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Modeling Inflation, Exchange Rate, and Interest Rate of Sri Lanka: Time Series Approach with Political, Natural, and Health Crises

W. E. Irohani* **and S. C. Mathugama**

Institute of Technology, University of Moratuwa, Sri Lanka

*iroshanie@itum.mrt.ac.lk

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ABSTRACT

In time series analysis, external shocks are essential for accurately capturing the effects of sudden, non-recurring events, enabling more precise estimation and forecasting. This study examines Sri Lankan economic variables including monthly year-on-year inflation rates, exchange rates, and interest rates using monthly data from 2003 to 2023 obtained from the International Monetary Fund (IMF) database and the Central Bank of Sri Lanka. Dummy variables for natural disasters, health crises, and political events were included to account for external shocks. Time series plots of inflation, exchange rates, and interest rates were generated to identify trends, seasonal patterns, and anomalies. Cointegration of the residuals of the fitted models was tested, revealing the presence of cointegration. Three Vector Error Correction (VEC) models were estimated, with one model selected based on information criteria and model diagnostic techniques. Model diagnostics ensured the reliability of the VEC models, and the VEC model with log transformed time series variables with dummy variables was chosen due to its lowest Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Diagnostic tests, including the Portmanteau test for serial correlation and stability checks, were conducted. The Portmanteau test revealed significant autocorrelation in the residuals, indicating that the VEC model may not fully capture the data's dynamics and might need modifications. However, stability analysis confirmed that all eigenvalues of the selected VEC model are within the unit circle, ensuring reliable forecasts. The selected VEC model provides valuable insights into Sri Lanka's economic variables. Nonetheless, *the findings suggest that further adjustments may be needed to address residual autocorrelation.*

Keywords: Exchange rate, Inflation, Interest rate, VEC

1 Introduction

Economic systems are frequently influenced by various external factors such as oil price fluctuations, geopolitical events, natural disasters, financial crises, global economic shifts, technological changes, and health crises. These disruptions can significantly alter the performance of macroeconomic indicators, including inflation, exchange rates, and interest rates. Understanding the dynamics of these variables is crucial, especially for emerging economies like Sri Lanka, where economic resilience and policy decisions are often challenged by such external shocks.

CForecasting key economic variables such as inflation, exchange rates, and interest rates is vital for policymakers, investors, and economists, as these indicators play a central role in maintaining economic stability. The Vector Autoregressive (VAR) model introduced by Sims (1980) has become a popular econometric tool for analyzing the interrelationships among multiple time series variables. Unlike univariate models, VAR captures the dynamic interdependencies among variables, making it especially suitable for modeling the feedback mechanisms between inflation, interest rates, and exchange rates. The Vector Error Correction (VEC) model further enhances this analysis by accounting for long-term equilibrium relationships when cointegration exists among variables. From an academic perspective, this study contributes to the growing field of macroeconomic modeling by applying advanced time series methods. The results of this study can support better-informed monetary and fiscal policy decisions in Sri Lanka.

Previous studies have analyzed the economic consequences of specific external shocks. Barro and Ursua (2008) explored the impact of geopolitical events and macroeconomic crises, showing how political instability can disrupt inflation, interest rates, and GDP growth. Cavallo and Noy (2011) highlighted the adverse effects of natural disasters on economic activity, emphasizing infrastructure damage and productivity losses. Similarly, Baker et al. (2020) investigated the implications of health crises such as COVID-19 on household spending and economic activity, revealing significant disruptions in consumer behavior and policy responses. In this context, inflation, exchange rates, and interest rates are not only influenced by their own past values but also by the past values of the other variables in the system. This makes the VAR model particularly useful for examining the interactions between these economic indicators. For instance, changes in interest rates can directly affect inflation and exchange rates, while movements in exchange rates can have a feedback effect on inflation (Kilian & Lutkepohl, 2017).

