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A Comparison of the VAR Model, ARIMA Model and Holt's Exponential Smoothing Approach in Forecasting Remittance and GDP for Bangladesh

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Abstract

As remittance is one of the most crucial factors driving our economy, this study employs various statistical techniques to analyze its impact on the Gross Domestic Product (GDP). First of all, Vector Autoregressive (VAR) model and Granger causality test were applied to assess the influence of remittances on GDP. Subsequently, the study utilized Autoregressive Integrated Moving Average (ARIMA), VAR and Holt's exponential smoothing technique to analyze and forecast the selected variables: Remittance and GDP.The yearly time series data on GDP and remittances were sourced from the Journals of Bangladesh Bank covering the period from 1990 to 2022.The VAR model analysis revealed a significant relationship between remittances and GDP, indicating that remittances play a vital role in driving economic growth. Forecasting remittances and GDP is crucial because these variables are essential indicators of economic stability and growth. By accurately forecasting remittance inflows and GDP trends, policymakers and businesses can better plan for future economic conditions, manage foreign exchange reserves and make informed decisions about resource allocation. Additionally, ARIMA and Holt's exponential smoothing technique were used for forecasting purposes and a comparison of these methods indicated that the VAR model is more efficient, particularly when applied to remittance and GDP data.

Keywords: Comparison of models, Forecasting, VAR Model, ARIMA, GDP, Remittance

I. Introduction

Remittance has become a significant source of national income for Bangladesh. The economic globalization of the 1980s and 1990s, coupled with increased external demand for Bangladeshi labor, has driven this development. Bangladesh is now the world's sixth-largest labor-sending nation and the eighth-largest recipient of remittances[1]. According to the Ministry of Expatriate Welfare and Overseas Employment's Bureau of Manpower Employment and Training (BMET), over twelve million Bangladeshis have left their country in search of employment during the previous 50 years, remitting a total of 275 billion dollar[2].

Since 1999, remittances have become the second-largest source of funds for developing nations, following foreign direct investment (FDI)[3]. Unlike FDI, remittances are direct cash transfers from abroad that incur no financial obligations for the recipient country[4]. Research indicates that as economies move from developing to developed status, total FDI flows decrease, while remittance inflows increase[5]. This shift has significantly improved living standards, reduced poverty and ensured that basic needs are met[6]. Consequently, remittance inflows greatly enhance economic activity by supporting consumption, investment and savings[7]. Before the onset of the COVID-19 pandemic, both migration and remittance flows were increasing[5]. In 2019, remittance inflows to low and middle-income countries had grown to 548 billion dollars, tripling the amount of official development assistance and surpassing foreign direct investment for the first time[8].

In Bangladesh, the inflow of foreign remittances has become a major financial conduit, showing a remarkable and consistent upward trend year over year. This context necessitates an examination of overseas remittances' effect on Bangladesh's economic expansion.

The economy of the recipient country gains a great deal from remittances in macro and microeconomic domains.Many of the remitters, who were unemployed in their home country, find work in the host countries. The inbound remittances they send support national savings, capital accumulation and investment, thereby creating jobs domestically. In addition to employment, important macroeconomic factors in Bangladesh have demonstrated positive correlations with remittances, including growth, poverty reduction, social security and balance of payments (BOP) stability[9-12]. The World Bank's Global Economic Prospects (GEP) (2006) report states that between 1990 and 2006, remittances helped Bangladesh's poverty headcount ratio drop by 6 percentage points[13].Previous studies, such as those by Rao and Hassan, have looked into how remittances affect economic growth directly as well as the growth consequences of the routes via which they may do so[14]. Islam and Azad (2024) found that remittances increase income inequality and that economic growth and Ready-Made Garments (RMG) exports also contribute to this inequality[15]. Their study used data from 1983 to 2018, with GDP as a control variable. Golder et al.(2023) carried out a study to investigate the unequal impacts of financial advancement and remittances on Bangladesh's economic growth using the Nonlinear Autoregressive Distributed Lag (NARDL) model[16].

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Sutradhar has studied the impact of remittances on economic growth in five south Asian country[17]. This study reveals a true impact of remittances on economic growth of the five countries. Hanif and Khanam analyzed the impact of remittance and FDI on GDP and found that remittance inflows have a significant impact on the growth of Bangladesh's economy[18].Khan and Gunwat used ARIMA to forecast Yemen's remittance inflows. Projections show a decline to 4.122% of GDP by 2030, signaling potential economic challenges.[19] Hassan, Doulah and Sathi applied ARIMA (1,1,0) to forecast Bangladesh's remittance inflow, projecting a continued upward trend[20]. Sakib et al. used machine learning algorithms to model and predict the impact of remittance inflows on Bangladesh's GDP growth[21].

