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Quantifying the Interconnection of Economic Growth and Key Macroeconomic Factors Using the VECM Perspective of Bangladesh

[1]Ahsanul Haque [2]Md. Shohel Rana, [2]Most. Sifat Muntaha Soni, [2]Md. Kamal Uddin, [2]Md. Sazzad Hossain, 2[*] Md. Matiur Rahman Molla

[1]Department of Statistics, University of Barisal, Bangladesh
[2]Department of Statistics, Islamic University, Kushtia, Bangladesh
[*]Corresponding Author: Department of Statistics, Islamic University, Kushtia, Bangladesh

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ABSTRACT: *The study examines the impact and signs of key macroeconomic factors on Bangladesh's economic growth from 1980 to 2016 using VAR, the Johansen cointegration test, and the Vector Error Correction Model (VECM). Results show that the inflation rate has a slightly positive impact on economic growth, but it is not statistically significant. The real interest rate has a significant negative impact on economic growth, while the exchange rate has a significant positive impact. This work concludes that all variables have long-term effects and long-run causality, as well as a weak short-run influence on the economic growth rate.*

KEYWORDS: macroeconomy, unit root, VAR, VECM, stationarity, coinetgration

INTRODUCTION

Economic growth is a major goal of every country in the world, as it measures the country's overall economic development. There are various factors that contribute simultaneously to maintaining the economic growth of a nation. This study will specifically look into how the real interest rate, exchange rate, and inflation rate affect economic growth and how they affect Bangladesh's economic development.

Time series modeling, especially Vector Autoregression (VAR), is an effective tool to extract the past and future movements of several interrelated variables that are endogenous in nature. Sim (1980) used the VAR model to describe the dynamic behavior of economic and financial time series for forecasting. It is found to exhibit greater predictive efficiency and accuracy than large scale structural economic models.

Inflation, interest, and exchange rates significantly impact Bangladesh's economic growth, causing aggregate economic performance issues. However, there is limited consensus on the relationship between these factors and macroeconomic activities, leading to significant debates both theoretically and empirically. Although the association between inflation and economic growth has been established, the precise cause is still obscure. In Bangladesh, researchers have shown a strong inverse relationship between inflation and economic growth, but other investigations have demonstrated the opposite. Thus, it is of the utmost importance to comprehend whether there is a substantial connection between inflation and economic growth in Bangladesh and whether the association is positive or negative. The aim of this study is to reveal the relationship amongst the selected variables, their contribution towards economic growth, and make inferences in the context of Bangladesh through VAR and VECM modeling.

LITERATURE REVIEW

In the study of macroeconomics, the relationship between Inflation, interest rates, exchange rates, and economic growth is a hotly contested topic. Different economists have expressed differing views on the relationship between key macroeconomic variables and economic growth. As a result, scholars have come to differing conclusions on how the mentioned factors and economic growth are related.

A large number of researchers at home and abroad have applied VAR and VEC models to predict multivariate time series data. Athanasopoulos and Vahid (2008) used VARMA versus VAR for Macroeconomic Forecasting. Khan and Hossain (2010) applied the VAR model to reveal the relationship between democracy and trade balance. Sayed (2014) used the VAR model to forecast the exchange rate of Bangladesh. In addition, Saeed (2007) used time series data from 1985 to 2005 and applied the Engle-Grange causality test (EGT) and Error Correction model (ECM) to illustrate the short-term and long-term inflation-growth relationship in Kuwait. Rahman (2014) determined the connection between inflation and economic growth in Bangladesh by using the VAR model. Kamal et al. (2013) diagnosed the fluctuation of the exchange rate by using the co-integration approach, and Ahmed and Mortaza (2005) explored the connection between inflation and economic growth in Asian countries using co-integration and error correction models. Mallik and Chowdhury (2001) conducted the short-run and long-run dynamics of the relationship between inflation and economic growth for four South Asian economies. Nuruzzaman et al. (2023) applied VAR model to forecast climatic variables. Agenor (1991) and Montiel (1997) studied the exchange rate and found that exchange rate fluctuations have significant implications for economic performance in Bangladesh. Kamal et al. (2004), using quarterly data from 1974 to 1999, find evidence of export-led growth for Bangladesh in both the long and short run. Zakir et al. (2006) found the existence of co-integration, that is, a stable long-run relationship between the trade balance of Bangladesh and its determinants.

