# FORECASTING EXCHANGE RATE DYNAMICS IN DEVELOPING COUNTRIES

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## Abstract

Given that volatility influences decisions about currency rates, monetary policy, and macroeconomic policy, it is crucial to predict and anticipate volatility in emerging economies. The study employed generalized autoregressive conditional heteroskedasticity (GARCH) asymmetric models to estimate and forecast exchange rate dynamics in developing countries. We found that South Africa model had similar variance and covariance proportion of 0.99356 percent and 0.995901 percent respectively and the exchange rate could rise or fall by 2 to 6 units of rand, in exchange for USD. In Kenya, exchange rates continually exhibited steady rise monthly with extremely low mean absolute percentage error of 0.01568 percent and this demonstrates how strongly the model predicts Kenya's future currency rates while the variance chart supports absence of persistence. In Ghana, exchange rates are projected to increase significantly as 99.5 percent of unsystematic error was un accounted for in the model. Volatility is highly persistent in Nigeria; hence the forecasting model reported a high error rate by taking 1.06 percent of the symmetric error into cognizance. Kenya, Ghana, and Mauritius had asymmetry in currency volatility, revealing turbulence in exchange rates when the bad news hit the market. Hence, local currencies are rendered worthless in the foreign exchange market.

**Keywords:** Forecasting, Volatility, Currency Rates, Asymmetric Effects, Africa

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## 1. INTRODUCTION

According to economists, the exchange rate is essential to a free market economy. The success of the high-performing East Asian economies, notably their strong export performance, has also been credited to exchange rate policies that promoted absolute exchange rate stability and prevented rate misalignment (Elbadawi & Soto, 1997). As a result, the laws governing a country's currency's value may significantly influence that country's economic progress. The importance of the foreign exchange market in international trade cannot be overemphasised. It is mainly so because most world economies are either directly or indirectly partaking in international trade. Since most of the raw materials and equipment needed for their necessary industrial output are typically imported, most developing or third-world countries are active in these many forms of connection. Nigeria is an excellent example. As a result, the foreign exchange market in Nigeria is crucial in this regard. Between 1959 and 2010, the Forex market was subject to four different policy regulatory regimes. It is impossible to overstate the role played by the foreign exchange market in global trade.

The dynamics of the rates are much more unpredictable under the floating exchange rate regime than under a fixed exchange rate system, making it difficult to anticipate future values with certainty. Increased exchange rate volatility may have far-reaching negative impacts. Since volatility influences decisions about currency rates, monetary policy, and macroeconomic policy, it is crucial to predict and anticipate volatility in emerging economies (Ioan et al., 2020; Bahmani-Oskooee, & Gelan, 2018; Hatmanu et al., 2020; Magweva & Sibanda, 2020). Understanding the dynamics of exchange rates of currencies could be very helpful in controlling currency risk. There is a critical need for modelling and forecasting volatility exchange rates in emerging African countries since it plays a significant role in the execution of monetary policy. Without proper monitoring, abrupt and unexpected changes in exchange rate dynamics could trigger economic crises like the peso crisis of Mexico and the financial situation of South East Asian countries.

Moreover, sudden and unforeseen changes in exchange rate dynamics could result in above mentioned currency crises. The study is significant because it focuses on exchange rate forecasting, which is essential for countries whose currency movements and exchange rates transmission significantly influence economic performance, foreign assets, output, government revenues, and money demand (Umoru et al., 2023; Senadza & Diaba, 2017). The study contributes to the knowledge of brokers and businesses by making available informed decisions to help curtail exchange rate risks and make the most of returns. By and large, policymakers and merchants can rely on the findings of this study as it relates to exchange rate forecasting rather than depend solely on monetary, trade, or fiscal policy decisions of the central financial authorities. In this regard, we attempted to estimate and forecast exchange rate dynamics in developing countries.

The structure of this paper is as follows. Section 2 presents theoretical and empirical literature related to the dynamics of exchange rates. Section 3 shapes the methodology and materials regarding the sample, data sources and measurement explanation. Section 4 analyses the research results. Section 5 draws concluding remarks.

## 2. LITERATURE REVIEW

Exchange rate forecasting has been shown to substantially impact the formulation of macroeconomic growth and development goals for medium and long-term goals (Ehikioya, 2019). Accoring to Abounoori and Zabol (2020), a day ahead, short-term variance predictions are mostly guaranteed and hence, supported models with precise performance in forecasting out-of-sample volatility. According to Naeem et al. (2021), exchange rate policies influence the goods market; consequently, portfolio managers and investors should predict the dynamics of exchange rates. They are forecasting exchange rate dynamics positions investors to hedge against exchange rate risk (Gokmenoglu et al., 2021). Ca'Zorzi et al. (2017) relied on the dynamic stochastic general equilibrium (DSGE) technique to forecast exchange rate movements, while Cheung et al. (2019) reported that forecasting exchange rate dynamics remains an empirical exercise for researchers because varying model specifications and different combinations of currency yield different performance results. Darvasa and Scheppb (2020) obtained forecast results that overcome random walk model prediction by 0.8% at one month, 11.2% at one year, 32.5% at three-year and 43.0% at five-year using the mean forecast error.

