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EVALUATING FORECASTING MODELS IN VOLATILE EXCHANGE RATE ENVIRONMENT: INSIGHTS FROM SIERRA LEONE

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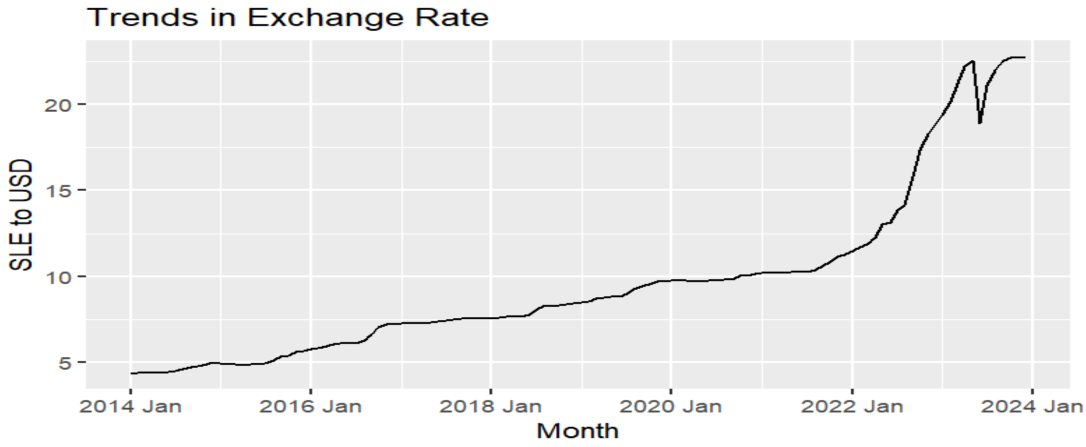
Abstract

This paper evaluates the predictive performance of several econometric models for exchange rate volatility, focusing on the Sierra Leonean Leone (SLE) to US Dollar (USD) exchange rate. Given Sierra Leone's dependency on imports and remittances, accurate forecasting of exchange rates is critical, particularly during periods of heightened political and economic uncertainty, such as the covid19 pandemic and the 2023 general elections. The analysis compares baseline models (mean, drift, naïve), traditional regression models (linear, exponential, stepwise), and advanced time series techniques (SARIMA, ETS) using monthly data from 2014 to 2024. Empirical results indicate that traditional models, while effective in capturing short-term trends, are insufficient during periods of structural breaks and volatility. Advanced models, particularly ETS, outperform others by dynamically adjusting to irregular seasonality and external shocks. ETS exhibits superior performance in volatile conditions, offering the lowest forecast errors (RMSE and MAE) and greater adaptability. Traditional models like ARIMA, SARIMA, and ETS are preferred over Prophet and GARCH in this context due to their superior interpretability, ability to handle small datasets and seasonality, and suitability for providing actionable insights in economic policy-making