The aforementioned study reveals that there is a lack of consistency in the empirical results about the correlation between macroeconomic factors and economic growth. As a result, we use the VAR model to reexamine the empirical link between key economic factors and economic growth in the context of the Bangladeshi economy.

MATERIALS AND METHODS

Data:
Secondary data has been used in this study, which was collected from the official websites of the Bangladesh Bank and World Bank from the period of 1980 to 2016, on key macroeconomic factors: Inflation rate, Exchange rate, and Real interest rate. Gross Domestic Product (GDP) growth rate is considered as economic growth rate.

Vector Auto Regression (VAR) model:
The vector autoregressive (VAR) model is one of the most well-known multivariate time series techniques and was introduced by Chris Sim in 1980 for macro-economic forecasts. The term auto-regressive is used due to the fact that the variables are regressed on their own past values, and the term vector is used due to the fact that we are dealing with a vector of two or more variables. Let, $Y_t = (y_{1t}, y_{2t}, \dots \dots y_m)$ denote an (n×1) random vector of time series variables. The basic p-lag vector autoregressive (VAR (p)) model has the form (Hamilton, (1994)):

$$Y_t = c + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \dots \dots \dots \dots + \Pi_p Y_{t-p} + \varepsilon_t \text{ ; } t = 1,2,3, \dots \dots T$$

Where $\prod$'s are (n×n) fixed coefficient matrices, $c = (c_1, c_2, \dots, c_n)$ is a fixed (n×1) vector of intercept terms allowing for the possibility of a non-zero mean $E(y_t)$. Finally $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{nt})$ is an (n×1) unobservable zero-mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix $\sum$ that is $E(\varepsilon_t)$= 0, $E(\varepsilon_t, \varepsilon_s) = 0$ for s ≠ t, the covariance matrix $\sum$ is assumed to be nonsingular in lag operator notation, the VAR (P) is written as

$$\Pi(\mathrm{L})Y_t = c + \varepsilon_t$$

$$\text{Where, } \Pi(\mathrm{L}) = I_n \Pi_1 L^1 - \dots \dots - \Pi_p \text{and } L^p Y_t = Y_{t-p}$$

The VAR (P) is stable if the roots of

$$\det(\, l_n - \Pi_{1z} - \dots \dots - \Pi_{1z}{}^p) = 0$$

lie outside the complex unit circle (have modulus greater than one) for complex z, |z|< 1, or, equivalently, if the eigen values of the companion matrix

$$F = \begin{pmatrix} 1 & 2 & \cdots & p \\ \mathrm{I_n} & 0 & \dots & 0 \\ 0\ddots & & 0 & \vdots \\ 0 & 0 & \mathrm{i_n} & 0 \end{pmatrix}$$

Johansen Cointegration Test:
Cointegration analysis helps identify long-term relationships or associations among the variables. When two series have the same stochastic trend, they are said to be cointegrated. The Johansen cointegration (1988) test depends on the maximum likelihood (ML) estimator of the parameters of the following VEC model of two cointegrating variables. Then we use the Akaike Information Criterion (AIC) to determine the number of lags in the cointegration test (order of VAR), and after that, we use the trace and maximal eigenvalue tests to determine the number of cointegrating vectors present.

$$\Delta X_t = \sum_{i=1}^{p-1} \mu_i \Delta X_{t-i} + \omega X_{t-1} + \varepsilon_t$$