Studies by Umar et al. (2019), Deka et al. (2019), Farhan et al. (2019), Mucaj and Sinaj (2017), Nwankwo (2014), Dhankar (2019), Al-Gounmeein and Ismail (2020), Asadullah et al. (2020), and Joshi et al. (2020) all implemented the autoregressive integrated moving average (ARIMA) techniques to forecast exchange rate behaviour for different countries. Umar et al. (2019) reported ARIMA (2, 1, 1) as the most efficient model for forecasting the exchange rate of Nigerian naira (NGN/GBP). Deka et al. (2019) said that ARIMA (3, 1, 3) yielded the best forecasting of the exchange rate of the Turkish lira (TRY/USD). According to Farhan et al. (2019), ARIMA (1, 1, 1) is the best model for forecasting the exchange rate of Iraqi dinar (IQD/USD). Mucaj and Sinaj (2017), Nwankwo (2014), and Asadullah et al. (2020) certified the ARIMA model as the best in predicting the EUR/USD exchange rate. Based on an analysis of out-of-sample prediction results, Dhankar (2019) reported that the exchange rate of USD, EUR, and GBP would rise shortly. In Jordan, Al-Gounmeein and Ismail (2020) said that ARIMA (1, 0, 1) and seasonal ARIMA (SARIMA) (1, 0, 1) delivered better forecasting of the Jordanian dinar (JOD). Asadullah et al. (2020) obtained a one percent difference between actual and forecasted exchange rate values for the Pakistani economy. According to Ishfaq et al. (2018), the volatility index of the exchange rate resulted in a fear prediction of the trend of the Chinese yuan (CNY) exchange rate. According to Mucaj and Sinaj (2017), exchange rate forecasting models depend on currency trends. Also, Zhang and Hamori (2020) applicability of a group of exchange rate models enhances the forecasted exchange rate values.

According to Rossi (2013), exchange rate prediction is a function of the periodicity of the sample, predictors, forecast horizon, and type of prediction model used. In related studies, researchers such as Balaban (2004), Asadullah et al. (2020), and Asadullah et al. (2021) have all successfully modelled currency rate dynamics to predict the volatility of the USD/DEM. Across various exchange rates and samples, the size of the projected persistent decline varies. The latter group of studies includes Thupayagale and Jefferis (2011) and Morana and Beltrati (2004). among ARIMA, autoregressive conditional heteroskedasticity (ARCH), generalized autoregressive conditional heteroskedasticity (GARCH), and exponential general autoregressive conditional heteroskedastic (EGARCH) finding the best time series model to provide the best exchange rate prediction was a realistic goal. Cheong Vee et al. (2011) used daily data from June 30, 2003, to March 31, 2008, to evaluate volatility projections of US dollars to Indian rupees (USD/INR) exchange rate. The GARCH (1, 1) model helped predict exchange rate dynamics. Alam and Rahman (2012) used daily data from March 2006 to April 2012 to demonstrate that historical volatility had a significant positive impact on the current fluctuations of BDT/USD exchange rates. In their study, Musa et al. (2017) reported that GARCH (1, 1) model performed better for out-sample data when taking into account weekly returns.

Some scientists have used Nigeria's univariate ARCH/GARCH models to examine the NGN exchange rates and other foreign currencies. For example, Olowe's (2009) findings provided compelling evidence that volatility persisted during the tested period and that asymmetry significantly impacted the volatility process. The findings of Awogbemi and Alagbe (2011) suggest that the exchange rate returns exhibit volatility persistence. Adeoye and Atanda (2012) used monthly data for the years 1986 through 2008 to investigate the consistency, perseverance, and level of volatility in the NGN/USD exchange rates. Their findings support the persistence of volatility in exchange rates. Bala and Asemota (2013) implemented GARCH models on monthly data from January 1985 to July 2011 to analyse the volatility of three currency rates (USD, GBP, and EUR) concerning the NGN. The results show that volatility breaks in estimated models improve model performance, but leverage effects in the volatility processes never occurred. Musa et al. (2014) used daily data from June 2000 to July 2011 and obtained significant asymmetric impact.

## 3. RESEARCH METHODOLOGY

There are numerous techniques for forecasting exchange rate dynamics in economic literature. These methodologies include the DSGE model, singular spectrum analysis (SSA), genetic algorithm, ARIMA, mean squared forecast error (MSFE), fuzzy inference system technique, extreme machine learning, structural vector autoregressive (VAR) technique, adaptive neuro-fuzzy inference system (ANFIS), etc. These methods predominantly suffer from distortionary measurements, especially when fundamental variables are included in the analysis. For example, the MSFE technique has been criticised by Clark and West (2006, 2007), and Khashei and Mahdavi Sharif (2020). We relied on GARCH estimation because of its sensitivity to outliers and volatility clusters. Hence, our estimation took off with a GARCH (0, 1), that is, ARCH model (1), to ascertain the presence or otherwise of the ARCH effect. Afterwards, the threshold generalised autoregressive conditional heteroskedasticity model (TGARCH or GJR-GARCH) specified in Eq. (1) was utilised to analyse reactions of the market to positive and negative shocks (otherwise referred to as good and bad news) relating to exchange rate volatility.

$$\sigma_t^2 = d_0 + \sum_{i=1}^{q} \phi_i e_{t-i}^2 + \sum_{i=1}^{q} \rho_i I_{t-i} e_{t-i}^2 + \sum_{i=1}^{p} \alpha_j \sigma_{t-j}^2 \quad (1)$$

where, $I_{t-i} = \begin{cases} 1\ ,\ if\ \ e_t^2 < 0 \\ 0\ ,\ otherwise \end{cases}$

The simplified form of the TGARCH ($p$, $q$) is:

$$\sigma_t^2 = d_0 + \phi_1 e_{t-1}^2 + \rho_i I_{t-1} e_{t-1}^2 + \alpha_1 \sigma_{t-1}^2 \quad (2)$$

The exponential GARCH model was also used to handle asymmetric shocks. Nelson (1991) advocated using this strategy to counteract the limitations of symmetric GARCH in time series analysis. In particular, the model is as specified:

$$ln(\sigma_t^2) = \gamma + \phi([|e_{t-1}| - E(|e_{t-1}|)]) + \beta e_{t-1} + \delta\, ln(\sigma_{t-1}^2) \quad (3)$$

where, $ln$ is a log of conditional variance, the size effect measured by the ARCH coefficient is given, while the leverage effect is presented as $\beta e_{t-1}$.

