARIMA models. Given that the researchers were empirically desirous of determining the volatility behaviour of exchange rate returns on African currencies in exchange for the United States dollar, we went beyond ARIMA modeling to test for the incidence or otherwise of fractional integration of all the currencies of selected countries in view of data availability. Hence, the order of integration test was carried out. Three different models of ARFIMA (1, d, q) were subjected to selection isometrics, and the best model was determined on the basis of the smallest ACF, AIC, and SBC values. The chosen models were estimated using the iterative algorithm, which encompasses the conditional maximum likelihood. The existence of a fractional integration was established for exchange rate returns for all the currencies. The study found an incidence of robust long-term memory in the volatility of currencies in selected countries, indicating that shocks to the exchange rates of BWP, KES, EGP, NGN, and TND in relation to the US dollar decay at a slow rate over time. In effect, the volatility in the currency exchange rates of the countries researched is long-lasting. The study also established that the ARFIMA (1, 0.0291, 1), ARFIMA (1, 0.250, 1), ARFIMA (1, 0.016, 1), and ARFIMA (1, 0.338, 1) models are the dominant models for analyzing the daily inter-temporal dynamics associated with the exchange rate returns of BWP, KES, EGP, and TND. Only for the Naira/dollar exchange rate, we found the ARFIMA (1, 0.197, 2) model to be the best. The robustness check of our estimates was ascertained when we estimated the hybrid ARFIMA (p,d,q)-GARCH (1,1) models that were highly significant with larger values of log-likelihood. So, we recommended the ARFIMA (1, d, 2) model for analyzing the long-term volatility of the Naira/dollar exchange rate returns, while the ARFIMA (1, d, 1) model should be applied in analyzing the exchange rate return dynamics of the currencies of the other countries researched. The research findings are significant because they pave the way for policymakers around the exchange rates of the researched countries to determine whether their exchange rate volatility is long-lasting, to use a model-based framework instead of observing only trends, and to revise their policies on exchange rates accordingly.

Keywords: Long memory, fractional integration, exchange rate returns, volatility of exchange rates, currencies, BRICS, ARFIMA, ARCH-LM test
JEL Classification: C22, C14, F30

Original research article

1. Introduction

Volatility is an important concept in financial market research since it helps businesses and analysts identify the risks associated with an investment or exchange (Wang et al., 2020).

Volatility is particularly important in finance given that it affects pricing decisions, management of risks, diversification of investments, and optimization processes. As a result, affected market participants monitor volatility to help with forecasts and investment diversification (Kalotychou & Staikouras, 2009). In most cases, volatility is calculated as the standard deviation of historical asset price returns. Exchange rate volatility exists when there are oscillations or irregular movements in the currency exchange value or returns on exchange rates (Umoru, 2023). The market that houses exchange rates is known for fluctuations, and this puts actors and market participants at risk. Accordingly, exchange rate volatility is associated with the risks involved in international trading, which makes investment decisions uncertain. This study aims at investigating the extent of the long-term volatility of African currencies in exchange for the US dollar. The African currencies include Botswana Pula (BWP), Kenyan Shillings (KES), Egyptian Pounds (EGP), Nigerian Naira (NGN), and Tunisian Dinars (TND). These countries are emerging countries; hence, they are more exporters of finished goods than importers and because of this, their currencies are internationally demanded. Presently, the volatility of the currency exchange rates of African countries with respect to the US dollar has been noticeable. Given that in the market that houses foreign exchange, volatility is said to occur when there are undulations or oscillations in the rates of exchange of different currencies that put actors like individual investors, firms, and multinational companies at risk, it is pertinent to investigate the volatility of currency exchange rates in African countries.

The study is scientifically robust and technically sound because all sorts of methodologies have been followed and each step has been adequately analyzed. The significance of this research is that it provides foreign exchange market participants with an empirical understanding of volatility clustering in order to make well-versed decisions. Large corporations, institutions, banks, and major players in the market will be well informed in order to take decisions that will aid profit maximization and cost minimization. These institutions are key players in foreign exchange because they import raw materials from the foreign nation, depending on the quality of the resource, with the sole aim of reducing cost as much as possible and maximizing gain. Also, the exchange rate of currencies in different countries can be influenced by their central bank, which is well informed about how to control the variables in the market with the most applicable policies to obtain the preferred results. The essentiality of all these is the improvement of the economies with better knowledge of the factors that affect the volatility and oscillations of the rate of exchange. This will also contribute to related studies and provide knowledge for researchers who would need it, especially as regards exchange rate volatility in selected African countries. The research findings are of immense benefit to third-world countries whose forex markets are highly unstable. The research findings are significant because they pave the way for policymakers around the exchange rates of the researched countries to determine whether their exchange rate volatility is long-lasting, to use a model-based framework instead of observing only trends, and to revise their policies on exchange rates accordingly. Knowledge and understanding of the nature of the market and the oscillations can positively influence the policies established within the nations to aid favourable balances and effects on the rates of exchange for the currencies involved. This will lead to achieving desired outcomes, and the economy of the nation will be enhanced. This study would serve as a guide for institutions involved in importation to know the movements in the market in terms of prices, which will enable them to know when and how to trade in foreign currency, either at the at the spot rate or the forward rate. The choice of which is dependent on the price that is in favour of the institution or player. The literature review is part two. Part three outlines the methodology of the study, which includes the theoretical framework, estimation techniques, and sources of data. The discussion of results is done in part four, and the summary of findings, recommendations, and conclusion of the study is done in part five.

2. Literature Review

2.1. Theoretical review

On the part of foreign exchange market theories is the asset market theory (AMT), which offers a theoretical lens for understanding exchange rate dynamics, centered on financial assets as primary influencers. According to Fischer (1973), the theory delves into the intricate interplay of interest rates, money supply, and expectations of future exchange rates. Central to the AMT is the role of interest rates: higher rates attract foreign investment and, as such, appreciate the currency, while a lower rate depreciates the value of the currency. Changes in the money supply wield influence, with increases potentially causing depreciation due to inflationary pressures (Alber, 2024; Krugman, Obstfeld, & Melitz, 2018). Expectations about future exchange rates are pivotal in shaping current currency demand. The model assumes market equilibrium, where exchange rates adjust based on supply and demand forces. Speculative activities also play a role in short-term fluctuations.

The balance of payments (BoP) theory emphasizes that a persistent current account surplus can lead to an appreciation of the domestic currency, as increased demand for the currency arises from foreign entities seeking to pay for the surplus goods and services. A surplus in the capital account could potentially lead to an appreciation of its currency. Conversely, a capital account deficit may exert downward pressure on the currency. The BOP theory posits that the combination of the current account and capital account balances influences a nation's exchange rates. The fluctuations in both the current and capital account balances can result in changes to exchange rates. For instance, if a country consistently runs a current account deficit and relies on capital inflows to finance it, the increased demand for foreign currency may lead to devaluation. The central proposition of the PBT is that investors make choices regarding the composition of their portfolios based on considerations of expected returns and perceived risks associated with different assets. This allocation decision extends beyond domestic assets to include foreign assets, particularly those denominated in different currencies. In essence, the PBT contends that the demand for a currency is influenced not only by trade-related factors but also by the attractiveness of that currency's financial assets to investors.