Given the critical role of remittances in influencing the economic growth of Bangladesh, understanding their dynamic relationship with GDP has become an essential focus in contemporary economic research. In this context, the present study serves as an academic endeavor to comprehensively assess the impact of remittance inflows on GDP, while simultaneously providing reliable forecasts for both variables. Our research study undertakes a comparative analysis of three prominent time series forecasting techniques—Vector Autoregression (VAR), Autoregressive Integrated Moving Average (ARIMA) and Holt's exponential smoothing. By evaluating the predictive performance and suitability of each model, the study aims to identify the most effective approach for forecasting Bangladesh's remittance inflow and GDP trends. The findings of this study are expected to significantly enrich the existing literature by offering deeper insights into the remittance–GDP nexus and by supporting policymakers with data-driven forecasts for strategic economic planning. So, the key objectives of this research are:

- To examine the relationship between the gross domestic product (GDP) and Remittance by using VAR model and Granger causality test.
- To forecast the associated variables of this study by using suitable ARIMA, Holt's smoothing and VAR model.
- To compare the forecasting accuracy of the results obtained from ARIMA, Holt's and VAR model.
- To make some recommendation that can assist future policy formulation inBangladesh.

II. Data and Methods

This study utilizes annual time series data on GDP and remittances spanning from 1990 to 2022, sourced from the *Monthly Economic Trend* reports of Bangladesh Bank.

Stationarity

Before Fitting the models, the stationarity of the data is checked using graphical analysis and Augmented Dickey-Fuller (ADF) test. The ADF test statistic is[22]:

$$\tau(ADF) = \frac{\hat{\gamma}}{S.E.(\hat{\gamma})}$$

where $\hat{\gamma}$ is the estimated coefficient on the lagged level of the seriesand $S.E\,(\hat{\gamma})$ is the standard error of the estimated coefficient $\hat{\gamma}$.

Lag Selection Criteria

In time-series analysis, the choice of the optimal lag length is critical because it influences the model's accuracy and predictive power. Too few lags may result in model underfitting, while too many can lead to overfitting. To address this, researchers commonly use information criteria such as the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC), which help in selecting the lag length by balancing model fit and complexity.

The AIC[23] and SIC[24] values are calculated using the following formulas:

$$AIC = 2k - 2ln(L)$$

$$SIC = -2ln(\hat{L}) + k.ln(n)$$

where $n, k \ and \ \hat{L}$ stand for the number of observations, the model's parametersand the maximum likelihood function, in that order.

Co-integration Test

In time series analysis, it is customary to describe one non-stationary time series (Y_t)as a linear combination of other non-stationary time series. $(X_{1,t}, X_{2,t}, \dots X_{k,t})$. In another way:

$$Y_t = \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \dots + \beta_k X_{k,t} + \epsilon_t \quad (2.1)$$

Regression models for non-stationary time series variables typically provide erroneous (nonsense) results. The only deviation occurs when the stochastic trend is eliminated and stationary residuals are produced by the linear combination of the (dependent and explanatory) variables[25],

$$Y_t + \beta_0 + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \dots + \beta_k X_{k,t} \sim I(0) \quad (2.2)$$

We call the collection of variables in this instance co-integrated.There are several ways to test for Co-integration. A common practice is using Engle and Granger two step test.

Granger Causality Test

It is important to understand that stating "X causes Y" does not imply that X is the cause of or follows from Y. Granger causality evaluates precedence and information content rather than expressing causation in the traditional sense. Let, X_t andY_t, be two stationary time-series. For this test the bivariate regression can be written as[26]:

$$X_t = \theta + \theta_1 X_{\{t-1\}} + \theta_2 X_{\{t-2\}} + \ldots + \theta_p X_{\{t-p\}} + \delta_1 Y_{\{t-1\}} + \delta_2 Y_{\{t-2\}} + \ldots + \delta_p Y_{\{t-p\}} + \epsilon_t \quad (2.3)$$

$$Y_t = \theta_0 + \theta_1 Y_{\{t-1\}} + \theta_2 Y_{\{t-2\}} + \ldots + \theta_p Y_{\{t-p\}} + \delta_1 X_{\{t-1\}} + \delta_2 X_{\{t-2\}} + \ldots + \delta_p X_{\{t-p\}} + \epsilon_t \quad (2.4)$$

Here, Y is a function of both its own and X's lagged values. If X does not Grangercause Y then coefficients of the lagged values of X will be 0. Alternatively, if$X$ Granger-causes Y then some or all of the coefficients of the lagged values of X will be non-zero. And same for the second equation. For each equation, the null hypothesis is:

$$H_0: \delta_1 = \delta_2 = \ldots = \delta_p$$

Null hypothesis can be tested for both equations by performing Wald F-test or χ^2 test.