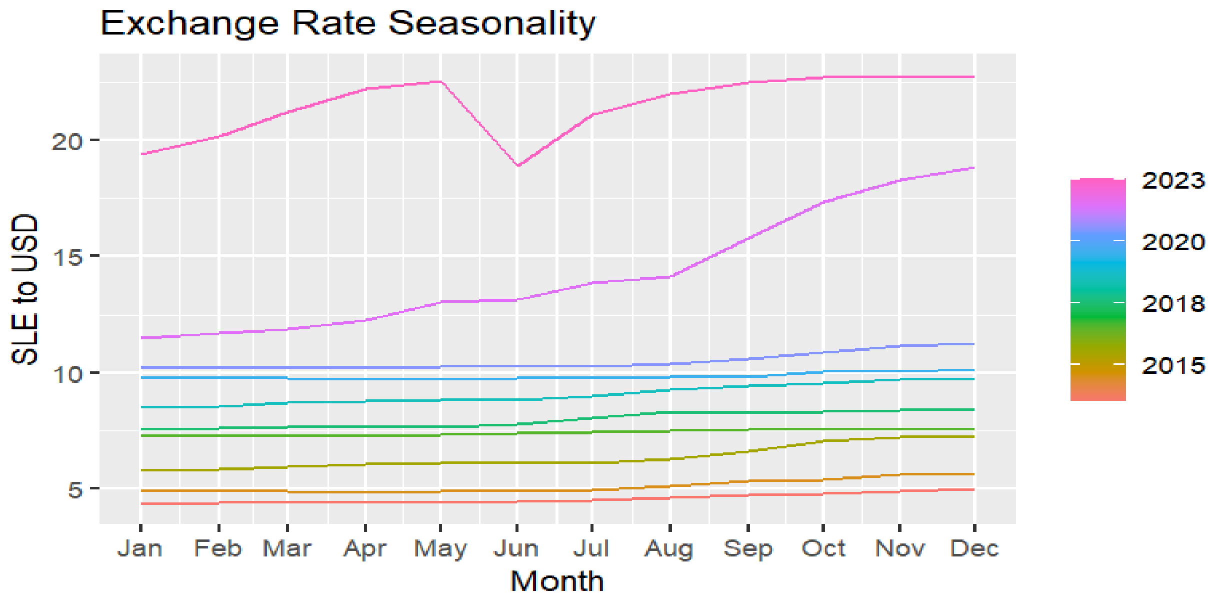
Introduction

The exchange rate between a nation’s currency and global benchmarks like the US Dollar (USD) is one of the most critical indicators of a country’s economic health. For emerging economies like Sierra Leone, where trade is heavily dependent on imports and remittances, currency volatility can have profound effects on inflation, investment, and economic growth. Political instability, such as the 2023 general elections, often triggers sharp movements in exchange rates, creating a challenging environment for economic planning and policy formulation.

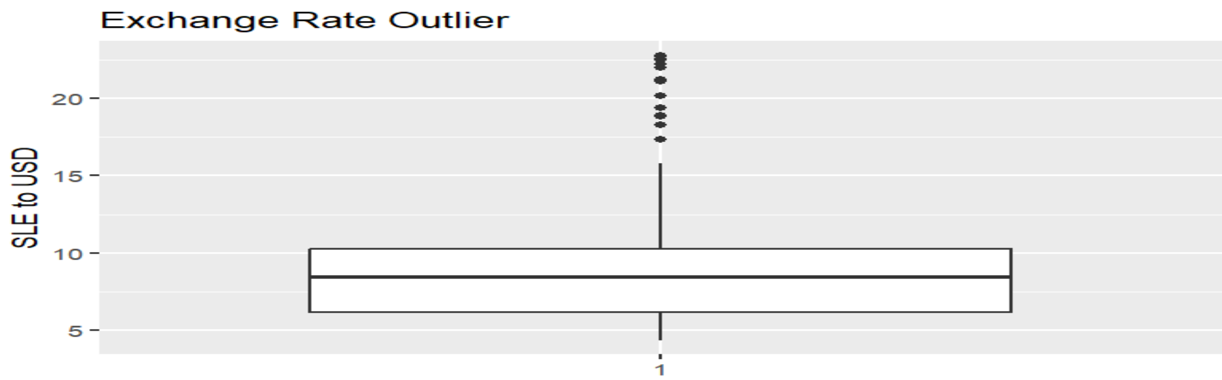
The data reveals a depreciating trend of the Leone against the US Dollar over time, reflecting the broader economic challenges faced by Sierra Leone, including inflation and reliance on imports. Notably, the exchange rate saw sharp declines during periods of political uncertainty, such as the 2023 elections, which disrupted normal exchange rate patterns and contributed to volatility.



Seasonality is observed in the exchange rate, with fluctuations during specific periods, such as remittance inflows during religious pilgrimages (Hajj) and agricultural harvest seasons. These seasonal patterns are crucial for understanding short-term movements in the currency market.



Outliers were detected, especially during the 2023 elections, representing sudden spikes in exchange rate volatility due to political uncertainty. These outliers necessitate the use of econometric models capable of handling structural breaks and volatility, which are characteristic of Sierra Leone's exchange rate dynamics.



Forecasting exchange rates under such volatile conditions is a complex task. While machine learning models like Prophet have gained popularity for handling irregular data patterns, traditional econometric models like ARIMA, ETS, and regression models continue to offer significant

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advantages. These models provide greater interpretability, are well-suited for smaller datasets, and are particularly effective when structural breaks and seasonality must be explicitly modeled. This paper evaluates a range of models, including baseline methods (mean, drift, and naïve), regression approaches (linear, step-wise and exponential), and advanced time series models (SARIMA and ETS). The goal is to assess their performance in predicting the Sierra Leonean Leone (SLE) to USD exchange rate under conditions of economic volatility. Traditional models like ARIMA, SARIMA, and ETS are preferred over Prophet and GARCH in this context due to their superior interpretability, ability to handle small datasets and seasonality, and suitability for providing actionable insights in economic policy-making (Hyndman & Athanasopoulos, 2018; Hamilton, 1994; Hansen, 2005).

Literature Review

Importance of Exchange Rate Forecasting

Exchange rate relates to the worth of a country's currency vis-à-vis the currency of other countries (Jackson, 2020). It also defined as the amount that a home currency costs to an overseas currency (Kamara et al., 2024). Exchange rate could be nominal or real. Nominal exchange rate expresses one currency's price with respect to the price of another currency while real exchange rate is the price of tradable goods compared to non-tradable goods (Johnson, 2020). The exchange rate regimes, which are classified into two broad classes, fixed and floating exchange system, influence the level of stability of the exchange. In fixed exchange rate regime where exchange rate is fixed to certain level, exchange rates are relatively stable unlike in floating exchange rate regime where market forces of demand and supply are determinants of exchange rate, there is instability in currency value. The continuous fluctuations or changes in the rate of exchange of a country's currency with other country's currency is termed exchange rate volatility. In other words, it is a continuous fluctuation in the currency or the instability currency rate (Umorun, Effiong, Umar, Okpara et al., 2023).