We also estimated the structural vector autoregressive (SVAR) model in addition to GARCH equations. The SVAR model analyses fluctuations in business cycles in response to shocks. The SVAR is an adjustment of VAR estimate errors using imposed restrictions on the model's parameters (Sims, 1980). The SVAR model can be specified as follows:

$$BEXR_t = \Gamma_0 + \Gamma_1 EXR_{t-1} + \varepsilon_t \quad (4)$$

Accordingly, we solved the reduced-form VAR equation $EXR$ in terms of $EXR_{t-1}$ and $\varepsilon_t$. Hence, we have the following:

$$EXR_t = B^{-1}\Gamma_0 + B^{-1}\Gamma_1 EXR_{t-1} + B^{-1}\varepsilon_t \quad (5)$$

Equation (2) can as well be rep-specified as:

$$\Rightarrow EXR_t = \Lambda_0 + \Lambda_1 EXR_{t-1} + u \quad (6)$$

where, $\Lambda_0 = B^{-1}\Gamma_0, \Lambda_1 = B^{-1}\Gamma_1, u = B^{-1}\varepsilon_t$

The SVAR model was deployed to analyse fluctuations and responses to VAR-error-adjusted shocks from macroeconomic variations. It can only be achieved through the imposition of long-run restrictions on the parameters of the structural VAR model (Blanchard & Quah, 1989). The exchange rate shock was defined as that effect that leads to a long-run change. With such restrictions, the SVAR model was identified. The study employed monthly exchange rates from twenty African countries from 1995M1 to 2021M12. Countries examined were: Mauritius, Nigeria, Kenya, Morocco, Ghana, Egypt, South Africa, Uganda, Tanzania, Mali, Burkina Faso, Burundi, Côte d'Ivoire, Mauritania, Senegal, Rwanda, Ethiopia, Congo Republic, Cameroon and Gabon. Exchange rates were measured in the value of local currency units per USD. Data were sourced from the World Bank databases.

## 4. RESULTS

The descriptive table contains the measures of averages for the twenty countries for which data were retrieved. Ghana has the most valued average exchange rate concerning the USD. Egypt, Morocco and South Africa occupy the positions in the table above, among the studied countries. Uganda, Tanzania and Burundi have the most devalued currencies among sampled countries. Data across the panel is platykurtic; thus, panels do not have fat tails. The descriptive graphs are shown in Figure A.1 (see Appendix).

**Table 1.** Statistics

| *Countries* | *Mean* | *Minimum* | *Maximum* | *Std. dev.* | *Kurtosis* |
|---|---|---|---|---|---|
| Burkina Faso | 555.4845 | 414.8476 | 779.324 | 75.71763 | 0.569785 |
| Burundi | 1176.831 | 234.61 | 2006.1 | 500.2452 | -0.88206 |
| Cameroon | 555.4845 | 414.8476 | 779.324 | 75.71762 | 0.569783 |
| Congo, Rep. | 555.4845 | 414.8476 | 779.324 | 75.71763 | 0.569785 |
| Côte d'Ivoire | 555.4845 | 414.8476 | 779.324 | 75.71763 | 0.569785 |
| Egypt | 7.493994 | 3.388 | 18.725 | 4.727336 | 0.212013 |
| Ethiopia | 15.35255 | 5.94 | 48.466 | 9.670488 | 1.203488 |
| Gabon | 555.4845 | 414.8476 | 779.324 | 75.71763 | 0.569785 |
| Ghana | 1.967831 | 0.106383 | 6.0061 | 1.80473 | -0.5621 |
| Kenya | 81.48568 | 43.5522 | 113.1412 | 16.01662 | -0.75683 |
| Mali | 555.4845 | 414.8476 | 779.324 | 75.71763 | 0.569785 |
| Mauritania | 27.31607 | 12.528 | 37.75 | 6.620728 | -0.265 |
| Mauritius | 29.86852 | 16.9579 | 43.5294 | 5.664574 | 0.252041 |
| Morocco | 9.18016 | 7.2582 | 11.968 | 0.92716 | 0.3558 |
| Nigeria | 160.8171 | 21.8661 | 414.4 | 100.6401 | 0.046504 |
| Rwanda | 589.122 | 134.7621 | 1009.618 | 200.6601 | -0.64235 |
| Senegal | 555.4845 | 414.8476 | 779.324 | 75.71763 | 0.569785 |
| South Africa | 9.044671 | 3.5345 | 18.06104 | 3.597281 | -0.73486 |
| Tanzania | 1387.504 | 538.3719 | 2299.53 | 582.6553 | -1.1802 |
| Uganda | 2273.46 | 925.41 | 3879.54 | 889.1083 | -1.07663 |

*Source: Authors' elaboration.*

**Table 2.** Optimal lag length

| *Lag* | *LogL* | *LR* | *FPE* | *AIC* | *SC* | *HQ* |
|---|---|---|---|---|---|---|
| 0 | -49614.81 | NA | 398591.8 | 15.73357 | 15.73464 | 15.73394 |
| 1 | -26899.64 | 45415.94 | 296.7372 | 8.530724 | 8.532864 | 8.531465 |
| 2 | -26870.23 | 58.79370* | 294.0759* | 8.521715 | 8.524925 | 8.522827 |
| 3 | -26870.20 | 0.049649 | 294.1668 | 8.522024 | 8.526305 | 8.523507 |
| 4 | -26864.52 | 11.34713 | 293.7307 | 8.520541 | 8.525891 | 8.522394 |
| 5 | -26852.41 | 24.19992 | 292.6976 | 8.517017 | 8.523438 | 8.519241 |
| 6 | -26851.72 | 1.391240 | 292.7258 | 8.517113 | 8.524604 | 8.519708 |
| 7 | -26843.20 | 17.02000 | 292.0285 | 8.514728* | 8.523290* | 8.517694* |
| 8 | -26841.21 | 3.967238 | 291.9371 | 8.514416 | 8.524047 | 8.517752 |

*Notes: * Significance at 0.05 level. LR — sequential modifiled LR test statistic; FRE — final prediction error; AIC — Akaike's information criterion; SC — Schwarz information criterion; HQ — Hannan-Quinn information criterion.*
*Source: Authors' elaboration.*

The information criteria of Table 2 choose lag 7 as the optima.