Furthermore, the inclusion of dummy variables such as political crises, health crises, and natural disasters in the VAR model allows for the assessment of the impact of these exogenous factors on the primary economic variables. These dummy variables are critical in capturing the effects of sudden and significant events that are not captured by the standard economic indicators but can have profound impacts on the economy (Lutkepohl, 2005). For example, political instability can lead to increased volatility in exchange rates, while a health crisis like the COVID-19 pandemic can disrupt economic activities, leading to changes in inflation and interest rates

By incorporating both the core economic variables and the dummy variables representing external effects, the VAR / VEC models provide a comprehensive framework for forecasting and policy analysis. This approach not only helps in understanding the historical dynamics between the variables but also in predicting future trends, which is essential for effective economic planning and decision-making. Therefore, main objective of this study is to forecast Inflation, exchange rates and interest rates of Sri Lanka by adopting the VEC or VAR models investigating the cointegration among variables.

Section Two explains the methodology, including data sources, variable selection, and model specification, along with relevant statistical concepts and theories. Section Three presents the empirical results and analysis. Section Four discusses the findings in relation to existing studies and concludes with policy implications and recommendations for future research.

2 Methodology

Sri Lankan monthly year-on-year inflation rates (INF) were calculated using the Consumer Price Index, which is available in the IMF database. Monthly exchange rates (ER) and interest rates (IR) were obtained from the Central Bank of Sri Lanka for the period of 2003-2023. Data on natural disasters and significant political events during the study period were sourced from event databases, news archives, and reports from relevant authorities. The data were first processed and cleaned, with attention paid to identifying and addressing outliers. The 90% of the data was used for modeling, while 10% was kept for model validation and testing. R statistical software was used for data analysis.

2.1 VAR model

The VAR model is particularly useful in economics and finance, where it is often used to analyze the dynamic relationships between variables such as interest rates, exchange rates, inflation, etc. The primary assumption behind a VAR model is that all variables in the system are endogenous, meaning there are no predetermined explanatory variables, and all variables influence each other over time.

In a VAR model, each variable is expressed as a linear function of its own lagged values and the lagged values of all other variables in the system. The model captures both short-term and long-term dynamics and can be used for forecasting and impulse response analysis. The multivariate time series Y(t) follows a VAR model of order p, VAR(p), if

$$Y_t = \phi_0 + \Sigma \phi_i Y_{t-i} + \alpha t \tag{1}$$

ϕ_0 is a k-dimensional constant vector.
ϕ_i are $k \times k$ matrices, for $(i > 0)$
αt is a sequence of independent and identically distributed random vectors with mean zero and a positive-definite covariance matrix Σa.

2.2 Stationarity

Initially, dummy variables for natural disasters (ND), health crisis (HC), and political events (PE) were created to capture the impact of these events on the time series data. Time series plots of the variables were generated to identify trends, seasonal patterns, and any anomalies. Subsequently, stationarity of the series was tested using augmented Dickey–Fuller test (ADF).
The ADF test uses the following regression equation:

$$\Delta Y_t = \beta Y_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta Y_{t-i} + \varepsilon_i \tag{2}$$

Where,
Y_t is the time series.
$\Delta Y_t = Y_t - Y_{t-1}$ is the first difference of the time series.
p is the number of lagged differences.
$\varepsilon_t$is the error term.
The key parameter of interest is β, which determines whether the series has a unit root:
$H_0 : \beta = 0$, meaning the series has a unit root (non-stationary).
$H_1 : \beta < 0$, meaning the series is stationary
Test Statistics

$$ADF = \frac{\hat{\beta}}{SE(\hat{\beta})} \tag{3}$$

The test statistic is tested against the DF tables. The decision rule is, to reject the H_0, if ADF < critical value at the relevant significance level.

In this study, log transformation was applied to the time series data before the model fitting. Log transformation is commonly used in econometric modeling to stabilize variance and linearize relationships between variables, especially in economic and financial data (Hamilton, 1994; Enders, 2014). This approach helps to address issues of heteroscedasticity and make the data more suitable for modeling long-run equilibrium relationships. Furthermore, log transformation allows for the interpretation of the model coefficients in terms of elasticities, which is beneficial when analyzing percentage changes in key variables such as inflation, exchange rates, and interest rates. This method aligns with best practices in the literature for improving model stability and interpretability in cointegration analysis (Johansen, 1991).