Most countries use the floating exchange rate regime because it allows for adverse shocks to be more easily absorbed than a fixed exchange rate regime (Johnson, 2020). Exchange rate in Sierra Leone has been volatile since the adoption of the flexible exchange rate in 1986 (Sesay et al., 2021). Volatility as a concept relating to fluctuations in security prices or asset values is important for investment decisions, asset pricing, portfolio allocation and risk management in finance (Akarım, & Akkoc, 2013). Therefore, exchange rate forecasting is very critical for macroeconomic stabilisation and planning; this is partly because exchange rate dynamics affect people's expectations about the economy, particularly about prices of goods and services (Jackson, 2020). Accurate exchange rate predictions have implication on investment decisions and economic outcomes in a country (Barrie, 2023). Exchange rate volatility also affected exports and trade balance and particularly in Sierra Leone, exchange rate is macroeconomic policy tool that improves the nation's competitiveness, trade balance, economic growth, and export promotion. (Kamara et al., 2024).

Furthermore, according to Gbadebo (2024), predicting exchange rate returns is crucial for financial stability, reserve management, market regulation, and the overall monetary policy framework. Exchange rate predictions also helps information for informed decisions by stakeholders in the foreign exchange market and also facilitate comparisons between forecasting techniques (Gbadebo, 2024).

Exchange Rate Forecasting in Sierra Leone

Sierra Leone's economy, heavily dependent on foreign trade and imports, has experienced significant exchange rate fluctuations, especially in times of political and economic instability. Traditional time series models like ARIMA have been widely used for exchange rate forecasting.

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Jackson (2020) employed the ARIMA model to forecast the Leone/USD exchange rate, demonstrating its effectiveness in capturing short-term trends. However, ARIMA struggles when it comes to accommodating structural breaks, such as those caused by the 2023 elections.

Tamuke et al. (2018) applied the GARCH-MIDAS (Generalized AutoRegressive Conditional Heteroskedasticity Mixed Data Sampling) model, which allows for the combination of macroeconomic variables and high-frequency data. This model was particularly effective in capturing volatility driven by external shocks. GARCH models, particularly those with skewed or fat-tailed error distributions, have been shown to outperform traditional ARIMA models in volatile markets (Hung-Chung et al., 2009).

Furthermore, Barrie (2023) employed Prophet, a machine learning model, in predicting daily exchange rate movements in Sierra Leone. The study found that the forecasting model offers probabilistic insights into future predictions, empowering decision-makers with accurate forecasts and valuable knowledge for strategic planning and risk management.

Exchange Rate Forecasting in West Africa

Similar challenges are observed in other West African nations like Ghana and Nigeria. Adjasi et al. (2008) employed the EGARCH model to analyze the Ghanaian Cedi (GHS) exchange rate, finding that exchange rate volatility negatively impacted stock market performance. In Nigeria, Sulaiman (2022) combined machine learning models like Prophet with traditional methods such as ARIMA, demonstrating that machine learning can outperform ARIMA in contexts of irregular data patterns and frequent external shocks. However, the downside of such machine learning models lies in their limited interpretability, particularly in economic policymaking, where understanding the underlying factors driving exchange rate movements is essential.

In a related study, Umorun et al. (2023) employed BEKK-GARCH and DCC-GARCH models to estimate volatility transmission and persistence respectively in selected African countries. Results show there is presence of spill-over effect in exchange rates of all countries. However, Eniayewu et al. (2024) examined the power of monetary fundamentals (interest rate and money supply growth) in forecasting daily exchange rate volatility in South Africa and Nigeria using the GARCH-MIDAS model. The study indicates the long-run persistence of exchange rate volatility in both countries and concludes that monetary fundamentals play a crucial role in determining exchange rate volatility in South Africa and Nigeria.

Moreover, Akintunde et al. (2025) assessed the monthly Naira-Dollar exchange rates (EXR) relationship using the non-seasonal Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA) models to examine the forecasting dynamics of the series. The results confirmed that SARIMA (0, 1, 1)(0, 1, 1)12 outperformed its ARIMA (3, 1, 0) counterpart.

Global Insights: Evolution of Forecasting Models

Globally, the evolution of forecasting models has expanded from linear models like ARIMA to more advanced methods that include machine learning techniques. While machine learning models such as Prophet excel in handling non-linear and irregular data patterns, traditional econometric models provide better insight into the underlying economic mechanisms. Hansen (2005) argued that traditional models like GARCH, combined with additional macroeconomic variables, remain valuable for their ability to forecast volatility in financial markets.