2.2. Empirical review

Wiri & Tuaneh (2022) carried out a study regarding the monthly exchange rate of the Nigerian currency in relation to the US dollar, basing their analysis on the ARFIMA method. The authors established the presence of a long memory in the data and reported that ARFIMA (1, 0.0868, 1) was the best model for analyzing the monthly inter-temporal dynamics associated with the Naira-dollar exchange rate. Afzal & Sibbertsen (2022) did a study on long memory and structural breaks in the spot exchange rates using daily data on thirty currencies over the dollar and found the presence of spurious memory, which they attributed to volatility shocks associated with the estimator. MGibson & Farah (2024) delved into the repercussions of exchange rate volatility on the international sourcing decisions of multinational corporations (MNCs) in the manufacturing sector. Focusing on firms based in the United States and Europe from 2015 to 2023, the study aimed to analyse how exchange rate fluctuations influence decisions regarding the location of supply chains and the sourcing of raw materials. Employing a Panel Granger Causality approach, it was found that higher exchange rate volatility led to a significant increase in near-shoring activities, with firms preferring suppliers from countries with more stable currency exchanges. The research revealed the strategic shifts MNCs are making in response to financial uncertainty, suggesting that more stable currency environments could attract more global supply chain investments. Thakur & Weaver (2024) analysed the connection between exchange rate volatility and tourism revenue in Small Island developing states (SIDS), covering a period from 2000 to 2023. The study used tourism revenue as the dependent variable, with exchange rate volatility, political stability, and global economic conditions as the explanatory variables. Employing a mixed-effects model to account for both fixed and random variations across different regions, the analysis highlighted a robust negative correlation between exchange rate volatility and tourism revenues. The findings also indicated that improved political stability and favourable global economic conditions could partially offset the negative impacts of exchange rate fluctuations. The research revealed the importance of macroeconomic stability and targeted policy interventions to bolster tourism in SIDS, suggesting that managing exchange rate volatility should be part of a broader economic strategy to sustain tourism-dependent economies. Ali & Gomes (2024) analyzed the interdependence between cryptocurrency volatility and traditional currency exchange rate fluctuations, focusing on the Bitcoin to USD exchange rate and its interaction with EUR/USD and JPY/USD from 2019 to 2023. The research was structured around two key objectives: (i) to determine the extent to which volatility in the cryptocurrency market influences traditional currency volatility clustering and (ii to identify the directional influence between these markets. Using a Dynamic Conditional Correlation (DCC) GARCH model, it found a significant, bidirectional relationship where spikes in Bitcoin volatility led to enhanced clustering in traditional currency pairs and vice versa, particularly during global financial uncertainties. The study suggests that cryptocurrency market dynamics are increasingly integral to traditional financial systems, and it recommends that central banks and financial institutions adjust their monitoring and policy frameworks to include influences from digital assets. Friedman & Rajagopal (2024) conducted a study on the impact of exchange rate volatility on real estate investments in major global cities, including London, New York, Tokyo, and Sydney, over the period from 2015 to 2023. The study aimed to determine how fluctuations in exchange rates affected international investment flows into the real estate market. Using a GARCH model to analyze volatility, the study revealed that exchange rate volatility had a deterrent effect on short-term real estate investments but was less significant for long-term holdings. The findings indicate that while short-term investors are sensitive to exchange rate risks, long-term investors may be more influenced by the intrinsic value and stability of real estate as an asset class. They suggest that real estate markets in globally recognized cities remain attractive to international investors who adopt a long-term perspective, despite currency volatility.

Mendez (2024) examined the impact of exchange rate fluctuations on the competitiveness of agricultural exports from Colombia within the period 2000–2023. Secondary data for exchange rates, export volumes, and price indices were used for estimation. The study utilized VECM for data estimation. The analysis found that exchange rate instabilities had a significant effect on the competitiveness of agricultural exports, with significance levels lower than 0.05. The study also found that exchange rate movements significantly explained the changes in export volumes and prices during the analyzed period. Long-run and short-run analyses were conducted, revealing that deviations from long-term equilibrium are adjusted at a speed of 4.8% annually. Additionally, the short-run coefficient for exchange rate fluctuations is 0.093, indicating that in the short run, a 1% increase in exchange rate volatility could lead to a 0.093% decrease in export competitiveness. Based on these findings, it is recommended that the government implement policies to stabilise the exchange rate to enhance the global competitiveness of Colombian agricultural products.

Umoru, Akpoviroro & Effiong (2023) investigated the basis of exchange rate volatility in seven African countries. The analysis was based on ARDL bounds testing for co-integration and ARCH/GARCH methodologies in Niger, Equatorial Guinea, Cote d'Ivoire, Sudan, Cameron, Tunisia, and the Congo. An adjustment speed of 39% of the volatility in the exchange rate was found for the Sudanese economy. The adjustment speed of 55% of the volatility in the exchange rate was found for the Tunisian economy, and the adjustment speed of 52% of the volatility in the exchange rate was found for Cameroon. In the Niger Republic, a 50% adjustment speed of the volatility in the exchange rate was reported. In Congo, a 32% adjustment speed of the volatility in the exchange rate was found. The adjustment speed of 58% of the volatility in the exchange rate was found for Equatorial Guinea, whereas in Côte d'Ivoire, the adjustment speed of 45% of the volatility in the exchange rate was reported, respectively. By implication, the causes of exchange rate volatility among African countries differ across countries. A study by Ezirim et al. (2023) considered the long-term determination of rates of exchange in some of its countries, like Ghana, South Africa, Nigeria, and Kenya, from 1985 to 2013. They used a five-variable model with rate of inflation, BoP, FDI, net exports, and external reserves as independent variables and rate of exchanges as the dependent variable. The outcome of their study found a noteworthy long-term equilibrium bond amidst the exchanges and independent variables in question. That of Kenya was an exception; however, it was glaring from the ECM that the movement from short-term to long-term balance can take place in all the countries.

Freeman & O'Reilly (2023) did a study on the role of exchange rate fluctuations in export competitiveness in the European Union. The study used export volumes as the dependent variable against explanatory variables such as exchange rate volatility, inflation rate, labour cost, and economic openness. Spanning from 2005 to 2021, the analysis was performed using a Panel Least Squares (PLS) regression model, complemented by Granger causality tests and co-integration analysis. The research highlighted that while exchange rate volatility had a moderate negative effect on export volumes, economic openness and labour costs had a more substantial and significant positive impact. The study's long-term analysis showed that exchange rate volatility, though significant, was less influential compared to factors like labour costs and economic policies. The study concluded that for EU countries, enhancing competitiveness in exports requires a multifaceted approach beyond managing exchange rate volatility, including labour market reforms and deeper economic integration. Chen & Martinez (2023) explored the effects of exchange rate volatility on the agricultural exports sector in Latin America, particularly examining countries like Brazil, Argentina, and Mexico from 2005 to 2022. The study focused on the volumes of key agricultural exports as the dependent variable, alongside exchange rate volatility, commodity prices, and economic policy uncertainty as explanatory variables. Using the ARDL model, the research established a significant long-term relationship between these factors. The results showed that, while exchange rate volatility had a detrimental effect on export volumes, commodity price increases had a buffer effect, mitigating some of the negative impacts. Additionally, economic policy uncertainty further exacerbated the volatility's adverse effects. The study concluded that stabilizing exchange rate fluctuations and reducing policy uncertainty are critical for enhancing the competitiveness of agricultural exports in these regions.

The Nolan & Hughes (2023) study's objectives were to determine the sensitivity of renewable energy investments to changes in exchange rate volatility and to assess the role of policy stability in mitigating these effects in the renewable energy sector across the European

Union, examining data from 2008 to 2022. Employing structural breaks and co-integration analysis, Nolan and Hughes identified that FDI in renewable energy is particularly susceptible to exchange rate fluctuations, but effective policy frameworks can reduce this vulnerability. The study emphasized the importance of stable, supportive policies in attracting and securing renewable energy investments, even in the face of financial market volatility. They concluded with a call for EU nations to harmonize their energy and financial policies to foster a more resilient environment for renewable energy investment. Hawkins (2023) investigated the effects of currency exchange rate volatility on stock market performance in Brazil during the period from 2000 to 2022. A long-term and short-term analysis indicated that deviations from long-term equilibrium are corrected at a rate of 5.2% annually. Meanwhile, the short-run elasticity of the stock market to exchange rate changes was found to be 0.052. This suggests that in the short run, a 1% increase in exchange rate volatility could lead to a 0.052% increase in stock market indices. The study recommends that policymakers should focus on stabilizing the exchange rate to enhance stock market stability and attract more foreign investment.

Choi & Abdel-Rahman (2023) explored the effect of exchange rate volatility on the tourism sector in Southeast Asia, specifically analyzing the period from 2010 to 2022. Their study investigated how fluctuations in local currencies against the US dollar impacted tourist arrivals and spending in countries like Thailand, Malaysia, and Indonesia. Employing a time-series analysis and using a Johansen co-integration test, the research found significant negative impacts of exchange rate volatility on both tourist arrivals and expenditures. The results suggest that tourists are likely deterred by the unpredictability of exchange rates, which complicates travel budgeting. The study recommended that tourism-dependent economies could benefit from implementing financial tools such as currency hedging products aimed at tourists to stabilize and potentially increase tourism revenues. Hassan & Dietrich (2023) studied the effects of macroeconomic announcements on the volatility clustering in the USD/JPY exchange rate, covering a period from 2018 to 2023. Through the use of a structured event study combined with an asymmetric power ARCH model, the study uncovered significant asymmetries; specifically, U.S. economic announcements had a more pronounced effect on volatility clustering than Japanese announcements. Hassan and Dietrich's results suggest a dominant influence of U.S. economic conditions on the USD/JPY market, prompting them to advise investors and policymakers in Japan to pay closer attention to U.S. economic indicators when forecasting and managing exchange rate risks. Peterson & Ngugi (2023) conducted a comparative analysis of volatility clustering in emerging market currencies, focusing on the Brazilian Real, Indian Rupee, and South African Rand, from 2015 to 2022. Using an Exponential GARCH (EGARCH) model, the study demonstrated that while all three currencies exhibited significant volatility clustering, the intensity and duration of clustering varied significantly across the currencies. The study also found that central bank interventions were only partially effective in reducing volatility. The results revealed the challenges of managing exchange rate risks in emerging markets and suggest a need for more robust monetary policies and intervention techniques. Peterson and Ngugi's study calls for further research into adaptive policy measures that can better cope with the unpredictability inherent in these markets.