Where, X_t is the (2×1) vector, respectively, Δ is a symbol of the difference operator, and ε_t is a (2×1) vector of residuals. The VECM model has information about the short and long-run adjustments to changes in X_t , via the estimated parameters μ_i and, ω respectively. Here, ωX_{t-1} is the error correction term and ω can be factored into two separate matrices α and β, such as $\omega = \alpha\beta$, where βdenotes the vector of cointegrating parameters while α is the vector of error correction coefficients measuring the speed of convergence to the long run steady state

Engel and Granger 2-step approach:
The first step of this method is to pretest the individual time series one uses in order to confirm that they are non-stationary in the first place. This can be done by standard unit root DF testing and Augmented Dickey Fuller test (to test if errors are serially correlated or otherwise). Take the case of two different series x_t and v_t. If both are $I(0)$, standard regression analysis will be valid. If they are integrated of a different order, e.g. one being $I(1)$and the other being $I(0)$, one has to transform the model. If they are both integrated to the same order (commonly $I(1)$, we can estimate an ECM model of the following form:

$$A(L)\Delta y_t = \text{ɣ} + \mathrm{B(L)}\Delta x_t + \alpha(y_{t-1} - \beta_0 - \beta_1 x_{t-1}) + v_t$$

If variables are integrated and this ECM exists, they are co-integrated by the Engle–Granger representation theorem.
The second step is then to estimate the model using ordinary least squares: $y_t = \beta_0 + \beta_1 + \varepsilon_{t.}$ If the regression is not spurious as determined by test criteria described above, ordinary least squares will not only be valid, but in fact super consistent (Stock, 1987). Then the predicted residuals $\hat{\varepsilon}_t = x_t - \beta_0 - \beta_1 x_t$ from this regression are saved and used in a regression of differenced variables plus a lagged error term

$$A(L)\Delta y_t = \text{ɣ} + \mathrm{B(L)}\Delta x_t + \alpha\hat{\varepsilon}_{t-1} + v_t$$

Unit Root Test:
A test of stationarity that has become widely popular over the past several year is the unit root test. Let us consider the following time series model:

$$y_t = \rho y_{t-1} + \mu_t$$

Where μ_t is a white noise error term.
Test procedure:
$H_o : \delta = 0$ i.e. the time series is non-stationary.
$H_\alpha : \delta \leq 0$ i.e. the time series is stationary. or,
$H_o : \rho = 1$
$H_\alpha : \rho \leq 1$
The appropriate test statistic is tau statistic or test is known as Dickey -Fuller test

(DF) test is defined by, $\tau = \frac{\hat{\delta}}{\mathrm{se}(\hat{\delta})}$

Decision: If $|\tau| \geq$ the DF critical value, then we reject the null hypothesis, otherwise accept it.

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The Augmented Dickey Fuller test:
In conducting the DF test, it was assumed that the error term was uncorrelated. But in cases where correlation exists, Dickey and Fuller (1980) developed a test known as the augmented Dickey-Fuller test. This test is conducted by adding the lagged values of the dependent variable. The ADF test here consists of estimating the following regression:

$$\Delta Y_t = \beta_1 + \beta_{2t} + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \mathrm{Y}_{t-1} + \varepsilon_t$$

Where ε_t is the pure white noise error term with mean zero & constant variance and where, $\Delta Y_{t-1} = (Y_{t-1} - Y_{t-2}), \Delta Y_{t-2} = (Y_{t-2} - Y_{t-3})$, etc. The number of lagged difference terms to include is often determined empirically, with the idea being to include enough terms so that the error term is serially uncorrelated. In ADF, we still test whether = 0, and the ADF test follows the same asymptotic distribution as the DF statistic, so the same critical values can be used.

Autocorrelation Function:
It measures the direction and strength of the statistical relationship between ordered pairs of observations in a single data series. The auto-correlation function (ACF) at lag k, denoted by, is defined as $\rho_k = \frac{\gamma_k}{\gamma_0}$, γ_k = Covariance at lag k
If we plot ρ_k against lag k, the graph we obtain is known as the population correlogram. For any time series, the autocorrelation of various lags remains around zero. Otherwise, the series is non-stationary (Gujarati, 2005, pp-808).