Exchange rate panel data were subjected to unit root tests to determine whether or not a unit root was present. After first differencing, it was discovered that the variable was stationary. Since the variable is stationary, as shown in Table 3, we investigated whether the long-term relationship holds.

A co-integration test was performed on a period-lagged exchange rate and seven period-lagged based on optimal lag selections to assess the long-term link between the current exchange rate and their lagged values. Results are presented in Table 4. The p-values for cointegration statistics are all 0.00, which is less than 0.05. Therefore, the null hypothesis of the absence of long-term relationships for both delays is rejected.

**Table 3.** Unit root test

| *Methods* | *EXR I(0)* | *EXR I(1)* |
|---|---|---|
| Levin et al.'s (2002) (LLC) t-statistics* | 1.3846 | -34.1644* |
| Breitung statistic | -0.0609 | -9.59441* |
| Im et al.'s (2003) W-stat (IPSW) | 2.7520 | -33.1301* |
| Fisher Chi-square | 1.3472 | 967.783* |

*Note: *Significance at 5%.*

**Table 4.** Pedroni residual cointegration test

| *Method* | *EXR(-1) Statistic* | *EXR(-7) Statistic* |
|---|---|---|
| V-statistic | 159.6744* | 17.21370* |
| Rho-statistic | -200.7874* | -29.35666* |
| PP-statistic | -73.64173* | -15.56239* |
| ADF-statistic | -71.38248* | -6.394286* |
| Rho-statistic | -195.7593* | -24.76382* |
| PP-statistic | -86.75359* | -16.08118* |
| ADF-statistic | -79.20007* | -4.042134* |

*Note: *Significance at 0.05.*

Panel ordinary least squares (OLS) findings were used. The ideal latency for the study was seven. Dynamic Panel generalized method of moments (GMM) estimation, driven by active panel wizard, was appropriate for the data having compared coefficient of lagged endogenous variables from the pool and fixed effects calculations (not reported here for brevity). Without regressors, the average exchange rate is 17.23 units of local currency. The current period's currency rates are 98% influenced by the exchange rate's 7-lagged value. In other words, the exchange rate in August will be 98% controlled by the value of the exchange rate in January. However, OLS regression on time series exhibits a downward bias and is unreliable for predicting.

The structural factorisation of VAR results was run on EViews 10 using the structural decomposition using the optimal lag 7. Current values of exchange rates had an immediate positive response within the next month from the constant weight of 17.23, as depicted by fixed effects estimates of Table 5. It stabilises slightly after the second month and continues to rise till its fourth period. The results then take a reverse and begin to fall till the sixth period and then increase again in the seventh period but by less magnitude by which it fell in the 6th period. After the seventh period, rates become relatively stable, rising gradually continually. The impulse response graph (see Figure A.2 in Appendix) also shows that exchange rates have short cycles.

**Table 5.** DGMM estimation

| *Variables* | *Coefficients* | *t* |
|---|---|---|
| C | 17.23015* | 13.74477 |
| EXR(-7) | 0.982286* | 430.1275 |
| S.E. of regression | 48.50711 | - |
| F-statistic (Pro.) | 53138.71 | 0.000 |

*Note: *Significance at 5%.*
*Source: Authors' elaboration.*

ARCH effects were significant for Kenya, Ghana, Nigeria, Mauritius, and South Africa. Table 6 has the results.

**Table 6.** ARCH results

| *Countries* | *Obs * R-squared* | *Prob.* | *Remarks* |
|---|---|---|---|
| Burkina Faso | 0.005455 | 0.9411 | No ARCH effects |
| Kenya | 18.6046* | 0.0000 | ARCH effects |
| Cameroon | 0.005455 | 0.9411 | No ARCH effects |
| Congo, Rep. | 0.005455 | 0.9411 | No ARCH effects |
| Côte d'Ivoire | 0.005455 | 0.9411 | No ARCH effects |
| Egypt | 0.007426 | 0.9313 | No ARCH effects |
| Ethiopia | 0.008258 | 0.9276 | No ARCH effects |
| Gabon | 0.005455 | 0.9411 | No ARCH effects |
| Ghana | 68.2451* | 0.0000 | ARCH effects |
| Nigeria | 56.68307* | 0.0032 | ARCH effects |
| Mali | 0.005455 | 0.9411 | No ARCH effects |
| Mauritania | 1.964552 | 0.1610 | No ARCH effects |
| Mauritius | 5.73963* | 0.0166 | ARCH effects |
| Morocco | 1.524301 | 0.2170 | No ARCH effects |
| Burundi | 1.356633 | 0,2441 | No ARCH effects |
| Rwanda | 0.001035 | 0.9743 | No ARCH effects |
| Senegal | 0.005455 | 0.9411 | No ARCH effects |
| South Africa | 5.41519* | 0.0200 | ARCH effects |
| Tanzania | 0.481550 | 0.4877 | No ARCH effects |
| Uganda | 2.807558 | 0.0938 | No ARCH effects |

*Note: The statistic labeled "Obs * R-squared" is the LM test statistic for the null hypothesis of no serial correlation. * Significance at 0.05.*
*Source: Authors' elaboration.*

The study employed GARCH models to estimate and forecast the volatility of exchange rates in sampled nations. The test for ARCH effects in each cross-section determined the suitability of GARCH in calculating volatility. Table 6 revealed that only five countries had ARCH effects: Nigeria, Ghana, Kenya, Mauritius and South Africa. Asymmetric GARCH models (the exponential GARCH and TGARCH/GJR-GARCH) were asymmetric models used. In cases where asymmetry was not found in the asymmetric term, GARCH estimates were used since it is a symmetrical model.