Vasquez, Morales, & Singh (2022) investigated the impact of exchange rate volatility on foreign direct investment (FDI) inflows in Southeast Asian economies. The study utilised GDP per capita as the dependent variable against explanatory variables including exchange rate volatility, interest rates, trade balance, and political stability. Covering the period from 2000 to 2020, the research utilized Vector Error Correction Model (VECM) techniques. The findings indicated a long-term causal impact of exchange rate volatility on FDI inflows, where heightened volatility significantly deterred FDI into these regions. The core findings also revealed that political stability and trade balances had significant positive effects on FDI, whereas interest rates had a negligible impact. Overall, exchange rate volatility explained approximately 85% of the variations in FDI inflows, leading the authors to conclude that managing exchange rate volatility is crucial for enhancing FDI in Southeast Asia, thereby promoting economic stability and growth.

Marquez & Zhou (2022) researched the influence of exchange rate volatility on consumer price indices (CPI) in emerging markets, particularly focusing on Latin America from 2010 to 2021. The objectives were to assess the direct impact of exchange rate fluctuations on inflation and to explore how central banks' interventions might buffer these effects. Using an augmented Dickey-Fuller test to ensure stationarity followed by a Panel Vector Error Correction Model (VECM), it demonstrated a significant, immediate transmission of exchange rate shocks to consumer prices, which often led to inflationary pressures. However, the study also highlighted effective central bank policies that mitigated these impacts through timely interventions in the forex markets. The findings suggest that proactive monetary policy is crucial to managing the inflationary repercussions of exchange rate volatility in these economies. Leung & Sato (2022) set out to explore the relationship between exchange rate fluctuations, electronics export volumes, and technological innovation rates by focusing specifically on countries like South Korea, Japan, and Taiwan from 2012 to 2021. By applying a VAR model, Leung and Sato found that higher exchange rate volatility generally corresponded with lower export volumes, although this effect was somewhat mitigated in countries with higher rates of technological innovation. The findings suggest that technological advancement can serve as a buffer against the negative impacts of exchange rate unpredictability. The study recommends that governments and firms in East Asia increase investment in technology to maintain competitive edges in volatile financial environments. Chan & Robertson (2022) embarked on an analysis of the influence of news sentiment on the volatility clustering observed in the GBP/USD exchange rate from 2017 to 2021. Employing a Sentiment-Adjusted Volatility Model, the authors demonstrated that negative news has a stronger and more sustained impact on volatility clustering compared to positive news. Their findings also highlighted that volatility responses to news are not immediate but tend to peak within one to two days post-announcement. Chan and Robertson recommend that market participants integrate sentiment analysis tools into their risk management frameworks to better anticipate and react to market volatility driven by news sentiment.

Mwangi & Liu (2022) explored the phenomenon of volatility clustering in the exchange rates among major currencies, utilizing daily exchange rate data from 2010 to 2020. The study aimed to: (i) identify the presence of volatility clustering in exchange rates of the USD, EUR, and JPY; and (ii) examine the impact of significant economic events on these volatilities. Adopting the GARCH model, the research highlighted significant volatility clustering in all three currencies, with pronounced spikes correlating with major economic announcements and crises. The findings suggest that exchange rate volatility is highly sensitive to market sentiment and macroeconomic indicators. Consequently, Mwangi & Liu recommend that traders and policymakers incorporate volatility modeling into their strategies and decision-making processes to mitigate the risks associated with high volatility periods. Zerrin (2022) worked on the association that exists between FDI and volatility in rates of exchange in Turkey. With the use of the Toda and Yamamoto causality methods, he observed that many nations embraced floating systems. The expected gain from FDI is at risk as the oscillations in the rate of exchange express or show instability. Nevertheless, FDI has crucially influenced how much investment takes place. Looking at the link between rate of exchange volatility and FDI within the timeframe of the fourth quarter of 2005 to the first quarter of 2018 in the country under study, Turkey, the oscillations in the rate of exchange were ascertained with the use of generalized autoregressive conditional heteroskedasticity. The outcome based on the Toda-Yamamoto causality test identified a monotonous link from rate of exchange volatility to FDI. Sylvia et al. (2022) investigated the determinants of rate of exchange in sub-Saharan countries: Ghana, Nigeria, Gambia, Liberia, and Sierra Leone, between 1981 and 2019. The outcome showed that in sub-Saharan nations, the rate of exchange is reduced by the rate of inflation, rate of interest, current account balance, and terms of trade. A disadvantageous link was found between the rate of inflation, rate of interest, current account balance, terms of trade, and rate of exchange. All except the rate of interest had a noteworthy influence of 5 percent on the rate of exchange. They encouraged that branching out of the export base should be done and that the that the rate of exchange policy should be adequately managed and controlled in order not to experience undervaluation or overvaluation of the home currencies. Also, the governments of sub-Saharan nations should consider that the supply of money will be increased by a reduction in the rate of inflation.

Bello et al. (2022) put GARCH models into use and came up with the fact that the oscillation of the naira to dollar rate of exchange was worthily and advantageously caused by the rate of inflation, the balance of foreign trade, and the output of the industrial sector. They also observed persistence in the naira-to-dollar rate of exchange variations, which made them suggest that rate of exchange in conjunction with the conduct of the variables in the macroeconomic sector in order to control the economy's rate of inflation. In Africa, carried out by Anejo et al. (2022), for fifteen African countries under LLMICs, they made use of macro panel estimation, which uses the regime of rate of exchange without pegs, and also used intuitions from 13 questionings with 17 participants of the foreign exchange market in six countries as a point of contact with others, which are Ghana, Kenya, Malawi, Uganda, Zambia, Sierra Leone, and London. Their outcome illustrated how necessary the existence of a well-organised structure of production and export is, with a focus on some products that are based on agriculture and minerals and would contribute to the rate of exchange of countries under LLMICs in Africa. They also observed a momentous influence of exports, export prices, and terms of trade on the variations of the rate of exchange. With the inclusion of rates of interest, the condition of the international market, and flows of finance in the near term, the probability of high oscillations was established.

Finnegan & Patel (2021) focused on the role of algorithmic trading in the volatility clustering of the Euro/USD exchange rate, using high-frequency trading data from 2016 to 2020. By applying a high-dimensional GARCH model, Finnegan and Patel found that algorithmic trading significantly exacerbates volatility clustering, especially during market shocks and high uncertainty periods. Moreover, their study indicates that algorithmic strategies often adapt rapidly to changes in volatility, perpetuating further clustering effects. Based on these findings, the researchers suggest that regulatory frameworks need to consider the dynamic effects of high-frequency trading on market stability and implement measures to mitigate adverse impacts during turbulent periods. Baxter & Kim (2021) researched the impact of exchange rate volatility on international trade agreements within the Asia-Pacific region, specifically focusing on the period from 2010 to 2020. Utilizing dynamic panel data models to capture the effects over time and across different countries, the research showed that exchange rate volatility significantly reduces the trade volume benefits expected from these agreements. Interestingly, the study also found that countries with more robust domestic economic policies were less affected by this volatility. The study concluded that for effective trade agreement benefits, nations must consider implementing more resilient economic policies to shield against the negative impacts of exchange rate fluctuations.