In emerging markets like Sierra Leone, where the availability of large datasets is limited, traditional models such as ARIMA, ETS, and regression models are particularly useful. They are not only computationally less intensive but also provide better explanatory power, which is critical for policy-

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making. This study bridges the gap by comparing these traditional models' performances under volatile conditions, focusing on their ability to accommodate structural breaks and seasonality.

Methodology

This section outlines the models used for forecasting the exchange rate between the Sierra Leonean Leone (SLE) and the US Dollar (USD). The models are organized into three stages: baseline models, regression models, and advanced time series models (SARIMA and ETS).

Baseline Models

Baseline models provide simple forecasts that serve as benchmarks for evaluating the performance of more complex models.

i. **Mean Model**: $\hat{y}_{t+1} = \bar{y}$
The forecast ($\hat{y}_{t+1}$) is simply the historical mean of the exchange rate(y).

ii. **Drift Model**: $\hat{y}_{t+1} = y_t + d$
where d is the drift, or the average change per period.

iii. **Naïve Model**: $\hat{y}_{t+1} = y_t$

This assumes that the next value is equal to the last observed value, which works well for short-term predictions in stable conditions.

Regression Models

i. **Linear Regression**: The linear regression model assumes a linear relationship between time and the exchange rate:

$$\hat{y}_{t+1} = \beta_0 + \beta_1 t + \varepsilon_t$$

Where: β_0 is the intercept, β_1 is the coefficient for time, and ε_t is the error term.

ii. **Exponential Regression**: This model captures exponential growth or decay in the exchange rate:

$$\hat{y}_{t+1} = \beta_0 e^{\beta_1 t} + \varepsilon_t$$

iii. **Stepwise Regression**: Stepwise regression iteratively adds or removes explanatory variables based on their statistical significance:

$$\hat{y}_{t+1} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \varepsilon_t$$

Where: x_1, x_2 , … are selected variables that best explain changes in exchange rates.

Each model is calibrated using the training dataset, and its predictive accuracy is tested against the testing dataset.

Advanced Time Series Models

SARIMA (Seasonal AutoRegressive Integrated Moving Average): SARIMA models both seasonal and non-seasonal components of the time series:

SARIMA (p, d, q) (P, D, Q) [s]

Where: p: non-seasonal autoregressive (AR) order; d: differencing order to make the series stationary; q: non-seasonal moving average (MA) order; P, D, Q: seasonal AR, differencing, and MA terms; and s: seasonal period.

The forecast for $\hat{Y}_{t+h}$ depends on past values, seasonal lags, and residuals:

$$\hat{Y}_{t+h} = \phi_1 \hat{Y}_{t+h-1} + \Phi_1 \hat{Y}_{t+h-12} + \theta_1 \varepsilon_{t+h-1} + \Theta_1 \varepsilon_{t+h-12}$$

Exponential Smoothing (Error, Trend, and Seasonality): The ETS models capture trends and seasonality in time series data. The model decomposes time series into error (E), trend (T), and seasonality (S) as:

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$$ETS\ (A, T, S)$$

Where:

- A: Error type (A for additive, M for multiplicative),
- T: Trend type (N for none, A for additive, M for multiplicative),
- S: Seasonality type (N for none, A for additive, M for multiplicative).

The general form is:

$$y_t = l_{t-1} + b_{t-1} + s_{t-1} + \epsilon_t$$

Where y_t is the monthly exchange rate, l_{t-1} is the level component, b_{t-1} is the trend component, s_{t-1} is the seasonal component, and ϵ_t is the error term.

The ETS model is particularly useful for capturing irregular seasonal patterns without pre-defined seasonality components.

Model Diagnostics and Validation

After fitting each model, diagnosis is performed to ensure the robustness of the forecasts:

- **Residual Analysis**: For each model, residuals are tested for white noise, normality and constant variance. The plots are generated to visualize the residuals and identify any patterns or correlations missed by the model.
- **Forecast Evaluation**: The models are evaluated using error metrics such as:
    i. **RMSE (Root Mean Square Error):** Measures the standard deviation of forecast errors, penalizing large deviations.
    ii. **MAE (Mean Absolute Error):** Calculates the average magnitude of errors.
    iii. **MAPE (Mean Absolute Percentage Error):** Expresses forecast error as a percentage of actual values, facilitating comparison across different models.

Testing ETS alongside SARIMA ensures robust model selection, balancing accuracy across different exchange rate dynamics.

Data and Sources

The data used in this study consists of monthly exchange rates between the Sierra Leonean Leone (SLE) and the US Dollar (USD) from January 2014 to May 2024. The dataset is split into training data (January 2014 to December 2023) and test data (January to May 2024), sourced from the Bank of Sierra Leone data warehouse. This setup allows for building and validating models using out-of-sample forecasts.