Vector Autoregressive (VAR) Model

In the structure of a Vector Autoregressive (VAR) model, each variable is expressed as a linear function of its own past-values as well as the past-values of other variables in the system. A basic VAR model includes a set of K endogenous variables,

$y_t = (y_{\{1t\}}, \ldots, y_{\{kt\}}, \ldots, y_{\{Kt\}})$ for $k = 1, \ldots, k$

The VAR (p) process is then defined as[19]:

$$y_t = A_1 y_{\{t-1\}} + A_2 y_{\{t-2\}} + \ldots + A_p y_{\{t-p\}} + u_t \ldots\ldots\ldots.2.5$$

with A_is, are $(K \times K)$ coefficient matrices for $i = 1,2,\ldots,p$ and u_t, is a K-dimensional process with $E(u_t) = 0$ and time invariant positive definite covariance matrix $E(u_t u_t^T) = \Sigma u$ (white noise). Stability is a key property of the VAR(p) model, ensuring that the system of equations behaves in a predictable manner over time. In our study, we have two VAR models:

Equation-1:

$$\Delta\sqrt{Remittance_t} = \alpha_1 + \sum_{i=1}^{6} \beta_{1i}\, \Delta\sqrt{Remittance_{t-i}} + \sum_{i=1}^{6} \gamma_{1i}\, \Delta^2\sqrt{GDP_{t-i}} + \epsilon_{1t}$$

where, $\Delta\sqrt{Remittance_t}$ is considered as response variable and lagged observation of GDP and remittance are considered as independent variable.

Equation-2:

$$\Delta^2\sqrt{GDP_t} = \alpha_2 + \sum_{i=1}^{6} \beta_{2i}\, \Delta\sqrt{Remittance_{t-i}} + \sum_{i=1}^{6} \gamma_{2i}\, \Delta^2\sqrt{GDP_{t-i}} + \epsilon_{2t}$$

where, $\Delta^2\sqrt{GDP_t}$ is considered as response variable and lagged observation of GDP and remittance are considered as independent variable.

Autoregressive Moving Average (ARIMA) Model

In econometrics and time series analysis, an Autoregressive Integrated Moving Average (ARIMA) model is commonly used to fit time series data for forecasting future values or for better understanding the underlying patterns in the data. The non-seasonal ARIMA model is constructed by combining differencing with autoregressive and moving average components.

The entire model is expressed as[27]:

$$y_t' = c + \phi_1 y_{t-1}' + \cdots + \phi_p y_{t-p}' + \theta_1 \epsilon_{t-1}' + \cdots + \theta_p \epsilon_{t-p}' + \epsilon_t \ldots 2.6$$

where $y_t'$is the differenced series (it may have been differenced more than once). The predictors on the right-hand side include both lagged values of y_t and lagged errors. This is referred to as an ARIMA(p, d, q) model; where p = order of the autoregressive part, q = order of the moving average part, d = degree of first differencing applied to make the series stationary.

Holt's Smoothing Model

Some of the most effective forecasting techniques were inspired by the late 1950s proposal of exponential smoothing[28-30]. The "Holt's linear trend" approach, which was developed by Holt in 1957[31], expanded basic exponential smoothing to enable trend-based data forecasting. This approach uses two smoothing equations (one for the trend and one for the level) in addition to a forecast equation:

Forecast equation: $\hat{y}_{\{t+h|t\}} = I_t + h * b_t \ldots\ldots 2.7$

Level Equation: $I_t = \alpha y_t + (1-\alpha)(I_{\{t-1\}} + b_{\{t-1\}}) .. 2.8$

Trend Equation: $b_t = \beta^*(I_t - I_{\{t-1\}}) + (1-\beta^*) b_{\{t-1\}} \ldots 2.9$

where $b_t$indicates the series' trend (slope) at time t and$I_t$defines the series' estimated level at time t. $\beta^*$is the smoothing parameter for the trend,

$0 \leqslant \beta^* \leqslant 1$ andα is the smoothing parameter for the level, $0 \leqslant \alpha \leqslant 1$.

Comparing the forecasting accuracy of the models:

To compare the accuracy of the models and determine the best fit for forecasting purpose, we used RMSE[32], MAE[33] and MAPE[34] values. And the values were calculated using the following formulas:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

$$MAE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|}$$

$$MAPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|\frac{y_i - \hat{y}_i}{y_i} * 100|}$$

where y_i is the actual and $\hat{y}_i$ is the predicted or forecasted value.