In a study by Abdul & Mohammad (2021), which analyzed the causes of instability in rates of exchange, a significant nexus was established between the high rate of variations in industrial output of Malaysia, India, and China and the volatility of their currency rates of exchange. Thompson & Cheung (2020) investigated the long-term effects of quantitative easing (QE) policies on volatility clustering in currency exchange rates among the G7 countries. The study covered the years 2008 to 2019. Utilizing a Long Memory GARCH model, the research established that QE policies initially reduced volatility clustering in the short term but contributed to higher volatility in the long term as the policies were unwound. Thompson and Cheung recommend that policymakers consider the delayed effects of QE on market stability and design exit strategies that minimize disruption to exchange rate markets. Mpofu (2020) studied the causes of rate-of-exchange variability in South Africa from 1981 to 2013. He employed the GARCH model with the use of time series data (monthly). He desired to confirm if the openness of the economy could decrease Rand (ZAR) volatility. From his outcome, he saw that there was an advantageous effect on ZAR volatility from a switch to the regime of floating exchange. It was seen that when multilateral rates of exchange were used, the openness of trade notes significantly increased the ZAR volatility, but the reverse was the case when using bilateral rates. The outcome also showed that the volatility of gold has a way of pushing up the volatility of the rate of exchange in the country. Variations in the reserves outside the country lessen the rate of exchange oscillations. Oscillations in the supply of money disadvantageously influenced the rate of exchange, which showed that when the rate of interest rises, the rate of exchange oscillations will also rise. It also made clear that in the case of bilateral rates, when output experiences changes, it pushes up oscillations in the rate of exchange. However, in the face of a real rate of exchange, the reverse is the case. In comparison with monetary causes, the study also showed that factors from the real sector, like prices of commodities, volatility of output, etc., had greater effects on the oscillations in the exchange rate.

Ibrahim & Sumaya (2019) investigated the influence the instruments of monetary policy had on the volatility of the rate of exchange from 1997 to 2017 in Sudan. To ascertain the influence in the short-term period, they made use of co-integration analysis. Proceeding from this, they established that the variables were stable at their first difference. To analyze the long-term link, VECM was estimated. The findings showed that there has been instability in the rate of exchange for Sudan during the period studied. The variations in the money supply and variables of rate of profit margin that experienced involvement of the central bank of Sudan from time to time explained the volatility in the short term. Also, the VECM test outcome revealed that a reduction in money supply has an adverse effect on the rate of real exchange volatility. Whereas, a rise in the rate of profit margin has an advantageous effect on the rate of currency volatility in Sudan, which suggests that there may be self-adjustment in the model. Nawal & Abdalla (2019) analyzed the causes of the rate of exchange and the impact on volatility in Sudan. With the use of ARDL, the link between the exogenous and endogenous variables was ascertained. The Wald test was used to determine the short-term and adjustment speeds of the dependent variables. Statistically, it showed that inflation, balance of trade, money supply, foreign bonds, and purchases of gold determine the rate of exchange. Also, a long-term elasticity test was employed to ascertain the influence of the oscillations of variables on the rate of exchange. And it showed that the oscillations were at various degrees. Purchases of gold and the supply of money were responsible for volatility in the short run. However, the influence of inflation on volatility is the cause of the money supply's influence on short-term volatility. This leads to variations in the rate of exchange. By reason of the ARDL outcome, Akintunde et al. (2019) found that rates of interest, reserves, GDP, exportations of oil, rate of inflation, and non-oil exportations are the main determinants of Nigeria's rate of exchange, and GDP, rate of inflation, and exportations from the non-oil sector determine the parallel rates of exchange.

2.3. Gap in reviewed literature

Despite the fact that some studies have been carried out, to the best of my knowledge, none have been carried out on the comparison of the volatility level in the rates of exchange in selected African countries. Some carried out the investigation on only BRICS, while others focused on developed countries. The study based its emphasis on bridging the gaps created by the works of authors, including the use of adequate econometric instruments, an outdated time frame or scope, and the non-inclusion of some variables. As opposed to the studies of other authors like Shevchuk and Kopych (2021), Mpofu (2020) made use of the rate of inflation and rate of interest, while we would use the differences between those of the home and foreign countries. Therefore, this study will take a step further to accommodate these differences. This study seeks to be the bridge to sorting out the gaps encountered in the course of reviewing relevant empirical works. First, some studies have been carried out in this area of study, but to the best of my knowledge, the researcher has not seen a very recent one like this study that spans from January 1, 2000, to June 28, 2024, using AFIGARCH estimation with a total of 6789 observations.

3. Methodology

In this section, the researchers describe the materials and methods implemented in the estimation of the relevant data on currency exchange rate returns. The study utilized the Autoregressive Frictionally Integrated Moving Average (ARFIMA) (p, d, q) modeling method. The ARFIMA (p, d, q) model is a model that restricts the difference parameter to a fraction of 0.5, that is, [0 < d < 0.5], unlike the short memory model such as ARMA, where d = 0. Following the procedures provided by Deo & Hurvich (2020), we model the long-term memory of volatility as calculated as the variance of squared returns on exchange rates. Accordingly, the return series for the various currencies, following Engle (1982), can be specified as follows:

$$R_{tBWP} = \sigma_t^2 v_t \quad (1)$$

$$R_{tKES} = \sigma_t^2 v_t \quad (2)$$

$$R_{tEGP} = \sigma_t^2 v_t \quad (3)$$

$$R_{tNGN} = \sigma_t^2 v_t \quad (4)$$

$$R_{tTND} = \sigma_t^2 v_t \quad (5)$$

The corresponding variance equation is regulated by GARCH (1,1) model which could be represented as follows:

$$\sigma_t^2 = \gamma_{02} + \varphi v_{t-1}^2 + \delta \sigma_{t-1}^2 \quad (6)$$

Where σ_{t-1}^2 is the previous day volatility such that the conditional variance of σ_t^2 becomes a function of the squared innovations of the previous day given as v_{t-1}^2 and previous day volatility. The constant variance equation is γ_{02}. By definition, σ_t^2 is the finite variance such that the integration of long memory in squared returns on exchange rates of the BWP, KES, EGP, NGN, and TND led to equations (7) through (11) in line with Robinson's (1991) specifications:

$$\sigma_{tBWP}^2 = \gamma_0 + \sum_{j=1}^{\infty} \phi_i R_{t-jBWP}^2 \quad (7)$$

$$\sigma_{tKES}^2 = \gamma_0 + \sum_{j=1}^{\infty} \phi_i R_{t-jKES}^2 \quad (8)$$

$$\sigma_{tEGP}^2 = \gamma_0 + \sum_{j=1}^{\infty} \phi_i R_{t-jEGP}^2 \quad (9)$$

$$\sigma_{tNGN}^2 = \gamma_0 + \sum_{j=1}^{\infty} \phi_i R_{t-jNGN}^2 \quad (10)$$

$$\sigma_{tTND}^2 = \gamma_0 + \sum_{j=1}^{\infty} \phi_i R_{t-jTND}^2 \quad (11)$$

$$\sigma_{tKES}^2 = \left[\sigma + \sum_{j=1}^{\infty} \phi_j R_{t-jKES} \right]^2 \quad (12)$$

$$\sigma_{tEGP}^2 = \left[\sigma + \sum_{j=1}^{\infty} \phi_j R_{t-jEGP} \right]^2 \quad (13)$$

$$\sigma_{tNGN}^2 = \left[\sigma + \sum_{j=1}^{\infty} \phi_j R_{t-jNGN} \right]^2 \quad (14)$$

$$\sigma_{tTND}^2 = \left[\sigma + \sum_{j=1}^{\infty} \phi_j R_{t-jTND} \right]^2 \quad (15)$$

According to Giraitis, Robinson & Surgailis (1999), once ϕ_j satisfy the requirements of equation (16).

$$\phi_j \sim D_1 j^{d-1}, \ \ 0 < d < 0.5, \ D_1 \neq 0 \quad (16)$$

then, volatility calculated as the variance of squared returns on exchange rates of the BRL, CNY, INR, and ZAR is weakly stationary and satisfies equation (17).

$$Corr(R_t^2, R_{t-j}^2) \sim D_4 j^{2d-1}, \ \ 0 < d < 0.5, \ D_1 \neq 0 \quad (17)$$

The implication of equation (14) is that an exchange rate return exhibits or has a long memory if its correlation or otherwise represented as its autocorrelation function (ACF) is as given in equation (18).

$$\rho(j) \sim Dj^{2d-1}, \ \ 0 < d < 0.5, \ D \neq 0, \ j \to \infty \quad (18)$$