*Kenya.* Kenya had leverage terms with asymmetry; GJR-GARCH had a positive leverage term, whereas E-GARCH had a negative one. It suggested that when good and bad news is released to the market, Kenya's exchange rates react in various ways. These asymmetric GARCH models demonstrate that exchange rates respond more strongly to positive news than negative news, in contrast to the GARCH (1, 1) model, which implies that impacts in both scenarios are equal. However, it was determined that this was not significant at the 5% level. The absence of auto and partial correlation was evident in the correlogram, and ARCH-LM was not substantial. For the forecast, the 2001M01 to 2021M12 periods was sampled from the total observations, as shown in Figure A.3 in Appendix. In Kenya, the mean absolute percentage error is very low at 0.01568% while 99.9% of unsystematic error is explained by the model with a high covariance proportion of 0.816021%. It illustrates how strongly the model predicts Kenya's future currency rates.

Looking at the forecast chart from January 2001 to December 2021, exchange rates will continue to experience a steady rise monthly. The forecast model had 0.309472 mean absolute error, and 99.7% of that unsystematic error is accounted for in the model with covariance proportion at 0.816021. It depicts that the model is weak in its predictive ability. Table 8 contains the forecast results.

**Table 7.** GARCH estimates

| *Methods* | *Nigeria* | *Ghana* | *Kenya* | *Mauritius* | *South Africa* |
|---|---|---|---|---|---|
| C | 5.206311* | -3.492870* | -0.157648 | -0.40783* | 0.023782* |
| ARCH term | 1.945128* | 2.793903* | 0.821705* | 0.70021* | -0.074367* |
| GARCH term | -0.097782* | 0.770080* | 0.696709* | 0.84482* | 0.984211* |
| Leverage term | -0.113116 | -0.215678 | 0.297987* | -0.158205 | 0.109678* |
| Persistence | 1.847346 | 3.563983 | 1.518414 | 1.54503 | 0.909844 |
| Log-likelihood | -1371.649 | 751.30 | -536.374 | -221.997 | -1233.69 |
| AIC | 8.5427 | -4.6148 | 3.3645 | 1.417 | 0.8092 |
| C | -0.022002 | 0.0000016* | 0.374685* | 0.1015 | 0.000360* |
| ARCH term | 0.308761* | 2.129247* | 0.567825* | 0.6412 | 0.085665* |
| GARCH term | 0.761748 | 0.3191* | 0.508075* | 0.545* | 0.980815* |
| Leverage term | 0.296113 | -1.8012* | -0.324937* | 2.2951 | -0.146690* |
| Persistence | 1.070509 | 2.448347 | 1.0759 | 1.1862 | 1.06648 |
| Log-likelihood | -1279.974 | 854.23 | -570.90 | -220.583* | -127.46 |
| AIC | 7.96268 | -5.2522 | 3.57216 | 1.409 | 0.8325 |
| C | - | - | 0.307452* | - | 0.0009190 |
| ARCH term | - | - | 0.415445* | - | 0.269624* |
| GARCH term | - | - | 0.542901* | - | 0.809545* |
| Persistence | - | - | 0.95634 | - | 1.078169 |
| Log-likelihood | - | - | -573.91 | - | -130.94 |
| AIC | - | - | 3.58458 | - | 0.8479 |

*Note: *Significance at 0.05.*

**Table 8.** Exchange rate forecast for Kenya

| *Measures* | *Values* |
|---|---|
| Forecast | EXR01F |
| Actual | EXR01 |
| Mean absolute error (MAE) | 0.309472 |
| Root mean squared error (RMSE) | 0.362585 |
| Mean absolute percentage error (MAPE) | 0.01568 |
| Thiel inequality coefficient | 9.16E-05 |
| Bias proportion | 0.037565 |
| Variance proportion | 0.146409 |
| Ccovariance proportion | 0.816021 |
| Theil U2 coefficient | 0.065199 |
| Symmetric MAPE | 0.997682 |
| Forecast sample | 2021M01 2021M12 |

*Source: Authors' elaboration.*

**Table 9.** Exchange rate forecast for Ghana

| *Measures* | *Values* |
|---|---|
| Forecast | EXRF |
| Actual | EXR |
| Mean absolute error (MAE) | 0.028416 |
| Root mean squared error (RMSE) | 0.033457 |
| Mean absolute percentage error (MAPE) | 0.48946 |
| Thiel inequality coefficient | 0.002871 |
| Bias proportion | 0.29662 |
| Variance proportion | 0.354761 |
| Ccovariance proportion | 0.348606 |
| Theil U2 coefficient | 0.913297 |
| Symmetric MAPE | 0.488400 |
| Forecast sample | 2021M01 2021M12 |

*Source: Authors' elaboration.*

*Ghana.* In Ghana, GJR-GARCH had a negative leverage term, but Ghana also had a negative E-GARCH leverage term. With a high positive likelihood, autocorrelation, and partial correlation, the GJR-GARCH model was likewise discovered to be inadequate. Ghana's currency rates respond more favourably to positive than negative news, according to the E-GARCH estimates, which are determined to be reliable given the results of post-diagnostic testing (lack of auto and partial correlation and negligible ARCH-LM). However, it was determined that this was not significant at the 5% level. From all of the observations, the forecast was derived. According to the forecast chart's rapid and upward movement in the variance curve starting from 1995, exchange rates are projected to increase significantly shortly (see Figure A.4 in Appendix). The forecast model has a mean absolute percentage error of 0.48946% while 99.5% of unsystematic error is accounted for in the model with a very low covariance proportion of 0.348606. It illustrates how highly predictive the model is. Table 9 contains the forecast results.