2.3 Cointegration

Cointegration among the variables was tested using the Johansen test. Cointegration vector represent the long-term equilibrium relationship between the variables INF, ER and IR. Johansen test gives the cointegration vectors as linear combinations of the variables that should be stationary.

The Cointegration test is based on the theory that if a group of non-stationary variables share a common stochastic trend, there may be a linear combination of these variables that is stationary. This stationary linear combination, known as a cointegration vector, represents the long-term equilibrium between the variables.
Hypothesis:
$H_0 : r = 0$; No cointegration exists.
$H_1 : r > 0$; at least one cointegration vector exists.

There are two versions of the Johansen test. First version is the Trace test and this test evaluates the null hypothesis that there are at most r cointegrating relationships among the variables.

$$\text{Test Statisic} = -T \sum_{i=r+1}^{n} \ln(1 - \lambda_i) \tag{4}$$

T is the sample size.
λ_i are the estimated eigenvalues from the estimated matrix.
If the trace statistic is greater than the critical value, reject the null hypothesis (H_0) and conclude that there are more than r cointegrating relationships.

Second version is Maximum Eigenvalue test and this test evaluates the null hypothesis that there are r cointegrating relationships against the alternative of $r + 1$ cointegrating relationships by looking at the largest eigenvalue.

$$\text{Test Statisic} = -T \ln(1 - \lambda_{r+1}) \tag{5}$$

Where:λ_{r+1} is the $(r + 1)$th largest eigenvalue.

If the maximum eigenvalue statistic exceeds the critical value, reject the null hypothesis and conclude that the number of cointegrating relationships is greater than r.

2.4 VEC Model

The Johansen test works within the framework of a VEC model, where it accounts for both short-term dynamics and long-term equilibrium relationships among the variables. It generates the cointegration vectors as linear combinations of the variables that should be stationary, implying that although the individual time series may wander due to external shocks, they are bound by a long-term relationship that keeps them aligned in the long run. This makes the Johansen test particularly suitable for the analysis of multiple time series, like inflation, exchange rates, and interest rates, where identifying such cointegrated relationships can help in forecasting and policy analysis.

In economic terms, even if individual variables such as inflation (INF), exchange rates (ER), and interest rates (IR) may be non-stationary, they can still move together over time, forming a stable relationship. Therefore, the cointegration equation is typically represented as:

$$\beta_1 \times INF_t + \beta_2 \times ER_t + \beta_3 \times IR_t + ... = 0 \tag{6}$$

Where $\beta_1, \beta_2, \beta_3$ are the coefficients from the cointegration vectors. Once the cointegration was confirmed, a VEC model was performed to forecast.

$$INF_d = \alpha_1 \times (\beta_1 INF_{t-1} + \beta_2 ER_{t-1} + \beta_3 IR_{t-1}) + \text{short-run terms} + \epsilon_t \tag{7}$$

Where, α_1 represents the speed of adjustment to equilibrium.

VEC models were estimated with the chosen lag length, incorporating the dummy variables of natural disasters (ND), health crisis (HC) and political events (PE). The General form of a VEC model with lag p and incorporating dummy variables is:

$$\Delta Y_t = \pi Y_{t-1} + \sum_{i=1}^{p-1} \tau_i \Delta Y_{t-i} + \beta_1 ND_t + \beta_2 HC_t + \beta_3 PE_t + \epsilon_t \tag{8}$$

Where:

ΔY_t is the first difference of the vector of endogenous variables Y_t.

π is the long-run impact matrix, which captures the cointegration relationship between the variables. $\pi = \alpha\beta'$ where α represents the speed of adjustment to the long-run equilibrium, and β contains the cointegration vectors.

τ_i are the short-run coefficient matrices for the lagged differences of the endogenous variables.

$ND_t, HC_t, andPE_t$ are dummy variables for natural disasters, health crises, and political events, respectively, with their corresponding coefficients β_1, β_2, and β_3.

ϵ_t is the vector of error terms (residuals), assumed to be white noise.