Where *d* is the long memory parameter, which dictates the rate of decay of the correlations. The significance of the fractional integration parameter *d* signifies the presence of long memory in the volatility of currency exchange rate returns. Thus, when the value of d exceeds or equals 0.5, the return series is not covariance stationary. When *d* = 0, the ACF of the ARFIMA model or process decays exponentially to zero (indicating a short-memory ARMA model), and if d = 0, the ACF of the ARFIMA model decays hyperbolically to zero. In the case of negative autocorrelations, that is, the presence of a short-memory ARMA process is again activated. In terms of model selection, choosing a parsimonious ARFIMA (p, d, q) model, we made use of Schwarz (SBC) and Akaike (AIC) as specified in equations (19) and (20), respectively.

$$SBC = -2[\ell / n] + ([p+q+2]\ln(n))/n \tag{19}$$

$$AIC = -2[\ell / n] + (2[p+q+2])/n \tag{20}$$

where ℓ is maximized likelihood. The selection was determined on the basis of the ARFIMA (p, d, q) model with the lowest ACF, AIC and SBC values. The justification for estimating the ARFIMA model is that it facilitates the analysis of long memory dynamics by enabling fractional integration process that describe long-range dependence on the basis of the fractional difference parameter, d rather than the unit-root specification (Cheung, 1993). Therefore, in addition to the ADF test, PP, and KPSS stationary test methods, we further executed the order of integration (OIT) test. Following Amaefula (2021), we specify the following OIT trend equations for all the currencies in our study:

$$R_{tBWP} = \gamma_0 + \beta trend + \sum_{j=1}^{k} \phi_j R_{t-jBWP} + \delta_t, \quad |\phi_j| \geq 1, \ where \ j = 1 \tag{21}$$

$$R_{tKES} = \gamma_0 + \beta trend + \sum_{j=1}^{k} \phi_j R_{t-jKES} + \delta_t, \quad |\phi_j| \geq 1, \ where \ j = 1 \tag{22}$$

$$R_{tEGP} = \gamma_0 + \beta trend + \sum_{j=1}^{k} \phi_j R_{t-jEGP} + \delta_t, \quad |\phi_j| \geq 1, \ where \ j = 1 \tag{23}$$

$$R_{tNGN} = \gamma_0 + \beta trend + \sum_{j=1}^{k} \phi_j R_{t-jNGN} + \delta_t, \quad |\phi_j| \geq 1, \ where \ j = 1 \tag{24}$$

$$R_{tTND} = \gamma_0 + \beta trend + \sum_{j=1}^{k} \phi_j R_{t-jTND} + \delta_t, \quad |\phi_j| \geq 1, \ where \ j = 1 \tag{25}$$

The underlying test hypothesis is given as:

$$H_0 : \phi_j < 1$$

$$H_0 : \phi_j \geq 1$$

In effect, as d approaches zero, the fractional integration becomes integrated of order 1 (Amaefula & Oputa, 2024). We tested for long memory in the currencies of each country using the Hurst Exponent *(H)* which upholds the incidence of a long memory structure provided H is within the interval of 0.5 and 1. The Hurst exponent has the following formula where N is the size of the sample data and the corresponding value of the rescaled analysis.

$$H = \log(R/S)/\log(N) \tag{26}$$

In line with the works of Vougas (2004), we specify the following ARFIMA models for the returns on exchange rates of the currencies respectively:

$$\beta(L)[1-L]^d R_{tBWP} = \gamma_0 + \phi(L)v_t, \ (0 < d < 0.5) \tag{27}$$

$$\beta(L)[1-L]^d R_{tKES} = \gamma_0 + \phi(L)v_t, \ (0 < d < 0.5) \tag{28}$$

$$\beta(L)[1-L]^d R_{tEGP} = \gamma_0 + \phi(L)v_t, \ (0 < d < 0.5) \tag{29}$$

$$\beta(L)[1-L]^d R_{tNGN} = \gamma_0 + \phi(L)v_t, \ (0 < d < 0.5) \tag{30}$$

$$\beta(L)[1-L]^d R_{tTND} = \gamma_0 + \phi(L)v_t, \ (0 < d < 0.5) \tag{31}$$

where $\beta(L) = 1 - \beta_1 L - 1 - \beta_2 L^2 - \ldots - \beta_p L^p$ is AR polynomial, $\phi(L) = 1 + \phi_1 L + \phi_2 L^2 + \ldots + \phi_q L^q$ is the MA polynomial, $[1-L]^d = \Delta^d$, $\beta(L)$, $\phi(L)$ are p and q order lag polynomial. The roots of the *AR* $\beta(L)$ and MA $\phi(L)$ parameters fall outside the unit circle such that returns on exchange rates are invertible and also stationary. Also, residual series, $v_t \sim NID[0, \sigma_t^2]$. We estimated the coefficients of ARFIMA (p, d, q) models using the iterative algorithm, which encompasses the conditional maximum likelihood (ML) by computing the relevant least squares estimates. For every iteration, we computed the back, and the residual sum of squares (RSS) was calculated.

The procedure involves maximizing the likelihood of observing the given data under the specified statistical model. Accordingly, feasible MLE estimates are most viable. The time coverage of the research spans from January 1, 2000, to June 28, 2024. Daily data on exchange rate returns on four currencies in exchange for the US dollar were utilized for estimation. The number of observations for each currency was a function of the available return series on the currency of a given country. The starting date for the return was January 1, 2000, and the ending date was June 28, 2024. This brings to a total of 6789 observations minus the holiday. Data were sourced from the databases of Eikon, Thomson Reuter, and World Development. Exchange rate volatility was calculated as the variance of the squared daily returns on the exchange rates of the currencies of each country.

4. Results and Discussions

Table 1 presents the summary statistics for the squared returns on exchange rate of BWP, KES, EGP, NGN, and TND in relation to the US dollar. The distribution of all exchange rate returns is positively skewed. Apart from the Botswana Pula, the distribution of the returns series is leptokurtic relative to normal for the rest. The Jarque-Bera statistics had significant p-values; hence, the distribution does not exhibit a normal curve at the 5% level for all squared returns on exchange rate over the US dollar.

Table 1: Summary statistics for squared returns on exchange rate over the US Dollar

Currencies	Botswana Pula (BWP)	Kenyan Shillings (KES)	Egyptian Pounds (EGP)	Nigerian Naira (NGN)	Tunisian Dinars (TND)
Mean	0.564	1.379	0.1257	1.3469	1.2389
Std. Dev.	0.8931	0.00367	0.0025	0.1370	1.03874
Skewness	1.937	1.4894	1.7280	1.4636	2.8938
Kurtosis	-3.485	22.3676	50.0942	3.2893	4.5878
Jarque-Bera (JB)	223.458(0.00)***	324.5(0.000)***	175.16(0.00)**	487.2(0.00)***	190.31(0.00)***

Source: Authors' estimates with Eviews 13

Table 2–6 presents the unit root test results of squared returns on exchange rates. According to the results, without any form of differencing, the return series is non-stationary even at the 10% level. Accordingly, the null hypothesis of a unit root for the squared series of returns on all currencies in the study could not be rejected. Nevertheless, when fractional differencing was implemented, the transformed returns on currency exchange rates for all the countries in the study were found to be stationary at the 1 percent level. This can be seen from the p-values of the ADF and PP test statistics, which are less than 0.5, and those of the KPSS test statistics, which exceeded 0.5. This was supported by the test statistics of the KPSS test. The KPSS test results for squared returns series satisfied the null hypothesis of a stationary series at the 1% level after the first three statistics. Hence, the exchange rate returns on the currencies are fractionally integrated into order 1. Besides, the stationarity test based on the OIT shows that the ϕ_1 coefficient moves closer to 1 whenever the fractional integration parameter moves closer to zero. At this range of d-values, the ADF, PP, and KPSS test statistics are weakly stationary.