Empirical Analysis and Discussion

Baseline Models Performance

Baseline models provided useful benchmarks, but their limited capacity to capture volatility and structural breaks became apparent during periods of political instability. The Mean Model delivered stable but overly simplistic forecasts. It failed to capture the sharp fluctuations caused by the 2023 elections. While the drift model captured linear trends, it struggled during periods of sharp volatility, such as those seen post-elections. The Naïve Model is effective for short-term stability, but inadequate when predicting larger trends or sudden changes in the exchange rate.

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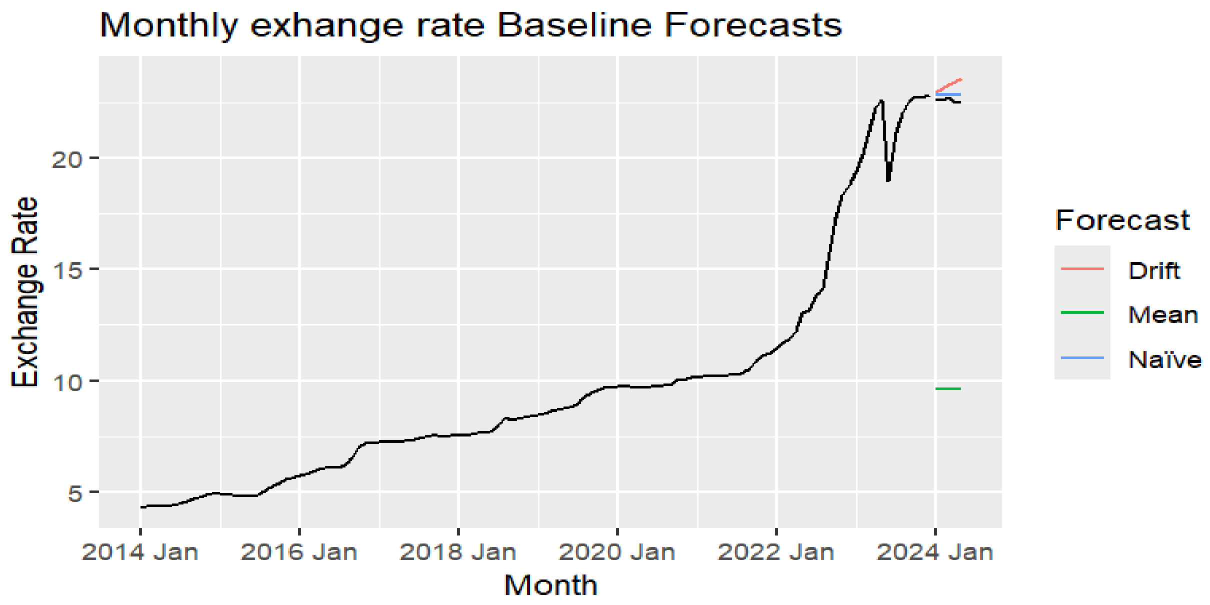
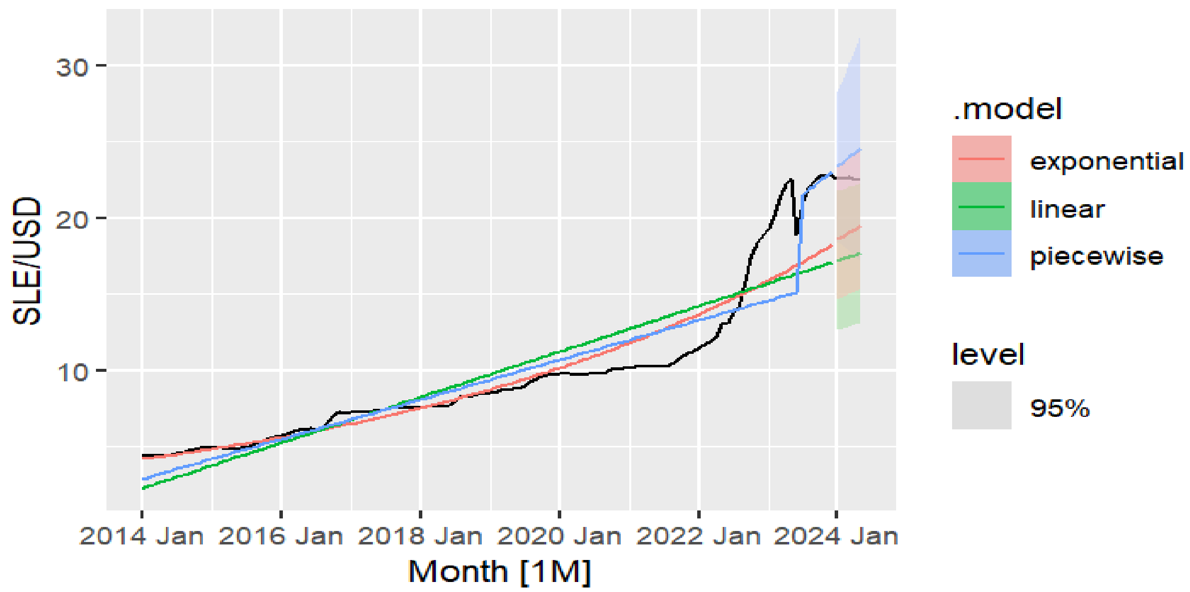