Partial autocorrelation function (PACF)
Partial autocorrelation function is analogous to the concept of partial regression coefficient. In the k-variable multiple regression model, the k^{th} regression coefficient β_k measures the rate of change in the mean value of the regressed for a unit change in the k^{th} regressor X_k, holding the influence of all other regressor constant. Similarly the partial autocorrelation ρ_k measures correlation between observations that are k time periods apart after controlling for correlations at intermediate lags. In other words, partial autocorrelation is the correlation between Y_t and Y_{t-k} after removing the effect of the intermediate Y's, (see for example, Gujarati (2007)).

VAR and VECM order Lag order selection:
Lag order Selection:
The first step in building a VAR model is to choose the order of the VARs which can be determined by Akaike Information Criteria (AIC) (Akaike, 1974). The mathematical form of AIC is as follows:

$$AIC = \log\left|\hat{\Omega}(p)\right| + \frac{2m(p^2+1)}{N}$$

With $\hat{\Omega}(p) = N^{-1}\sum_{i=1}^{N}\varepsilon_t\hat{\varepsilon}_t'$ and $m(p^2+1)$ is the total number of the parameters in each equation, m is the number of equation or variables in VAR model, and p determines the lag order.

Impulse Response Functions:

Any covariance stationary VAR (p) process has a Wold representation of the form

$$Y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \cdots\cdots$$

Where the (n × n) moving average matrices Ψ_s are determined recursively using

$$\Psi_s = \sum_{j=1}^{p} \Psi_{s-j} \Pi_j$$

It is tempting to interpret the (i, j)-th element, Ψ_{ij}^s, of the matrix Ψ_s as the dynamic multiplier or impulse response i.e. Ψ_{ij}^s represents the effect of unit shocks on system variables.

$$\frac{\delta yi,t+s}{\delta \varepsilon\, j,t} = \frac{\delta yi,t}{\delta \varepsilon\, j,t-s} = \Psi_{ij}^s \qquad i, j = 1, 2, \ldots\ldots\ldots, n$$

However, this illustration is only possible if var (ε_t) $= \sum$ is a diagonal matrix in which the elements of ε_t are uncorrelated.

Vector Autoregressive Model:

It is assumed that a K-dimensional multiple time series $y_1, y_2, \cdots, y_T$ with $y_t = (y_{1t}, y_{2t}, \cdots, y_{Kt})'$ is available that is known to be generated by a stationary, stable VAR (p) process

$$y_t = v + A_1 y_{t-1} + \cdots + A_p y_{t-p} + u_t.$$

All symbols have their usual meanings, that is, $v = (v_1, \cdots, v_k)'$ is a (K×1) vector of intercept terms, the A_i are *(K×K)* coefficient matrices and u_t is white noise with nonsingular covariance matrix $\sum_u$. The coefficients $v, A_1, A_2, \cdots, A_p,$ and $\sum_u$ are assumed to be unknown in the following. The time series data will be used to estimate the coefficients. Note that notation wise we do not distinguish between the stochastic process and a time series as a realization of a stochastic process. The particular meaning of a symbol should be obvious from the context (Lütkepohl, H., (2005)).