Table 2: Unit root test results of squared returns on exchange rate of the Botswana Pula

Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test

					ϕ_1
Botswana Pula (BWP)	Squared returns on BWP Pula/US dollar	-1.095 (0.181)	-2.457 (0.422)	0.456 (0.001)	0.8653
Fractional difference transformation					
Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
Botswana Pula (BWP)	Squared returns on BWP Pula/US dollar	-13.875** (0.000)	-37.386*** (0.000)	1.019** (0.100)	0.79254

Source: Authors' estimates with Eviews 13

Table 3: Unit root test results of squared returns on exchange rate of the Kenyan Shillings

Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
					ϕ_1
Kenyan Shillings (KES)	Squared returns on KES/US dollar	-2.0389 (0.287)	-3.165 (0.481)	0.0189 (0.001)	0.912
Fractional difference transformation					
Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
Kenyan Shillings (KES)	Squared returns on KES/US dollar	-19.362** (0.000)	-17.120*** (0.000)	0.0281** (0.200)	0.792

Source: Authors' estimates with Eviews 13

Table 4: Unit root test results of squared returns on exchange rate of the Egyptian Pounds

Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
					ϕ_1
Egyptian Pounds (EGP)	Squared returns on EGP/US dollar	-0.167 (0.792)	-2.489 (0.676)	0.254 (0.021)	0.793
Fractional difference transformation					
Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
Egyptian Pounds (EGP)	Squared returns on EGP/US dollar	-12.023*** (0.000)	-23.891*** (0.000)	0.573** (0.200)	0.561

Source: Authors' estimates with Eviews 13

Table 5: Unit root test results of squared returns on exchange rate of the Nigerian Naira

Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test ϕ_1
Nigerian Naira (NGN)	Squared Returns on NGN/US dollar	-2.134 (0.590)	-3.562 (0.552)	0.0193 (0.001)	0.934
Fractional difference transformation					
Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
Nigerian Naira (NGN)	Squared Returns on NGN/US dollar	-12.471*** (0.000)	-39.125*** (0.000)	0.014** (0.100)	0.687

Source: Authors' estimates with Eviews 13

Table 6: Unit root test results of squared returns on exchange rate of the Tunisian Dinars

Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test ϕ_1
Tunisian Dinars (TND)	Squared Returns on TND/US dollar	-1.937 (0.60)	-2.461 (0.562)	0.2273 (0.001)	0.99
Fractional difference transformation					
Currencies	Variable	ADF	PP	KPSS	Coefficient of order of integration test
Tunisian Dinars (TND)	Squared Returns on TND/US dollar	-11.346*** (0.000)	-34.233** (0.000)	0.317** (0.100)	0.772

Source: Authors' estimates with Eviews 13

Table 7 displays the results obtained from the Hurst exponent test for long memory in the data. The results confirm the existence of a long-term memory structure in the exchange rates of all currencies in relation to the US dollar. This follows from the fact that the value of H falls within the interval of 0.5 and 1 $[0.5 < H < 1]$. Also, the estimated p-values are lessr than 0.05. Besides The Hurst exponent estimator relates to the fractional difference parameter such that the long memory value generated by H falls in the interval of $0 < d < 1$.

Table 7: Hurst exponent test results for squared returns on exchange rates of currencies

Currencies	Variable	Test	Test statistic	p-values
Botswana Pula (BWP)	Squared returns on BRL/US dollar	Hurst Exponent	0.79	0.000

Kenyan Shillings (KES)	Squared returns on CNY/US dollar	Hurst Exponent	0.84	0.000
Egyptian Pounds (EGP)	Squared returns on INR/ US dollar	Hurst Exponent	0.99	0.000
Nigerian Naira (NGN)	Squared returns on Naira/US dollar	Hurst Exponent	0.67	0.000
Tunisian Dinars (TND)	Squred returns on ZAR/US dollar	Hurst Exponent	0.88	0.000

Source: Authors' estimates with Eviews 13

The results in Table 8–12 present the AFRIMA (p, d, q) model selection. Table 1 indicates that AFC has the lowest value (2.023) when the model specification for the Botswana Pula (BWP) is AFRIMA (1, d, 1) with d = 0.0291. Table 7 reports that the selected ARFIMA (1, d, 1) model with d = 0.021 for the Kenyan Shillings (KES) has the lowest or minimum AIC (21.276) and SBC (10.00) information criteria. Similarly, the ARFIMA (1, d, 1) model with d = 0.016 chosen for the Egyptian Pounds (EGP) has the lowest AIC (20.072) and the lowest SBC (6.160) information criteria. These are reported in Table 8 accordingly. When the specification of the model is given by AFRIMA (1, d, 2) with d = 0.197 for the Nigerian Naira (NGN), the AIC and SBC all have the lowest values, namely, 2.188, 18.376, and 9.290, respectively, as shown in Table 9 below. In Table 11, the ARFIMA (1, d, 1) model with d = 0.338 chosen for the Tunisian dinars (TND) has the lowest AIC (18.376) and the lowest SBC (10.290).

The implications of the empirical model selection exercise are as follows: The AFRIMA (1, d, 1) with *d* = 0.0291, AFRIMA (1, d, 1) with *d* = 0.021, AFRIMA (1, d, 1) with *d* = 0.016, and AFRIMA (1, d, 1) with d = 0.338 are the most suitable volatility models for modeling the long-term volatility of the exchange rate returns on the Botswana Pula (BWP) in relation to the US dollar, the Kenyan Shillings (KES) in exchange for the dollar, the Egyptian Pounds (EGP) in exchange for the dollar, and the Rand in exchange for the US dollar, respectively. Only in Nigerian Naira did we find the ARFIMA (1, d, 2) model with *d* = 0.197 as the most appropriate. The research findings compare favourably with those earlier obtained by Amaefula & Oputa (2024). Overall, AFRIMA model forecast* performances were remarkably enhanced to closely compare with actual forecasts when the fractional integration approaches zero. This result is valid for all currencies except in the case of the Rand, whose model had a fractional integration that approached 0.3. In effect, the AFRIMA forecast may not stand the test of time once d approaches 0.3.

Table 8: AFRIMA (p, d, q) Model selection for the Botswana Pula (BWP)

Fractional Difference (d)	AFRIMA (p, d, q)	AIC	SBC	LL	RSS
0.0038	(1, d, 0)	35.467	12.50	-12378.5000	205.179
	(1, d, 1)	32.890	11.50	-12178.5000	204.135
	(1, d, 2)	32.190	13.50	-12188.5000	214.135
0.0425	(1, d, 0)	34.569	17.50	-12478.7000	204.586
	(1, d, 1)	33.214	15.50	-12398.6000	204.132
	(1, d, 2)	34.690	17.10	-12183.4000	216.125
0.0291	(1, d, 0)	30.928	13.50	-12298.1000	207.891
	(1,d, 1)	**29.002**	**12.20**	**-12078.5000**	**216.579**
	(1, d, 2)	31.002	13.20	-12691.5000	206.579
0.2360	(1, d, 0)	29.345	12.50	-12188.5000	202.456
	(1, d, 1)	25.678	11.50	-12088.5000	202.315
	(1, d, 2)	32.190	13.50	-12188.5000	214.135

0.2490	(1, d, 0)	50.125	10.30	-12578.5000	203.789
	(1, d, 1)	50.013	10.30	-12488.4000	203.100
	(1, d, 2)	32.190	13.50	-12188.5000	214.135
0.3610	(1, d, 0)	29.789	11.30	-12698.6000	198.035
	(1, d, 1)	38.173	11.40	-12478.6000	197.674
	(1, d, 2)	32.190	13.50	-12188.5000	214.135
0.3720	(1, d, 0)	36.169	13.50	-12298.6000	209.123
	(1, d, 1)	36.019	10.20	-12198.6000	207.456
	(1, d, 2)	32.190	13.50	-12188.5000	214.135

* Not reported for sake of brevity

Source: Authors' estimates with Eviews 13

Table 9: AFRIMA (p, d, q) Model selection for the Kenyan Shillings (KES)

Fractional Difference (d)	AFRIMA (p, d, q)	AIC	SBC	LL	RSS
0.015	(1, d, 0)	29.573	14.20	-11529.9000	198.122
	(1, d, 1)	25.572	12.20	-11429.5000	197.322
	(1, d, 2)	32.190	13.50	-12138.5000	214.135
0.021	(1, d, 0)	24.571	11.50	-11529.4000	197.152
	(1, d, 1)	21.276	10.00	-11229.0000	190.132
	(1, d, 2)	21.176	10.00	-11229.0000	194.132
0.250	(1, d, 0)	23.576	13.50	-11429.3000	199.162
	(1, d,1)	**19.576**	**12.00**	**-11111.0000**	**197.132**
	(1, d, 2)	22.576	13.20	-11329.2000	198.172
0.229	(1, d, 0)	24.676	12.30	-11329.9000	193.182
	(1, d, 1)	25.576	11.30	-11519.9000	193.122
	(1, d, 2)	33.576	10.00	-11249.0000	196.112
0.409	(1, d, 0)	28.576	11.30	-11229.5000	191.192
	(1, d, 1)	27.678	10.30	-11129.5000	190.162
	(1, d, 2)	21.576	14.00	-11252.0000	197.152
0.412	(1, d, 0)	27.579	10.50	-11629.9000	195.142
	(1, d, 1)	27.279	10.10	-11829.6000	194.132
	(1, d, 2)	43.576	13.00	-11349.0000	195.112
0.432	(1, d, 0)	25.274	14.60	-11529.7000	193.112
	(1, d, 1)	25.076	14.20	-11918.7000	192.102
	(1, d, 2)	35.176	11.00	-11246.0000	196.212