*Nigeria.* The forecast model has a mean absolute percentage error of 0.644848% while 99.35% of unsystematic error is explained by the model with a high covariance proportion of 0.815757%. Given the historical levels of the exchange rates, volatility is also persistent. By implication, the NGN/USD exchange rates are so volatile, forecasting models have a high error rate. Table 10 contains forecast results.

**Table 10.** Exchange rate forecast for Nigeria

| *Measures* | *Values* |
|---|---|
| Forecast | EXRF |
| Actual | EXR |
| Mean absolute error (MAE) | 0.81105 |
| Root mean squared error (RMSE) | 0.708408 |
| Mean absolute percentage error (MAPE) | 0.644848 |
| Thiel inequality coefficient | 0.003785 |
| Bias proportion | 0.051538 |
| Variance proportion | 0.132705 |
| Ccovariance proportion | 0.815757 |
| Theil U2 coefficient | 0.96079 |
| Symmetric MAPE | 1.0644995 |
| Forecast sample | 2021M01 2021M12 |

*Source: Authors' elaboration.*

*Mauritius.* In terms of asymmetry, Mauritius and Burundi both had some, albeit not very significant, asymmetry in the market for currency rates. Figure A.6 (in Appendix) shows short-cycle increases in exchange rates in Mauritius. Early months saw an evening of exchange rates, which then experienced a significant spike in instability in mid-year periods before levelling off again. In Mauritius, the mean absolute percentage error of the forecasting model is high as it reported 0.805114% while 99.2% of unsystematic error is accounted for by the model with a high covariance proportion of 0.792779. The prediction power of the model is fair. Table 11 contains the forecast results.

**Table 11.** Exchange rate forecast for Mauritius

| *Measures* | *Values* |
|---|---|
| Forecast | EXRF |
| Actual | EXR |
| Mean absolute error (MAE) | 0.57162 |
| Root mean squared error (RMSE) | 0.338155 |
| Mean absolute percentage error (MAPE) | 0.805114 |
| Thiel inequality coefficient | 0.006842 |
| Bias proportion | 0.200888 |
| Variance proportion | 0.006333 |
| Ccovariance proportion | 0.792779 |
| Theil U2 coefficient | 0.940630 |
| Symmetric MAPE | 0.81390 |
| Forecast sample | 2021M01 2021M12 |

*Source: Authors' elaboration.*

*South Africa.* Asymmetric models did not find any asymmetric impacts on the exchange rate volatility in South Africa. The coefficients for TGARCH and E-GARCH were positive and negative, respectively. Thus, symmetric effects suggested modelling and forecasting using the GARCH (1, 1) model. The country's currency rate is volatile, although not persistent, as the sum of ARCH and GARCH parameters exceeds 1. The South African exchange rate will remain constant within a certain margin of error for the foreseeable future. It may increase or decrease by 2 to 6 units when converting USD to local currency. The forecast variance chart depicts what appears to be a cycle of high and low volatility. Therefore, South Africa's EXR is anticipated to experience substantial volatility soon. In the South African model, the mean absolute percentage error is very high at 0.995424% with a high variance and covariance proportion of 0.99356% and 0.995901% respectively. It illustrates how poor the model predicts South Africa's future currency rates. The forecast charts' demonstrates similar findings. Table 12 contains the forecast results.

**Table 12.** Exchange rate forecast for South Africa

| *Measures* | *Values* |
|---|---|
| Forecast | EXRF |
| Actual | EXR |
| Mean absolute error | 0.09226 |
| Root mean squared error | 0.05976 |
| Mean absolute percentage error (MAPE) | 0.995424 |
| Thiel inequality coefficient | 0.001259 |
| Bias proportion | 0.924132 |
| Variance proportion | 0.99356 |
| Ccovariance proportion | 0.995901 |
| Theil U2 coefficient | 0.78629 |
| Symmetric MAPE | 0.02940 |
| Forecast sample | 2021M01 2021M12 |

*Source: Authors' elaboration.*

## 5. CONCLUSION

The study aimed at forecasting exchange rate dynamics in developing countries using asymmetric volatility models. The research uses GARCH modelling, and panel SVAR model to analyze the dynamics of exchange rates based on monthly data. Out of 20 countries, only 5 (Kenya, Ghana, Nigeria, Mauritius, and South Africa) had ARCH effects on exchange rate dynamics. Lagged values of exchange rates had a positive and notable impact on current values. This trend depicts constant devaluation of currencies of all the countries in this study. An indication that Stagflation due to devaluation may soon take its course on these economies with the implication for high cost of living in these countries. Overall, the volume of local investments would continually be reduced as local investors would prefer to hold investments in foreign currencies rather than local ones.

Further, all countries had subtle asymmetries in their exchange rates volatility patterns, indicating that exchange rates are more volatile when bad news affects the market than when positive news does. In effect, each country's local currency markets responded in a distinguishable pattern to both positive and bad news of the same magnitude. As owners of local investments and currencies start to fear when bad news hits the exchange market, currency rates begin to drop faster. However, when positive news is announced, exchange rates only marginally fall (overvaluation) compared to the same magnitude of negative information. In sum, the regulatory agencies of governments of these emerging countries should deploy monetary policies as viable tools for influencing currency rates in favour of participants in the FX market.

This study benefits local and foreign investors by providing future knowledge on exchange rate movements. By so doing, the study empowers such investors with the relevant information sets to diversify portfolios resourcefully. It is as essential as it provides a trend of future values of exchange rates needed to avert the risk of fluctuations in currency rates. Therefore, given that global transactions and investments are adversely affected by variations in exchange rates, the study contributes to the knowledge of financiers in extrapolating future stock market movements through forecasting of exchange rates market. In this research, we utilised a sample of twenty countries as informed by data available to the researchers. Hence, a minor sample limitation could be beckoning the paper's empirical findings. We accordingly suggest that future investigators take into cognisance a larger sample of countries of developing countries to conduct a comparative forecast performance analysis between daily exchange rates and quarterly rates. Better still, the empirical research could be applied to currencies of Asian-pacific countries' exchange rates.