Regression Models Performance

The Linear Regression captured long-term trends but underperformed during periods of volatility. The model's linearity made it unsuitable for forecasting during periods of rapid change, such as the 2023 elections. The exponential model captured the rapid depreciation of the Leone better than the linear model but still struggled to account for structural breaks. Stepwise regression proved more effective than linear and exponential models, particularly during the political volatility of 2023. By including variables related to political events, it better captured the rapid shifts in the exchange rate.



Extract forecasted point estimates

A tibble: 15 × 4

S/N.	Month	Piece_values	Actual_values	Residuals
1	2024 Jan	23.4	**22.6**	**-0.809**
2	2024 Feb	23.7	**22.6**	**-1.12**
3	2024 Mar	24.0	**22.7**	**-1.32**
4	2024 Apr	24.3	**22.5**	**-1.81**
5	2024 May	24.6	**22.5**	**-2.12**

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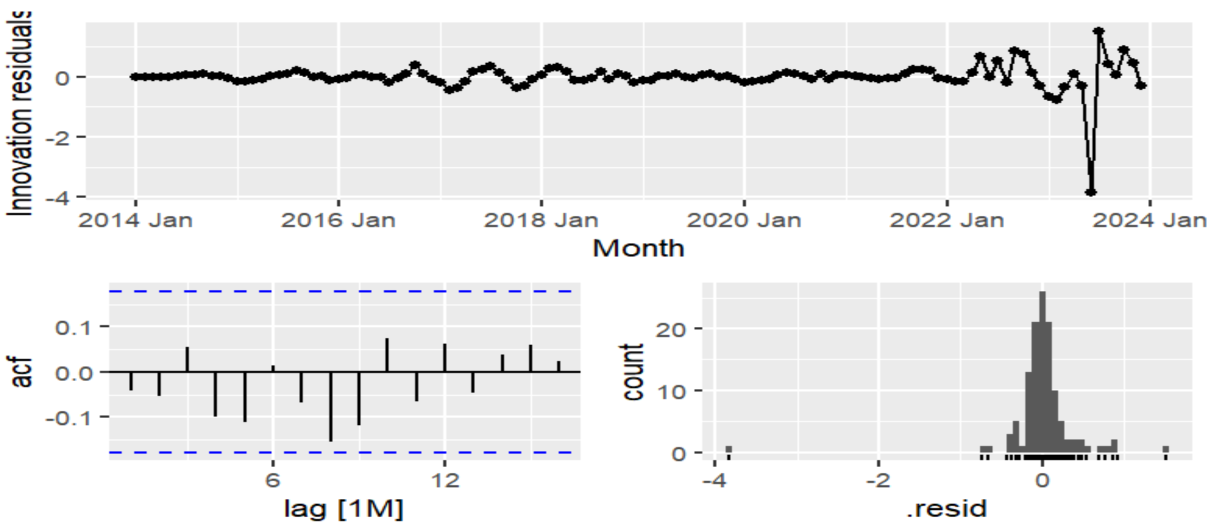
Advanced Time Series Models Performance

SARIMA Model: A SARIMA model of (3,2,2) (0,0,1) [12] was selected as the best ARIMA model based on lowest AIC and AICc . The SARIMA model performed better than the baseline and regression models, especially in capturing seasonal patterns. However, it struggled with the abrupt shifts caused by political events in 2023, as evidenced by some residual autocorrelation. The model residuals was white noise as confirmed by Ljung-Box p-value = 0.336.

```
Series: Rate
        Model: ARIMA(3,2,2)(0,0,1)[12]
        Coefficients:
              ar1     ar2      ar3      ma1     ma2    sma1
           0.2671 -0.4456 -0.3076 -1.2577 0.7847 0.4499
        s.e. 0.1407 0.0949 0.1240 0.1290 0.1042 0.1862

        sigma^2 estimated as 0.2143:  log likelihood=-76.45
        AIC=166.91   AICc=167.92   BIC=186.3
        >
        > fit_arima |> gg_tsresiduals(lag_max = 16)
```




```
         > augment(fit_arima) |>
        +   features(.innov, ljung_box, lag = 16, dof = 5)
        # A tibble: 1 × 3
          .model       lb_stat lb_pvalue
          <chr>         <dbl>     <dbl>
        1 ARIMA(Rate)    12.4     0.336
```