2.5 Model Diagnostic

Information criteria are statistical tools used to compare models with different parameter values and select the one that best fits the data while balancing model complexity and goodness of fit. The Akaike Information Criterion (AIC) (Akaike, 1973), the Bayesian Information Criterion (BIC) (Schwarz, 1978), and the HQ(l) criterion, introduced by Hannan and Quinn (1979) and Quinn (1980), can be utilized to determine the appropriate order for a VAR model. The model order corresponding to the lowest information criterion (IC) is typically selected.

$$AIC(l) = \ln|\hat{\Sigma}_{a,l}| + \frac{2}{T} lk^2 \tag{9}$$

$$BIC(l) = \ln|\hat{\Sigma}_{a,l}| + \frac{\ln T}{T} lk^2 \tag{10}$$

$$HQ(l) = \ln|\hat{\Sigma}_{a,l}| + \frac{2\ln[\ln(T)]}{T} lk^2 \tag{11}$$

Model diagnostics are critical to evaluating the validity and robustness of econometric models, ensuring that the model's assumptions are satisfied, and that the results are reliable for forecasting. In this study, several diagnostic tests were performed, including tests for serial correlation and stability checks.

The Portmanteau test for serial correlation assesses whether the residuals from the model are uncorrelated over time. Serial correlation, or autocorrelation, occurs when residuals from one period are correlated with those from another, indicating that the model may have missed capturing some of the dynamics in the data. The hypothesis of the Portmanteau test is:
H_0: There is no autocorrelation in the residuals up to a specified lag.
H_1: There is autocorrelation in the residuals up to a specified lag.

The test statistic can be defined as:

$$Q = n\Sigma_{h=1}^{H} \frac{1}{n} trace(\hat{\gamma}(h)\hat{\gamma}(0)^{-1}) \tag{12}$$

n is the number of observations.
H is the maximum lag considered for the test.
$\gamma(0)$ is the autocovariance matrix at lag zero.

The test statistic Q follows a chi-squared distribution. If the test rejects the null hypothesis, it suggests that serial correlation exists, meaning that the model may need further refinement, such as including additional lags or variables, to improve its accuracy.

The eigenvalue stability condition is another key diagnostic tool used to check the stability of VEC and VAR models. For a model to be stable, the eigenvalues of its coefficient matrix must lie within the unit circle in the complex plane. If the eigenvalues exceed this threshold, the model is considered unstable, meaning that the system is prone to explosive behavior, which undermines the reliability of the forecasts. Stability checks are particularly important in time series analysis because unstable models can lead to highly inaccurate predictions and incorrect policy implications.

The Jarque-Bera (JB) test is a statistical test used to assess whether a given sample of data comes from a normal distribution. The hypothesis is:
H_0: Residuals follow a normal distribution
H_1: Residuals does not follow a normal distribution.
The Jarque-Bera test statistic J is defined as:

$$J = \frac{n}{6}(S^2 + \frac{(K-3)^2}{4}) \tag{13}$$

n is the sample size
S is the sample skewness
K is the sample kurtosis

If the test statistic is greater than the critical value, H_0 is rejected, suggesting that the data significantly deviate from normality.

By conducting these diagnostic tests, such as the Portmanteau test for serial correlation and stability checks for eigenvalue conditions, the model's overall performance is evaluated. These tests ensure that the model is free from significant autocorrelation and is stable, thereby confirming that the selected model configuration is robust and suitable for accurate and reliable forecasting of inflation, exchange rates, and interest rates.

3 Results and Discussion

Time series plots of the variables were obtained to observe fluctuations and possible patterns within the data series, including the monthly inflation, exchange rate, and interest rates.

According to the Figure 1, from 2003 to 2009, inflation fluctuated moderately, peaking around 2008-2009, likely due to economic instability. The period from 2010 to 2019 indicates a stabilization of inflation, reflecting economic steadiness. However, from 2020 to 2022, a significant spike occurred,

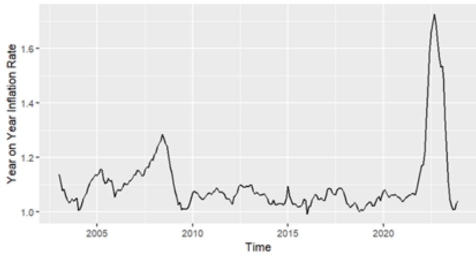

Fig. 1: Time series plot of monthly inflation rates

with inflation reaching its highest point by 2022, indicating extreme economic stress possibly linked to the COVID-19 pandemic, or political events. A sharp drop in inflation from 2023 to 2024 suggests a recovery or effective control measures.