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# APPENDIX

**Figure A.1.** Graphs of exchange rates for each country

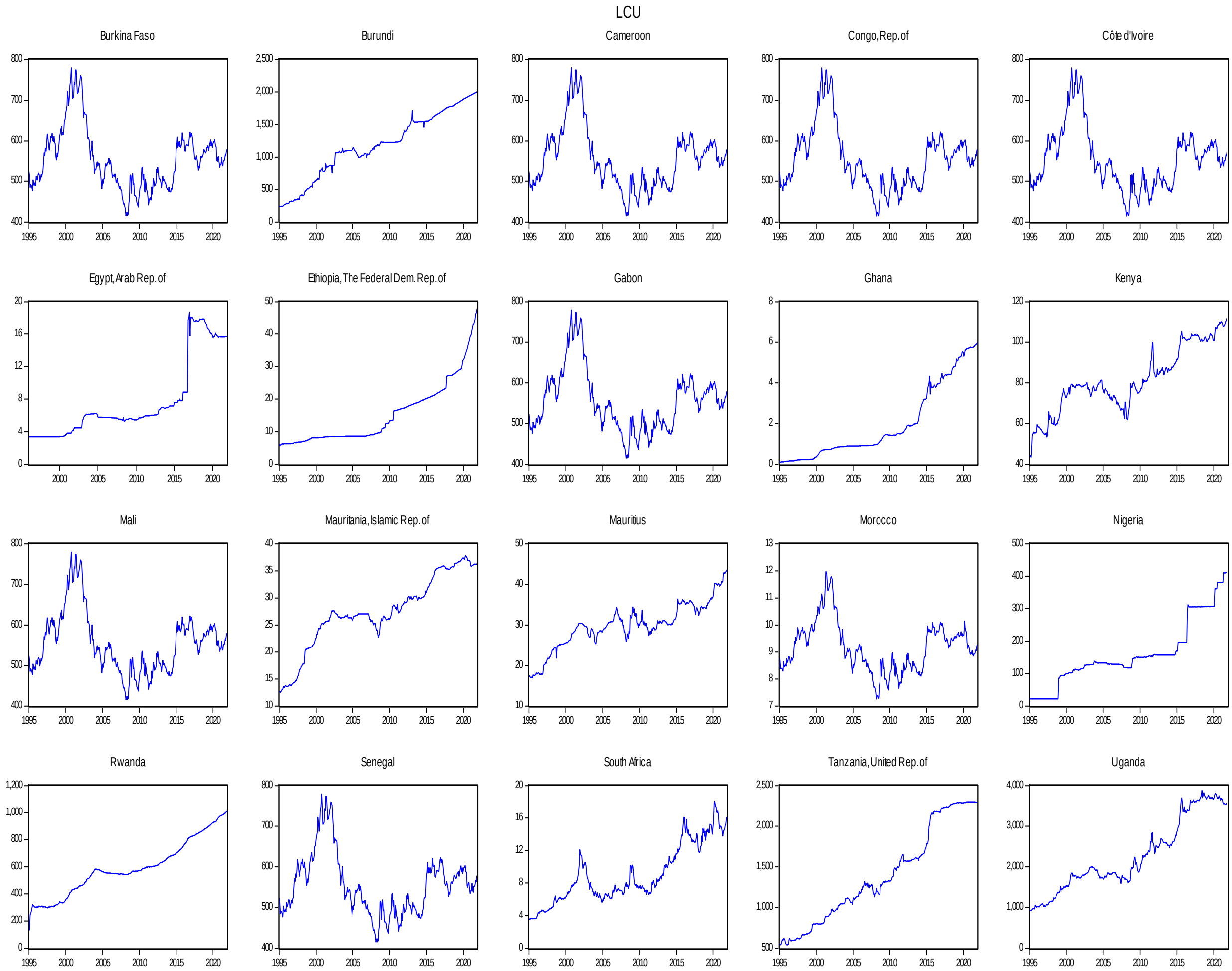


**Figure A.2.** Response of exchange rate to shocks

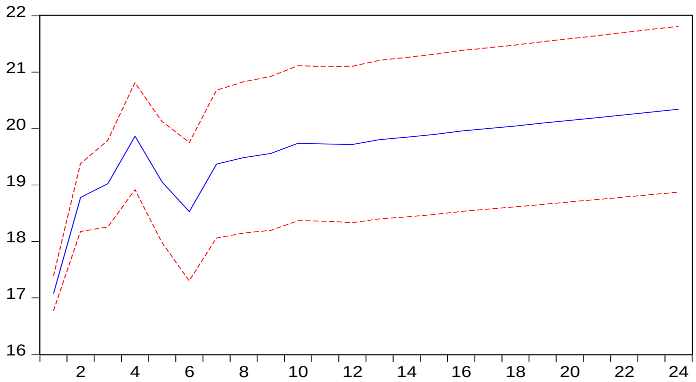

**Figure A.3.** Forecast of exchange rate for Kenya

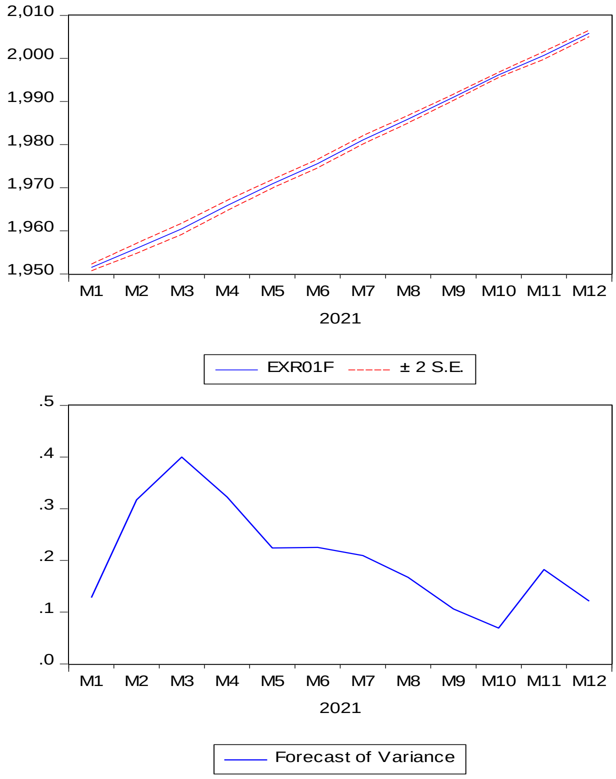