ETS Model: The ETS model outperformed all other models. Its flexibility in handling irregular seasonality and external shocks made it the most effective for forecasting exchange rates during periods of political instability. The ETS (M, A, N) was selected as the best among all the ETS models. The residuals plots wshow it is white noise, has constant variance and relatively normal.

```
Series: Rate
Model: ETS(M,A,N)
  Smoothing parameters:
          alpha = 0.9136602
          beta  = 0.1456301
```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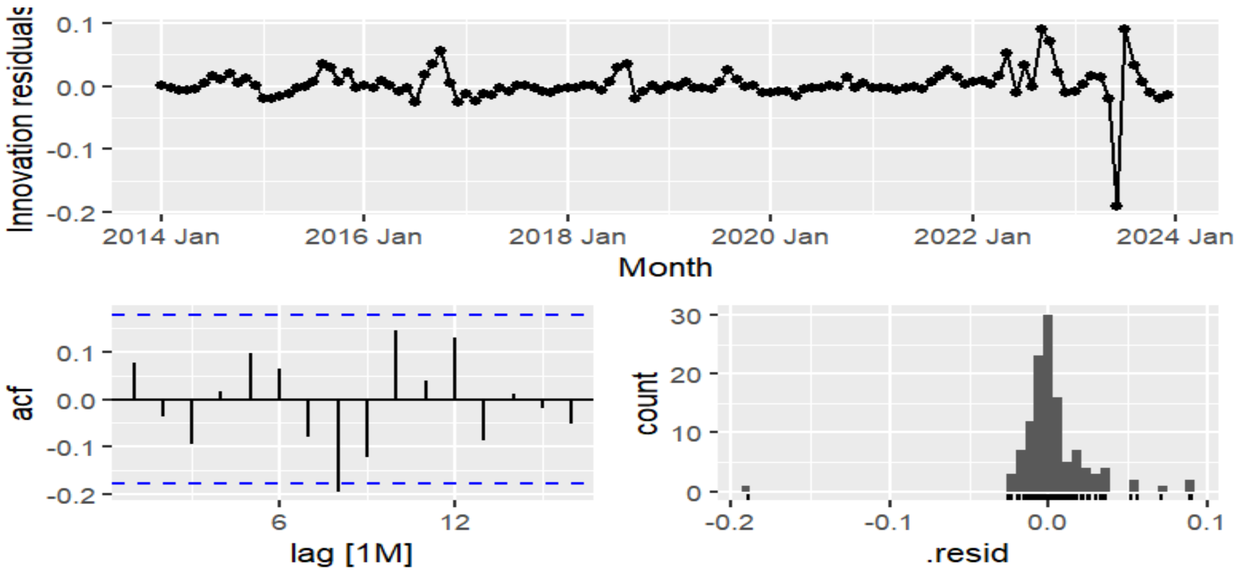
```
 Initial states:
   l[0]      b[0]
4.301303 0.03107023

 sigma^2:  7e-04

   AIC     AICc     BIC
229.3308 229.8571 243.2682
>
> fit_ets |> gg_tsresiduals(lag_max = 16)
```




```
> augment(fit_ets) |>
+   features(.innov, ljung_box, lag = 16)
# A tibble: 1 × 3
 .model    lb_stat lb_pvalue
 <chr>      <dbl>     <dbl>
1 ETS(Rate)   18.4     0.298
```

With an RMSE of 1.28 and a MAE of 1.19, ETS provided the most effective for capturing both short-term volatility and long-term trends. The ETS model's strength lies in its ability to adjust dynamically to new data, which makes it highly suitable for volatile environments like Sierra Leone. Unlike SARIMA, ETS does not require explicit seasonal decomposition and instead adapts to changes in trends and volatility automatically. This flexibility was particularly beneficial in capturing the effects of the 2023 elections, which created a significant structural break in the exchange rate trend. The model's lower RMSE and MAE indicate that ETS can provide more reliable forecasts in the presence of irregular seasonality and political shocks (Ljung-Box p-value = 0.298, suggesting minimal autocorrelation).

Table 1. Accuracy tests

S/N.	.model	.type	RMSE	MAE	MAPE	MASE	RMSSE
1	ARIMA(Rate)	Training	0.447	0.202	1.81	0.107	0.149
2	ETS(Rate)	Training	0.490	0.172	1.39	0.0911	0.163
3	ARIMA(Rate)	Test	2.36	2.28	10.1	1.21	0.786
4	ETS(Rate)	Test	1.28	1.19	5.26	0.629	0.426

The ETS (M, A, N) show that the five months Jan 2024 to May 2024 predicted values with 80% prediction intervals falls in line with the actual values. The point estimates in Table 2 shows minimal variation between the model forecasts and the actual values for the 5 months out of sample comparison.