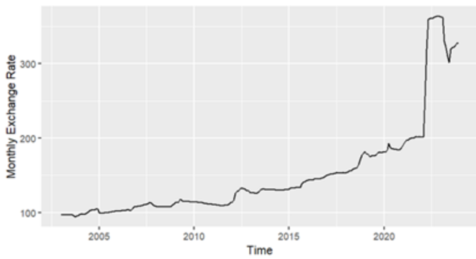

Fig. 2: Time series plot of monthly exchange rates

In Figure 2, the exchange rate data reveal the depreciation of the Sri Lankan Rupee, particularly from 2021 to 2022, when dramatic spike in the exchange rate occurred. Initially stable between 2003 and 2010, the Sri Lankan rupee began a slow depreciation from 2011 to 2015, followed by a more pronounced decline from 2016 to 2020. The steep increase in the exchange rate during 2021-2022 reflects severe economic crises, possibly driven by the pandemic, political instability, or financial mismanagement.

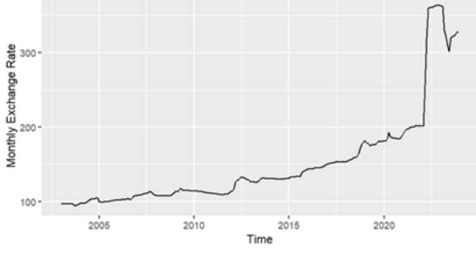

Fig. 3: Time series plot of exchange rates

Interest rates in Sri Lanka display in Figure 3 display a cyclical pattern, responding to various economic challenges. Starting around 7.5% in 2003, rates fell before rising sharply to near 13% by 2009, likely in efforts to control inflation. After 2009, the rate declined but indicate another peak around 2012-2013. After stabilizing during the mid-2010s, rates fell sharply in 2020, reflecting monetary policy adjustments to support the economy during the COVID-19 pandemic.

3.1 Stationarity

Stationarity is a key assumption for many time series models. The stationarity of the time series variables was tested using Augmented Dickey Fuller (ADF) test, and the results are presented in Table 1.

Table 1: ADF Test results of first differenced series

Data Series	ADF test statistics	P-value
DINF	-5.473	0.01
DER	-5.6088	0.01
DIR	-4.0477	0.01

All the differenced series (DINF, DER, DIR) are stationary, as indicated by the highly negative test statistics and low p-values (0.01). This confirms that the series have been appropriately transformed to meet the stationarity requirement, making them suitable for use in time series modeling.

The optimal number of lags which should be included in the model was identified first before performing co-integration test and VEC modelling. Relevant information criteria values are given in Table 2.

Table 2: Information criteris for different lag lengths of VEC models

	Original Data Series					Log transformed series				
Model	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5
AIC	320.13	-39.01	-53.33	-74.62	-70.16	-3574.2	-3862.2	-3865.8	-3844.6	-3839.0
BIC	394.17	66.63	83.85	94.03	129.87	-3500.2	-3756.2	-3728.6	-3695.9	-3639.0

According to the lowest information criteria, a VEC model with lag 2 using the original time series variables, and VEC models with lags 1 and 4 using the log-transformed series, were fitted.

3.2 Cointegration

A cointegration test, which indicates a long-term equilibrium relationship among the variables, was conducted, and the results are provided in Table 3.

According to Table 3, the trace statistic for the eigenvalue $r \leq 1$is 22.91, which is greater than the 5% critical value of 19.96. Thus, the null hypothesis that there is at most one cointegrating vector is rejected, suggesting that

Table 3: Cointegration test statistics and critical values

Values of	Test statistic	Critical value (at 5% level of significance)
$r \leq 2$	3.38	9.24
$r \leq 1$	22.91	19.96
$r = 0$	60.77	34.91

there are at least two cointegrating relationships. Therefore, the VEC model is suitable for long-term predictions.