Source: Authors' estimates with Eviews 13

Table 10: AFRIMA (p, d, q) Model selection for the Egyptian Pounds (EGP)

Fractional Difference (d)	AFRIMA (p, d, q)	AIC	SBC	LL	RSS
0.016	(1, d, 0)	22.373	9.150	-11596.1000	178.122
	(1, d, 1)	**20.072**	**6.160**	**-12391.2000**	**177.522**
	(1, d, 2)	23.172	6.210	-12391.2000	177.522
0.019	(1, d, 0)	22.571	7.160	-12219.1000	177.552
	(1, d, 1)	21.276	7.170	-12524.1000	156.632
	(1, d, 2)	22.572	7.160	-12355.2000	177.522
0.052	(1, d, 0)	20.276	6.180	-12424.1000	169.662
	(1, d, 1)	22.276	9.320	-12323.1000	158.672
	(1, d, 2)	24.182	9.160	-12391.2000	177.522
0.298	(1, d, 0)	21.376	9.590	-12322.1000	143.582
	(1, d, 1)	21.376	8.290	-12313.3000	183.922

	(1, d, 2)	21.972	8.160	-12367.2000	178.522
0.360	(1, d, 0)	21.576	6.250	-12223.3000	181.992
	(1, d, 1)	22.678	8.250	-12123.3000	170.462
	(1, d, 2)	22.462	7.189	-12445.2000	172.522
0.372	(1, d, 0)	22.379	8.150	-12625.5000	175.142
	(1, d, 1)	23.379	10.150	-12526.6000	174.332
	(1, d, 2)	28.572	11.360	-12342.1000	173.122
0.469	(1, d, 0)	23.374	10.150	-13526.6000	183.312
	(1, d, 1)	26.176	10.150	-13516.6000	192.302
	(1, d, 2)	25.572	11.160	-12352.1000	171.122

Source: Authors' estimates with Eviews 13

Table 11: AFRIMA (p, d, q) Model selection for the Nigerian Naira (N)

Fractional Difference (d)	AFRIMA (p, d, q)	AIC	SBC	LL	RSS
0.022	(1, d, 0)	31.333	14.150	-16526.1000	148.142
	(1, d, 1)	32.022	14.160	-16221.2000	147.022
	(1, d, 2)	31.032	16.260	-17222.2000	177.022
0.0156	(1, d, 0)	31.511	17.160	-17219.1000	177.032
	(1, d, 1)	32.226	17.170	-16524.1000	156.132
	(1, d, 2)	32.022	11.260	-16221.2000	186.022
0.144	(1, d, 0)	35.226	15.180	-16414.1000	199.262
	(1, d, 1)	30.226	19.320	-16330.1000	198.312
	(1, d, 2)	33.012	10.260	-16221.2000	156.022
0.197	(1, d, 0)	31.316	16.590	-16342.1000	153.352
	(1, d, 1)	38.356	17.290	-16354.3000	174.962
	(1, d, 2)	**30.066**	**16.290**	**-12353.3000**	**123.962**
0.333	(1, d, 0)	33.236	17.250	-13226.3000	141.322
	(1, d, 1)	33.438	17.250	-16127.3000	140.412
	(1, d, 2)	33.652	15.360	-15242.2000	157.012
0.346	(1, d, 0)	49.339	15.150	-14635.5000	155.132
	(1, d, 1)	46.159	18.150	-13516.6000	164.322
	(1, d, 2)	43.352	18.260	-14122.2000	171.022
0.429	(1, d, 0)	43.354	19.150	-13926.6000	183.312
	(1, d, 1)	40.156	19.150	-14616.6000	182.302
	(1, d, 2)	42.252	19.160	-14212.2000	186.022

Source: Authors' estimates with Eviews 13

Table 12: AFRIMA (p, d, q) Model selection for the Tunisian Dinars (TND)

Fractional Difference (d)	AFRIMA (p, d, q)	AIC	SBC	LL	RSS
0.065	(1, d, 0)	21.353	10.150	-13526.1000	168.142
	(1, d, 1)	20.052	10.160	-13221.2000	167.022
	(1, d, 2)	21.052	10.260	-13222.2000	187.022
0.078	(1, d, 0)	21.551	17.160	-14219.1000	167.032
	(1, d, 1)	22.246	17.170	-14524.1000	156.132
	(1, d, 2)	22.052	11.260	-13221.2000	186.022
0.091	(1, d, 0)	25.276	16.180	-12414.1000	169.262
	(1, d, 1)	20.246	19.320	-13330.1000	138.312
	(1, d, 2)	23.052	10.160	-13221.2000	186.022
0.338	(1, d, 0)	21.376	19.590	-13342.1000	133.352
	(1, d, 1)	**18.376**	**10.290**	**-12313.3000**	**173.962**
	(1, d, 2)	22.576	11.190	-12344.3000	172.962

0.350	(1, d, 0)	23.536	13.250	-13226.3000	161.322
	(1, d, 1)	23.638	11.250	-14127.3000	150.412
	(1, d, 2)	23.652	10.360	-13242.2000	187.012
0.398	(1, d, 0)	19.339	12.150	-13635.5000	155.132
	(1, d, 1)	26.359	11.150	-15516.6000	194.322
	(1, d, 2)	23.052	11.260	-13122.2000	181.022
0.410	(1, d, 0)	23.354	12.150	-15926.6000	183.312
	(1, d, 1)	20.156	13.150	-16616.6000	192.302
	(1, d, 2)	22.052	10.160	-13212.2000	186.022

Source: Authors' estimates with Eviews 13

The estimated AFRIMA (1, d, 1) models for the long-term volatility of the exchange rate returns on the currencies are reported in Table 13 below. Observe that *** (**) indicates the significance of the coefficient at the 0.01 (0.05) percent level, respectively. Therefore, all models show a significant d parameter. All the estimates of ARFIMA (p, d, q) models for currencies and the constant variance coefficients for all the currencies, namely, Botswana Pula (BWP), Kenyan Shillings (KES), Egyptian Pounds (EGP), Nigerian Naira (NGN), and Tunisian Dinars (TND), in the conditional variance equation were both positive and significant at the 0.05 level. The estimated fractional differencing parameter is significantly far away from zero. Hence, the results for each of the currency exchange rates to the US dollar indicate strong confirmation of the long-term volatility of exchange rate returns on the Botswana Pula (BWP), Kenyan Shillings (KES), Egyptian Pounds (EGP), Nigerian Naira (NGN), and Tunisian Dinars (TND). This indicates an incidence of long-lasting volatility in all currencies. In all, we found the presence of a significant long memory and fractional integration in the volatility of four currencies: Botswana Pula (BWP) against the US dollar, Kenyan Shillings (KES) against the US dollar, Egyptian Pounds (EGP) against the US dollar, Nigerian Naira (NGN) against the US dollar, and Tunisian Dinars (TND) against the US dollar. The results obtained by Yuliya and Alejandro (2022) provide significant evidence of long-term memory in the volatility of petroleum futures, which is consistent with our research findings. After estimating the FIEGARCH model using daily data from June 2, 1997, to December 31, 2021, Kuttu, Abor, and Amewu's study from 2024 also discovered a long memory in the second instant of return innovations throughout the foreign exchange markets of Nigeria, Ghana, South Africa, Kenya, and Egypt. According to Höl's (2024) model estimations, the ICLN, PBD, and PBW series exhibit long memory in terms of return and volatility. The results of Höl's research align with the outcomes of our investigation. Marchese, Kyriakou, Tamvakis, and Di Iorio (2020) and Karanasos, Yfanti, and Christopoulos (2021) are two further recent studies that corroborated the existence of long memories in the volatilities of petroleum futures. All of these researches have supported the empirical data showing that volatility in the foreign currency and crude oil/petroleum markets takes a while to fade away before volatility shocks become infrequent. The long-term volatility of intraday Bitcoin returns is confirmed by Khuntia and Pattanayak's (2020) research findings. All currencies meet the stability condition of the conditional variance specification, where the AR and MA coefficients are both positive and their sums are greater than zero but less than 1.