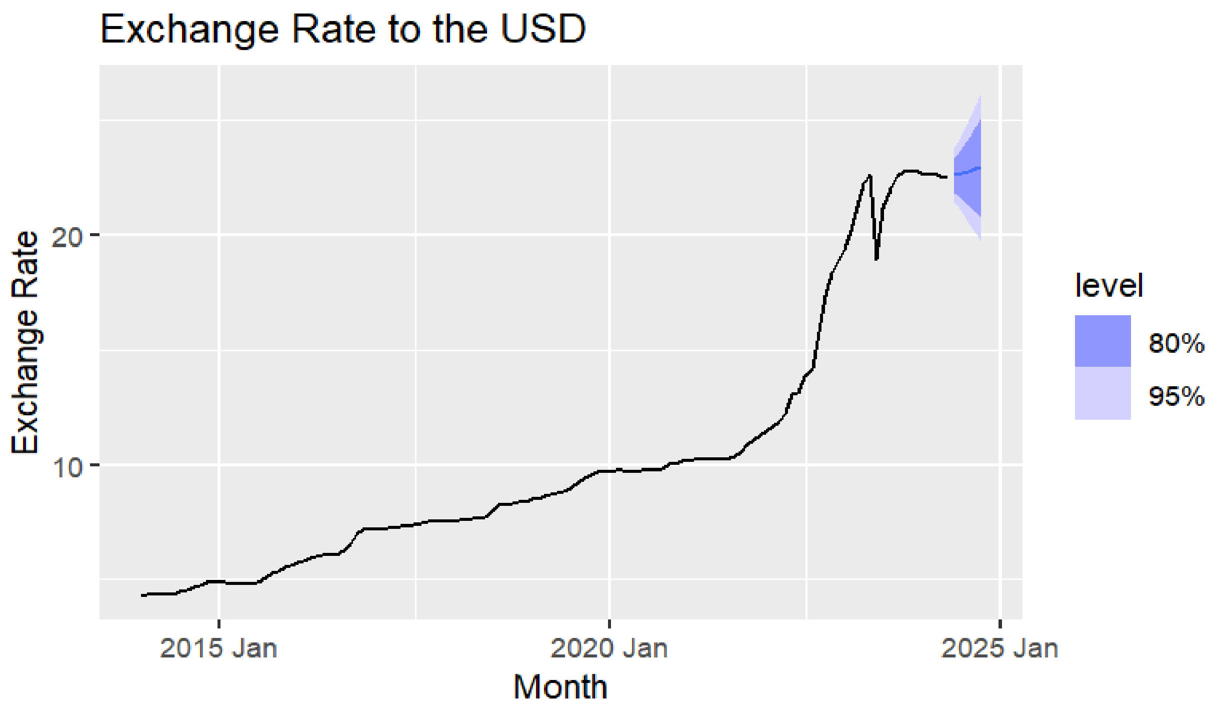


Table 2. ETS point forecasts comparison

S/N.	Month	ETS_values	Actual_values	Residuals
1	2024 Jan	23.1	**22.6**	**-0.549**
2	2024 Feb	23.4	**22.6**	**-0.896**
3	2024 Mar	23.8	**22.7**	**-1.07**
4	2024 Apr	24.1	**22.5**	**-1.57**
5	2024 May	24.4	**22.5**	**-1.88**

Conclusion

The evaluation of different forecasting models for predicting the Sierra Leonean Leone (SLE) to US Dollar (USD) exchange rate demonstrates that advanced econometric models outperform baseline and traditional regression models in volatile environments. The 2023 elections created a structural break in the exchange rate data, leading to higher volatility and challenging many of the simpler models' abilities to provide accurate forecasts.

Baseline models (mean, drift, naïve) were found to be inadequate for capturing both the upward trend in the exchange rate and the sharp fluctuations caused by political events. While they provided stable forecasts during periods of relative calm, they failed during high-volatility periods. Regression models, particularly stepwise regression, showed improvements by capturing some of the external shocks, like political events. However, they were still insufficient in predicting the full extent of exchange rate volatility. Advanced time series models, particularly ETS, emerged as the most effective model. ETS's ability to dynamically adjust to changes in trend, seasonality, and irregular patterns made it well-suited for the volatile conditions observed in Sierra Leone. While SARIMA captured regular seasonal patterns, ETS's flexibility and adaptability in handling irregular shocks were particularly valuable in times of political and economic instability.

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The findings of this study align with previous research in other emerging markets, such as the work by Sulaiman (2022) in Nigeria, where models that could adapt to structural breaks and irregular seasonality outperformed traditional linear methods. The superior performance of ETS is also consistent with studies in other African economies (Balaban, 2004; Adjasi et al., 2008) that highlight the need for models that handle non-linear dynamics in exchange rate movements.

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