3.3 VEC Model Estimation

Three VEC models were fitted based on the selected three lag values. The estimated coefficients are given in Table 4.

3.4 Model Diagnostic

The Portmanteau test results of the three models were obtained and results are given in table 5.

The Portmanteau test reveals a high Chi-squared value and an extremely low p-value, indicating significant autocorrelation in the residuals. This suggests that the model may not fully capture the data's dynamics and might require further refinement, such as adding more lags or including additional variables. The ARCH (Autoregressive Conditional Heteroscedasticity) test in a multivariate context was applied to assess whether there is significant heteroscedasticity.

Only the model 2 reveals that there is no heteroscedasticity in residuals and other two model give smaller p-values which evidence of heteroscedasticity in the residuals, meaning the volatility of the residual changes over time, indicating that the residuals are not homoscedastic.

The Jarque-Bera (JB) test checks whether the residuals of a model follow a normal distribution.

The Jarque-Bera (JB) test checks whether the residuals of a model follow a normal distribution. Since the p-value are extremely small, the null hypothesis that the residuals are normally distributed is rejected.

Based on the diagnostic checks using Portmanteau, ARCH, and Jarque-Bera tests (Tables 5, 6, 7). While models 1 and 3 showed signs of autocorrelation and heteroscedasticity, Model 2 exhibited no such issues. Therefore, Model 2 was selected for forecasting due to its superior residual behavior. The stability check for the VAR (1) model was performed using eigenvalue analysis. The output is given in Figure 2.

The eigenvalue plot reveals that all eigenvalues lie within the unit circle, indicating that the VEC (2) model is stable. This stability ensures that the model's forecasts are reliable and that the dynamics captured by the model will remain consistent over time. The stability test results confirm that the maximum modulus of the eigenvalues is less than 1, further validating the

Table 4: Model Estimation

Model 1: VEC model with lag 2 for INF, ER and IR					
DINF		DER		DIR	
Variable	Coefficients	Variable	Coefficients	Variable	Coefficients
ect 1	-0.03657	ect 1	-2.522	ect 1	0.8384
ect 2	-0.00001944	ect 2	-0.00123	ect 2	0.0004645
PE	0.0009298	PE	0.5471	PE	-0.0221
HC	0.003044	HC	1.909	HC	-0.1505
ND	0.001763	ND	0.4382	ND	-0.0354
INF_{t-1}	0.4432	INF_{t-1}	-30.75	INF_{t-1}	1.087
ER_{t-1}	0.001596	ER_{t-1}	0.6168	ER_{t-1}	0.00958
IR_{t-1}	0.003015	IR_{t-1}	-0.4541	IR_{t-1}	0.5212
ect 1 $= INF_{t-2} + 1.31825.IR_{t-2} - 11.0917$ ect 2 $= 1.ER_{t-2} - 2431.846.IR_{t-2} + 18384.58$					
Model 2: VEC model with lag 1 for log transformed variables LINF, LER and LIR					
DLINF		DLER		DLIR	
Variable	Coefficients	Variable	Coefficients	Variable	Coefficients
ect 1	-0.411930	ect 1	-0.0059095	ect 1	0.1196528
ect 2	-0.0023083	ect 2	0.002053	ect 2	0.0187238
PE	0.0012419	PE	0.0022407	PE	-0.0008297
HC	0.0012419	HC	0.0043779	HC	-0.0246384
ND	0.0017546	ND	0.0050551	ND	-0.0032891
LINF$_{t-1}$	0.4459145	LINF$_{t-1}$	-0.1183821	LINF$_{t-1}$	0.1744323
LER_{t-1}	0.2565616	LER_{t-1}	0.5703832	LER_{t-1}	0.3738801
$LLER_{t-1}$	0.0352696	LIR_{t-1}	-0.0349021	LIR_{t-1}	0.4722186
ect 1 = LINF $_{t-1} - 2.77558 \times 10 - 17 + 0.3722119$ LIR $_{t-1} - 0.7944223$ ect 2 $= LER_{t-1} - 3.642268LER_{t-1} + 2.387953$					
Model 3: VEC model with lag 4 for log transformed variables LINF, LER and LIR					
DLINF		DLER		DLIR	
Variable	Coefficients	Variable	Coefficients	Variable	Coefficients
ect 1	-0.06237	ect 1	-0.04123	ect 1	0.08844
ect 2	-0.006138	ect 2	-0.003729	ect 2	0.01083
HC	0.005841	HC	0.01259	HC	-0.01884
LINF$_{t-1}$	0.3445	LINF$_{t-1}$	-0.1363	LINF$_{t-1}$	0.08032
LER_{t-1}	0.2915	LER_{t-1}	0.6265	LER_{t-1}	0.3008
LIR_{t-1}	-0.04208	LIR_{t-1}	-0.07757	LIR_{t-1}	0.271
LINF$_{t-2}$	-0.002696	LINF$_{t-2}$	0.7613	LINF$_{t-2}$	0.08384
LIR_{t-1}	0.02115	LIR_{t-1}	0.1117	LIR_{t-1}	0.06207
LER_{t-3}	0.1154	LER_{t-3}	-0.09964	LER_{t-3}	-0.02222
ect 1 = LINF $_{t-4} + 1.602825$ LIR $_{t-4} - 3.227867$ ect 2 $= LER_{t-4} - 15.63464LER_{t-4} + 26.09106$					