**Figure A.4.** Forecast of exchange rate for Ghana

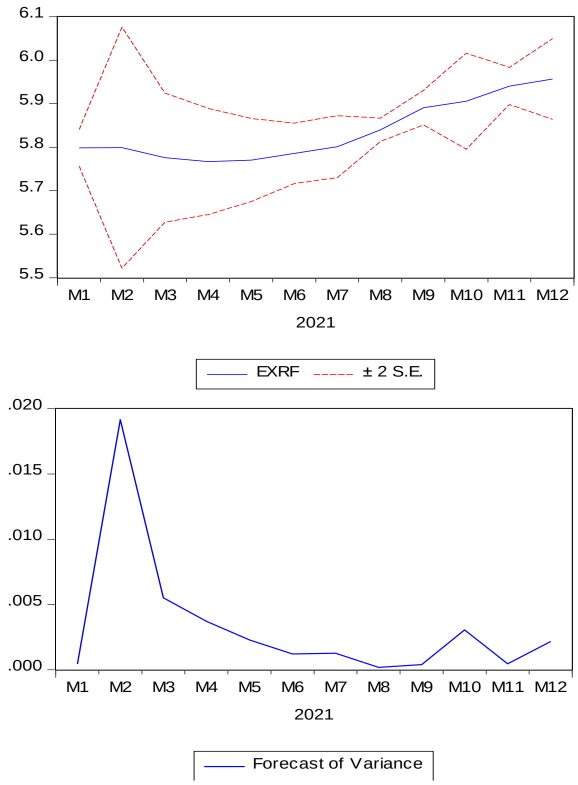

**Figure A.5.** Forecast of exchange rate for Nigeria

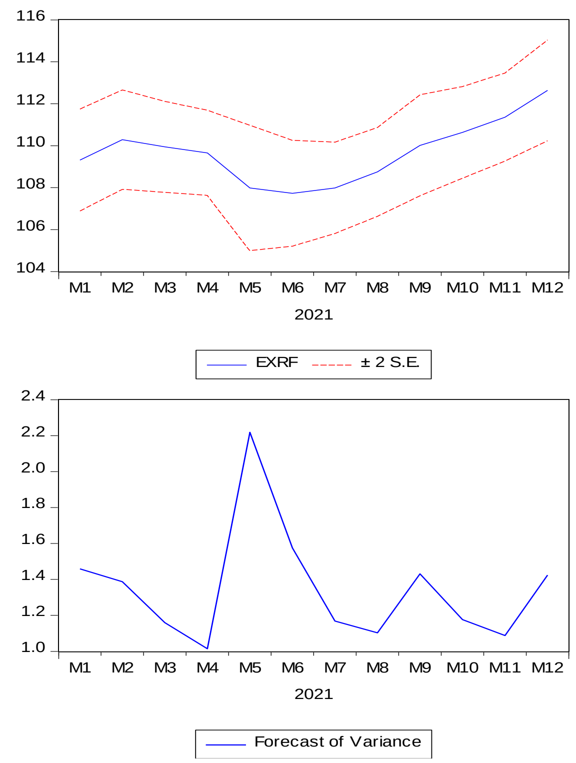


**Figure A.6.** Forecast of exchange rate for Mauritius

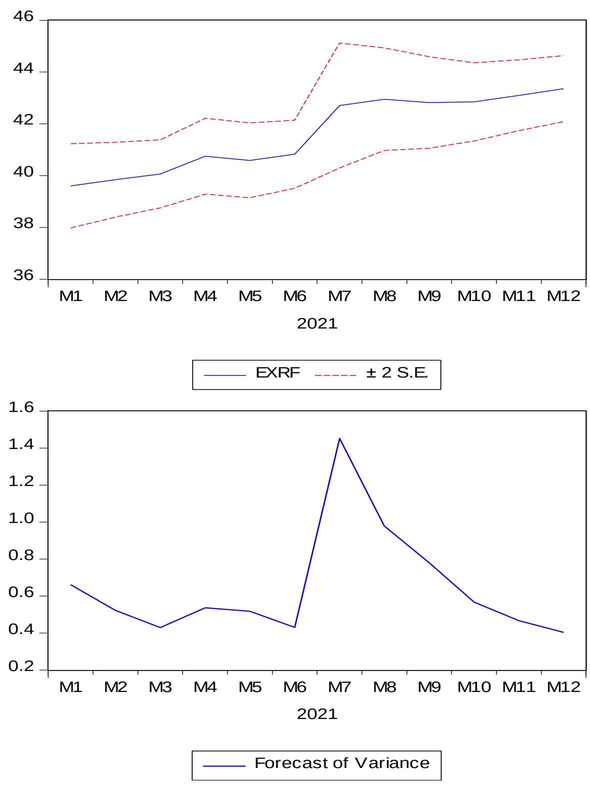

**Figure A.7.** Forecast of exchange rate for South Africa