Forecast Error Variance Decompositions:

The Forecast Error Variance Decomposition (FEVD) quantify the question, how much of the forecast error variance is caused by the structural shock? Using orthogonal shocks η_t, the h-step forward forecast error vector with well-known VAR determinants can be written as

$$Y_{T+h} - Y_{T+h|T} = \sum_{s=0}^{h-1} \Theta_s \eta_{T+h-s}$$

Where $Y_{T+h|T}$ is h-step forecasts based on information available at time T

For a particular variable $Y_{i,T+h}$, this forecast error has the form

$$Y_{i,T+h} - Y_{i,T+h|T} = \sum_{s=0}^{h-1} \theta_{i1}^s \eta_{1,T+h-s} + \cdots + \sum_{s=0}^{h-1} \theta_{in}^s \eta_{n,T+h-s}$$

Where $\sigma_{\eta j}^2 = \mathrm{var}(\eta_{jt})$, is the fraction of var($Y_{i,T+h} - Y_{i,T+h|T}$) cause by the shock η_j,

$$FEVD_{i,j}(h) = \frac{\sigma_{\eta j}^2 \sum_{s=0}^{h-1} (\theta_{ij}^s)^2}{\sigma_{\eta 1}^2 \sum_{s=0}^{h-1} (\theta_{i1}^s)^2 + \cdots + \sigma_{\eta n}^2 \sum_{s=0}^{h-1} (\theta_{in}^s)^2}, i, j = 1, \ldots n$$

A VAR with n variables has n^2 $FEVD_{i,j}(h)$ values. It is important to note that FEVD is dependent on the causal order used to determine structural shocks (η_t), and is not unique. Alternatively, different sequences of causal produce different FEVD values.

RESULTS AND DISCUSSIONS

Unit Root Test:

Table 1: Unit root test of the selected variables.

Variables	*Constant & no trend*		*Constant & trend*		*No constant & no trend*	
	At level	At 1st difference	At level	At 1st difference	At level	At 1st difference
GDP growth rate	0.92	0.00	0.30	0.00	0.99	0.00
Inflation rate	0.08	0.00	0.43	0.00	0.07	0.00
Real interest rate	0.00	0.00	0.28	0.00	0.24	0.00
Exchange rate	0.73	0.00	0.10	0.00	1.00	0.0

Comments: Results of the above table indicate study variables are non-stationary at level but stationary at the first difference, which satisfies the preliminary condition of using VECM model.

Optimal Lag Length Selection:

Table 2: Lag order selection by AIC

Lag	Log L	AIC
0	-356.40	21.20
1	-269.85	17.05*
2	-259.18	17.36
3	-245.19	17.27

* indicates lag order selected by the criterion

Comment: AIC from Table-2 confirmed that the maximum lag length of the model is '1', and it is selected on the basis of the minimum value of AIC.

Johansen Test of Cointegration Analysis:
As it has been found that all variables have become free from the unit root problem at the first difference, it is suitable to apply the Johansen Maximum Likelihood Approach.

Table 3. Results of Johansen co-integration test

Maximum rank (r)	parms	LL	Trace statistic	5% critical value
None (0)	20	-293.61	53.21	47.21
At most 1	27	-281.05	28.09*	29.68
At most 2	32	-271.25	8.48	15.41
At most 3	35	-267.35	0.68	3.76

* denotes rejection of the null hypothesis that there is no co-integration

Comments: In this case, as standard practice, we often use the 5 percent critical value as a reference. The r in the table represents the rank, and we know that this is some indication of the number of cointegrating relationships. When r = 0, the test stats 53.21>47.21. This means that we reject the null hypothesis, which suggests that r > 0. As such, there is some cointegration present. When r is at most 1, we fail to reject the null hypothesis because 28.09* < 29.68 Hence, the sequence stops here. Therefore, we conclude that there is at most one cointegrating relationship present. This infers the existence of a long-term relationship among the variables.

Vector Error Correction Estimates:
If the variables are co-integrated or have long-run association, we can run restricted VAR that is VECM model. That is why, the informations support to run VECM model which is at first differenced model. As a result, the lag order will be one less than the lag order chosen for unrestricted VAR. Since our optimal lag order chosen is 1, so VECM lag order would be zero or at no lag order. VECM outputs are given below for appropriate interpretation.