Table 5: Portmanteau Test Results

Model	Chi square value	p -value
1	207.16	3.057×10^{-7}
2	108.45	2.2×10^{-16}
3	208.45	1.6×10^{-16}

Table 6: ARCH test results

Model	Chi square value	p -value
1	845.95	2.2×10^{-6}
2	19.65	0.125
3	185.24	1.5×10^{-5}

Table 7: Normality test of residuals

Model	Chi square value	p-value
1	22790	2.2×10^{-16}
2	1033	2.2×10^{-16}
3	702.8	3.1×10^{-15}

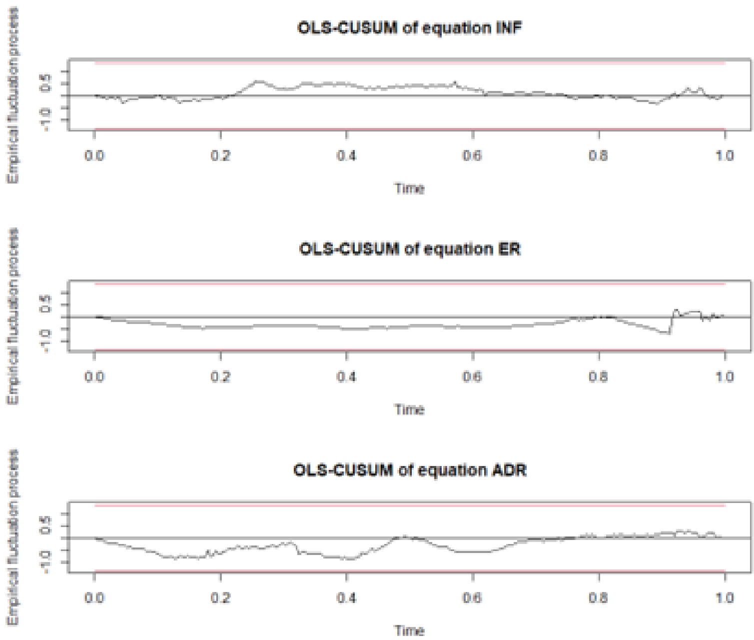

Fig. 4: Eigenvalue plot of residuals

model's stability. Therefore, the VEC model 2 is selected for the predictions with log transformed variables.