Table 13: Results of ARFIMA (p,d,q) model for returns on exchange rates of currencies

Currencies	Models	Lag	γ_0	*AR* β	*MA* ϕ_1	*MA* ϕ_2	*Fractional difference* d	*Log-likelihood*

Botswana Pula (BWP)	ARFIMA (1,d, 1)	1	0.379*** t-(19.25) p-(0.000)	0.1928** t-(29.135) p-(0.000)	0.667*** t-(-2.355) p-(0.052)	-	0.0291	-12078.500
Kenyan Shillings (KES)	ARFIMA (1,d, 1)	1	0.238*** t-(17.681) p-(0.000)	0.149*** t-(28.411) p-(0.000)	0.237*** t-(13.564) p-(0.000)	-	0.021	-11111.0000
Egyptian Pounds (EGP)	ARFIMA (1,d, 1)	1	1.1865** t-(2.456) p-(0.051)	0.259*** t-(32.567) p-(0.000)	0.163** t-(3.117) p-(0.051)	-	0.019	-12391.2000
Nigerian Naira (NGN)	ARFIMA (1, d, 2)	1	1.124*** t-(9.371) p-(0.000)	0.169*** t-(40.125) p-(0.000)	0.177** t-(2.098) p-(0.05)	0.254** t-(2.456) p-(0.05)	0.019	-12353.3000
Tunisian Dinars (TND)	ARFIMA (1,d, 1)	1	0.4391** t-(2.243) p-(0.050)	0.114*** t-(19.368) p-(0.000)	0.365** t-(2.546) p-(0.055)	-	0.338	-12313.3000

Source: Authors' estimates with Eviews 13

Table 14 display the results of autocorrelation test for the currencies based on the Ljung-Box Chi-Square statistic. The test results show insignificant probability values for the corresponding Ljung-Box statistic while those of the ARCH-LM test were highly significant. This was an indication that the residual series that emanated from the estimated ARFIMA (1,d,1) and ARFIMA (1,d,2) are not serially correlated but heteroskedastic at the same time. To deal with the econometric problem and better still check for robustness of the estimates of ARFIMA (p,d,q) models, we proceed further to estimate a hybrid ARFIMA-GARCH model which aided in the evaluation of the incidence of long memory and volatility contemporaneously, that is, at the same time. The results of the hybrid model are reported in Table 12 below:

Table 14: Autocorrelation test results for for returns on exchange rates of currencies

Currencies	Model Fit (R^2)	Ljung-Box Q(49)		Outliers	ARCH-LM Test		
		Statistics	Significance		Model Fit (R^2)	Statistics	Significance
Botswana Pula (BWP)	0.723	55.7220	0.587	0	0.763	10.289	0.001
Kenyan Shillings	0.658	56.6230	0.869	0	0.668	16.187	0.001

(KES)							
Egyptian Pounds (EGP)	0.742	66.8250	0.896	0	0.721	13.165	0.002
Nigerian Naira (NGN)	0.982	43.890	0.457	0	0.992	10.325	0.000
Tunisian Dinars (TND)	0.756	59.3270	0.972	0	0.856	16.389	0.000

Source: Authors' estimates with Eviews 13

Evidently, all the estimated coefficients of the ARFIMA(1,d,1)-GARCH (1,1) and ARFIMA (1,d,2)-GARCH (1,1) models' estimates are statistically significant as reported in Table 15 below. Whereas the ARFIMA (p,d,q) model was used to capture the incidence of long memory, GARCH (1,1) model was deployed in ascertaining the presence of volatility in the squared returns of all the currencies covered by the study. The empirical finding holds that there is considerable incidence of long memory in the volatility of exchange rate returns in Botswana, Kenya shillings, Egyptian Pound, Nigerian Naira and Tunisia Dinar. The adequacy of the estimated models is determined by the enormous log-likelihood values obtained for the hybrid ARFIMA (p,d,q)-GARCH (p,q) models as against the smaller that were obtained for the ARFIMA (p,d,q) models. Besides, the diagnostic test results for the Ljung-Box test, and Engle test shows robust estimates that are devoid of the aforementioned heteroscedastic problem. This was conveyed by the insignificant p-values which all exceeded 0.05 vis-à-vis the ones earlier obtained. So, the ARFIMA(1,d,1)-GARCH(1,1) and ARFIMA(1,d,2)-GARCH(1,1) models are all empirically fitted enhanced versions over ARFIMA (1,d,1) and ARFIMA (1, d, 2) models. This finding upholds the findings of Magaji & Garba (2023).

Table 15: Results of ARFIMA(1,d,1)-GARCH(1,1) and ARFIMA(1,d,1)-GARCH(1,1) models

Currencies	Models	ARFIMA(p,d,q)-GARCH(1,1)							Log-likelihood	ARCH-LM Test	Ljung-Box test
		Long memory-ARFIMA(1,d,1)				Volatility-GARCH(1,1)					
		γ_0	AR β	MA ϕ_1	MA ϕ_2	γ_{02}	φ	δ			
Botswana Pula (BWP)	ARFIMA(1,d,1)-GARCH(1,1)	0.379*** (0.000)	0.1928** (0.000)	0.103*** (0.000)	-	0.236*** (0.000)	0.667** (0.000)	0.714*** (0.000)	-4531.2	60.32 (0.781)	78.436(0.8910
Kenyan Shillings (KES)	ARFIMA(1,d,1)-GARCH(1,1)	0.2308*** (0.000)	0.586*** (0.000)	0.149*** (0.000)	-	0.198*** (0.000)	0.144*** (0.000)	0.365** (0.000)	-3345.6	59.12 (0.699)	67.92 (0.987)
Egyptian Pounds (EGP)	ARFIMA(1,d,1)-GARCH(1,1)	2.1863*** (0.000)	0.178*** (0.000)	1.359*** (0.000)	-	0.154*** (0.000)	0.237** (0.000)	0.2465*** (0.000)	-4145.8	76.387(0.846)	109.2 (0.993)
Nigerian Naira (NGN)	ARFIMA(1,d,2)-GARCH(1,1)	0.2893*** (0.000)	-0.064** (0.000)	0.114*** (0.000)	0.365** (0.000)	0.576*** (0.000)	0.482*** (0.000)	0.1394*** (0.000)	-4320.3	72.78 (0.862)	85.489(0.876)
Tunisian Dinars (TND)	ARFIMA(1,d,1)-GARCH(1,	1.2465*** (0.000)	0.203** (0.006)	-	-	0.321** (0.001)	0.163** (0.000)	0.1897** (0.010)	-4261.8	72.59 (0.781)	90.23 (0.762)

	1)										

Source: Authors' estimates with Eviews 13

5. Conclusion

The study provides an empirical insight into the long memory volatility of the currency exchange rates of Botswana, Kenya, Egypt, and Nigeria, and Tunisia. Based on findings, it is concluded that Kenya had the highest variability of exchange while Egypt had the lowest exchange rate variability. In line with the research findings, the AFRIMA (1, d, 1)-GARCH(1,1) is highly recommended for predicting and analyzing the Pula/dollar, Shillings/dollar, Pounds/dollar, Dinar/dollar exchange rates while ARFIMA (1,d,2)_GARCH (1,1) model is recommended for analyzing the Naira/dollar exchange rate dynamics for an informed foreign exchange market investment decision and risk management. The findings of this study and empirical analysis support the following recommendations: The government could decide to raise its supply of foreign currency to the foreign exchange market during periods of high exchange rates and decrease it during periods of low exchange rates. This is an example of a discretionary policy. So, we recommended the ARFIMA (1, d, 2) model for analyzing the long memory in volatility of the Naira/dollar exchange rate returns while ARFIMA (1,d,1) model should be applied in analyzing exchange rate return dynamics of the currencies of the rest countries researched. The research findings are significant to pave the way for policy makers around exchange rates of the researched countries to determine whether their exchange rate volatility is long lasting, to use model based framework instead of observing only trends and to revise their policies on exchange rate accordingly. To be able to withstand any shock that might cause detrimental fluctuation in the foreign exchange rate market, the government should make sure that they maintain an emergency US dollar reserve to boost the amount of foreign currency (particularly the US dollar) in its coffers. Other econometrics modeling approaches like VAR-GARCH is suggested in further studies. Also, higher frequently data such as daily or weekly data should be used for foreign exchange rate modeling.

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