Significance of the Equations:

Table 4: Significance of the equations

Equation	parms	RMSE	R-sq	Chi2	P>chi2
D_GDPG	2	0.91	0.72	90.04	0.00
D_IR	2	2.71	0.01	0.66	0.71
D_RIR	2	4.26	0.08	3.14	0.20
D_EXC	2	2.01	0.44	27.40	0.00

Comment: Among all the equations, only two are significant, i.e., the equations for D_GDPG (first difference of GDP growth rate) and D_EXC (first difference of Exchange rate) at both the 1% and 5% levels of significance.

Vector Error Correction Estimations:
The estimation results for all the equations are presented in Table 5.

Table 5: VECM estimation results

Equations	Coefficients	Standard error	z	p>|z|
D_GDPG _CE1 L1 _cons	 -1.31 0.12	 0.13 0.15	 -9.42 0.82	 0.00 0.41
D_IR _ CE1 L1 _cons	 -0.24 -0.25	 0.41 0.45	 -0.60 -0.57	 0.55 0.56
D_RIR _ CE1 L1 _cons	 -1.12 0.20	 0.64 0.71	-1.74 0.28	 0.08 0.77
D_EXC _ CE1 L1 _cons	0.18 1.75	0.30 0.33	0.61 5.22	0.54 0.00

Comments: From the output results of vector error correction model of the equation where GDP growth is considered as dependent variable (i.e. 1st equation), we see that the error correction term is -1.31 is negative and significant at 5% level. This is a clear indication of having long run relationship GDP growth with inflation, real interest and exchange rate. Also this results indicates the existence of the long run causal relationships among the variables. This means that the selected variables causes GDP growth rate in the long run.

Significance of the Co-integrated Equation:

Since the cointegration rank test using Johansen cointegration tests suggests that there is one cointegration equation. From VECM result we can check whether the co-integration equation is significant or not.

Table 6: Significance of the co-integration equation

Equation	Parms	Chi2	P>chi2
Cointegration Equation	3	73.06	0.00

Comment: From the above table, we see that the p-value is less than 0.05. So we fail to accept the null hypothesis. As a result, we may conclude that the cointegrating equation of our study variables is statistically significant.

Variance Decomposition for VECM:
Since there is no lag order in the estimated vector error correction model. So, there is a lack of sufficient evidence in favor of short-run causality among the study variables. Now, based on the variance decomposition results from the vector error correction model, we can infer the short-run causality among the study variables.

Table 7: Variance Decomposition of GDP growth for VECM

Period	S.E.	GDPG	IR	RIR	EXC
1	0.91	100.00	0.00	0.00	0.00
2	0.99	91.83	0.04	6.58	1.52
3	1.02	89.34	0.06	8.60	1.99
4	1.04	85.52	0.08	11.68	2.70
5	1.07	82.56	0.09	14.07	3.26
6	1.09	79.64	0.11	16.43	3.80
7	1.11	77.02	0.12	18.54	4.29
8	1.13	74.57	0.14	20.52	4.75
9	1.15	72.30	0.15	22.35	5.18
10	1.17	70.19	0.16	24.05	5.57

Comments: In the short run, or first period, 100% of the forecast error variance of GDPG is explained by itself; other variables don't have a strong influence. In the second period, the real interest rate (RIR) has a moderately strong impact both in the long run and in the short run on the GDP growth rate, but EXC and IR have a low influence.

Diagnostics Checking of the VEC Model
It is essential to check the validity of our estimated model so that the interpretations made from this model are considered valid in reality. Several diagnostic checking methods are described below to check the validity of the model.

Portmanteau test for autocorrelation
H_0: No residuals autocorrelation up to lag h
H_1: Residuals autocorrelation up to lag h

Table 8: Portmanteau test results

Lags	Q-Stat	Prob.*	Adj Q-Stat	Prob.*	df
1	19.09	0.89	19.63	0.87	28

Comment: Since P-value> 0.05, we fail to reject the null hypothesis at 5% level of significance. Therefore, residuals are not autocorrelated.