For $\Delta LINF$

$$\Delta LINF_t = -0.411930(ect)_1 - 0.0023083(etc)_2 + 0.0012419(PE)_t + 0.0012419(HC)_t + 0.0017546(ND)_t + 0.4459145\Delta(LINF)_{t-1} + 0.256561\Delta(LER)_{t-1} + 0.0352696\Delta(LIR)_{t-1}$$

For ΔLER

$$\Delta(LER)_t = -0.0059095(ect)_1 + 0.002053(ect)_2 + 0.0022407(PE)_t + 0.0043779(HC)_t - 0.005551(ND)_t - 0.118382\Delta(LINF)_{t-1} + 0.5703832\Delta(LER)_{t-1} - 0.0349021\Delta(LIR)_{t-1}$$

For ΔLIR

$$\Delta(LIR)_t = 0.1196528(ect)_1 + 0.0187238(ect)_2 - 0.0008297(PE)_t - 0.0246384(HC)_t - 0.0032891(ND)_t + 0.1744323\Delta(LINF)_{t-1} + 0.3738801\Delta(LER)_{t-1} + 0.4722186\Delta(LIR)_{t-1}$$

Cointegrating Equations:

$$(ect)_1 = (LINF)_{t-1} - 2.77558 \times 10^{-17} + 0.3722119(LIR)_{t-1} - 0.7944223$$
$$(ect)_2 = (LER)_{t-1} - 3.642268(LER)_{t-1} + 2.387953$$

3.5 Model Validation

Data from 2003 to 2021 were used for model fitting, while data from 2022 to 2023 were used for model validation. After predicting the monthly year-on-year inflation, interest rate, and exchange rate, forecast errors were calculated by comparing the predicted values with the actual values. The error percentages were then obtained to assess the model's accuracy.

The prediction of monthly inflation, monthly exchange rates and interest rates

Table 8: Model Adequacy Checking

Model	Variable	MSE	MAE	MAPE
Model 2	Inflation	0.122991	0.017213	0.097713
	Exchange Rate	8.309243	142.145	0.025162
	Interest Rate	1.83559	3.505448	0.15045

of Sri Lanka using the selected model for the period of Jan 2024 – December 2024 are given in table 9.

4 Conclusion

This study analyzed Sri Lankan economic variables, including monthly year-on-year inflation rates, exchange rates, and interest rates, using data from the

Table 9: Predictions

Month	INF	ER	IR
January	1.054678	322.8986	11.46051
February	1.062897	317.6416	11.43448
March	1.06637	311.6774	11.486
April	1.066314	305.474	11.57268
May	1.064192	299.3016	11.67086
June	1.061216	293.2926	11.76756
July	1.058209	287.4963	11.85613
August	1.055644	281.9187	11.93367
September	1.053741	276.5471	11.99951
October	1.052558	271.364	12.05429
November	1.052067	266.3533	12.09935
December	1.052202	261.5025	12.13634

IMF and the Central Bank of Sri Lanka, supplemented by information on natural disasters, health crises, and political events incorporating dummy variables.

Time series plots were used to identify trends, seasonality, and anomalies. The Johansen cointegration test confirmed the presence of long-run equilibrium relationships among the variables, justifying the use of the Vector Error Correction (VEC) model. Accordingly, three VEC models were fitted: one with level data using lag 2, and two with log-transformed variables using lags 1 and 4.

Diagnostic tests, including the Portmanteau test for serial correlation and stability analysis via eigenvalue plots, were conducted to assess model performance. The stability test confirmed that the selected model (lag 1 with log-transformed data) is stable, as all eigenvalues lie within the unit circle, indicating that the model's forecasts are consistent and reliable over time. However, the Portmanteau test results indicated the presence of significant autocorrelation in the residuals, and the Jarque-Bera test showed that the residuals deviate from normality.

Despite these diagnostic issues, Model 2 (log-transformed variables with lag 1) was selected for forecasting due to its superior performance in terms of MSE, MAE, and MAPE. The presence of autocorrelation and non-normality in the residuals suggests that the model may not capture all underlying dynamics or structural breaks in the data. These issues could be attributed to the complexity of macroeconomic interactions or omitted variables that were not fully captured by the dummy variables.

Future research should consider expanding the set of explanatory variables to include detailed data on local and global political instability, health crises, and oil price shocks. Incorporating these elements may reduce residual autocorrelation and improve residual distribution characteristics, thereby enhancing overall model accuracy and reliability. Such extensions would contribute to a more comprehensive understanding of macroeconomic behavior and improve the predictive power of time series models in emerging economies.

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