Normality Test of Residuals:
H_0: Residuals are multivariate normally distributed.
H_1: Residuals are not multivariate normally distributed.

Table 9: Normality test results

Component	Jarque-Bera	df	P-value
1	0.06	2	0.96
2	2.36	2	0.30
3	8.27	2	0.09
4	0.78	2	0.67
Joint	11.49	8	0.17

Comment: Jarque-Bera P-values are greater than the level of significance, so we may accept the null hypothesis at the 5% level of significance. This means the residuals are normally distributed.

VEC Residuals Heteroscedasticity Test:
H_0: Residuals are Homoscedastic (joint test)
H_0: Residuals are not Homoscedastic (joint test)

Table 10: Residuals heteroscedasticity test

Chi-sq	df	P-value
28.80	20	0.09

Comment: Since the p value is greater than 0.05, we may accept the null hypothesis. Hence, we can conclude that the residuals are homoscedastic.

Residual Plot:

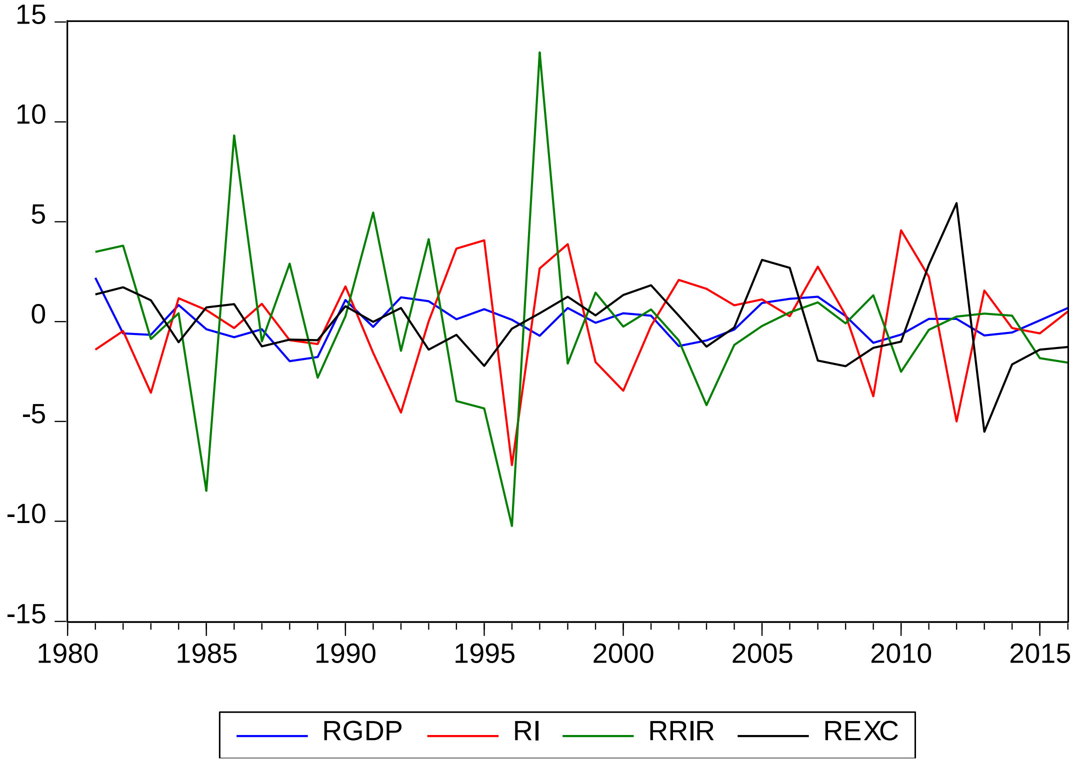

Figure 5: Plot of the residuals

Comment: Figure 5 represents the combined plot of residuals for all the study variables. It clearly shows the stationarity for all the residual series. So, we conclude that all the residual series are stationary.

Unit Root Test of Residuals:
We can use our estimated model only when all the residual series are non-stationary, i.e., free from unit root problems. That's why group unit root test results for all residual series are presented below.

Table 11: Group unit root test summary

Method	Statistic	P-value	Cross sections	Observation
Null: Unit root (assumes common unit root process) Levin, Lin & Chu t*	-7.96	0.00	4	128
Null: Unit root (assumes common unit root process) Im, Pesaran and Shin W-stat	-8.25	0.00	4	128
ADF - Fisher Chi-square	74.99	0.00	4	128
PP - Fisher Chi-square	114.56	0.00	4	140

Comment: Since the p value is smaller than the 5% level of significance, we fail to reject the null hypothesis. This means that the residuals series does not have a unit root problem.

Impulse Response Function:
The impulse response function shows the responses of each variable to the response variable. Here, the responses of the inflation rate, real interest rate, and exchange rate to GDP growth (i.e., economic growth) are shown in the graphs below in the vector error correction system.

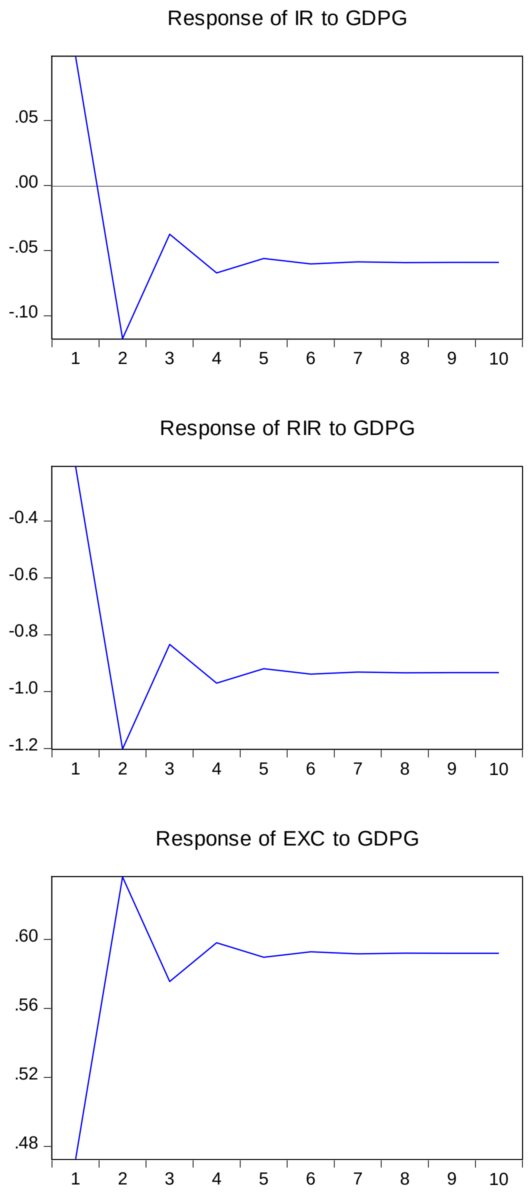

Figure 6: Impulse Response Function

Comments: Among these three graphs of impulse responses, we see that real interest rates have a negative impact on economic growth in the long run, exchange rates have a positive impact on economic growth in the long run, and the graph shows a negative constant response of the inflation rate to economic growth in the long run.

CONCLUSION

All selected variables are nonstationary at level 1, but the first difference is stationary. The Johansen cointegration test satisfies that the variables are cointegrated at the same level as order 1. At a significance level of 0.05, the trace test supports one cointegrating equation. This infers the existence of a long-run relationship among the variables, which suggests that interest rates, inflation rates, and exchange rates have a long-run impact on economic growth in Bangladesh. The Vector Error Correction Model (VECM) exhibits the existence of a long-run causality between three variables and the GDP growth rate. As per the findings of the study, the real interest rate (RIR) has a moderately strong impact both in the long run and in the short run on the GDP growth rate, but EXC and IR have a low influence.

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