Econometric Validation

One of the most crucial econometrics criteria is data sufficiency. If the data is insufficient, the research will stay invalid. For this reason, we must do several adequacies checks in order to validate the data collection. In econometrics, there are several criteria to determine whether the data set is enough[35], including Autocorrelation test,Heteroscedasticity test, Multicollinearity test and Normality assumptions check.

For checking autocorrelation, Breusch-Godfrey Serial Correlation Test[37] has been used.

For checking Heteroscedasticity, Breush-Pagan Test[38]is applied using the following formula to compute the Chi-square or F-statistic.

$$F = \frac{\frac{R^2}{1}}{\frac{1-R^2}{n-2}}$$

Here:

R^2 = coefficient of determination (explained variance)

n = sample size

Checking the normality assumption is helpful using Jarque-Bera Test, since once verified, we may use enormous number of procedures to get the estimate accurately. For multivariate it can be defined as[39]:

$$JBMV = s_3^2 + s_4^2$$

where $s_3{}^2$ and $s_4{}^2$ can be computed as:

$$s_3^2 = \frac{Tb_1b_1'}{\sigma}$$

$$s_4^2 = \frac{(b_2 - 3k)(b_2 - 3k)'}{24}$$

Here,$b_1$and b_2 are 3^{rd} and 4^{th} non-central moment vectors of standardized residuals. Test statistic is distributed as $\chi^2_{(2k)}$. Skewness S_3^2 and Kurtosis S_4^2, are also distributed as $\chi^2_{(2k)}$

Table 1. Stationarity of the variables

Variable	Level/Difference	*p*-value	Decision
Square Root of Remittance	Level	0.187	Not Stationary
	First Difference	0.029	Stationary
Square Root of GDP	Level	0.403	Not Stationary
	First Difference	0.076	Not Stationary
	Second Difference	0.047	Stationary

III. Results and Discussion

Table 1 shows the stationarity test results for two variables: the square root of remittance and the square root of GDP. To summarize, the square root of remittance becomes stationary after the first difference, while the square root of GDP requires a second differencing to attain stationarity.

Co-integration Analysis Between Remittance and GDP.

Null hypothesis that there exists no co-integration was tested and the results are given below:

Table 2. Engel-Granger co-integration test results for the data

Type	Test statistic	*p*-value	Decision
No trend	-0.850	≥ 0.100	No co-integration
Linear trend	1.010	≥ 0.100	No co-integration
Quadratic trend	-1.770	≥ 0.100	No co-integration

From Table 2, we found that we don't have enough evidence to reject the null hypothesis that there is no co-integration. Hence, the Vector Autoregressive (VAR) Model has been utilized.

Table 3. Optimal lag length selection for VAR model

Criteria	1	2	3	4	5	6
AIC	7.560	7.790	7.920	7.74	7.91	7.12
HQ	7.670	7.960	8.15	8.02	8.23	7.50
SIC	7.940	8.360	8.69	8.70	9.08	8.48
FPE	1936.600	2459.50	2867.0	2484.3	3238.4	1662.4

Lag Length Selection for VAR Model

From Table 3, we can see that the AIC, HQ and FPE have their least-value for lag-6, while SIC indicates to lag 1. This evidence certifies that lag-6 can be used as an appropriate lag length for the forthcoming analysis purpose.

Analysis of the Vector Autoregressive (VAR)Models:

The results obtained from fitting the above two models are given below:

Table 4. VAR model output for Equation-1

Variable	**Estimate**	**S. E.**	**t-value**	***p*-value**
$\Delta\sqrt{Remittance_1}$	0.390	0.284	1.376	0.194
$\Delta^2\sqrt{GDP_1}$	-0.206	0.177	-1.163	0.267
$\Delta\sqrt{Remittance_2}$	-0.189	0.351	-0.539	0.599
$\Delta^2\sqrt{GDP_2}$	0.097	0.212	0.459	0.654
$\Delta\sqrt{Remittance_3}$	0.625	0.317	1.969	0.072
$\Delta^2\sqrt{GDP_3}$	-0.003	0.216	-0.014	0.989
$\Delta\sqrt{Remittance_4}$	-1.252	0.314	-3.985	0.002 **
$\Delta^2\sqrt{GDP_4}$	0.274	0.213	1.285	0.223
$\Delta\sqrt{Remittance_5}$	0.961	0.466	2.060	0.062
$\Delta^2\sqrt{GDP_5}$	0.170	0.226	0.748	0.469
$\Delta\sqrt{Remittance_6}$	-0.408	0.431	-0.948	0.362
$\Delta^2\sqrt{GDP_6}$	0.271	0.208	1.305	0.216
Constant	3.288	2.141	1.536	0.151
Multiple R-Squared:	0.727			
F-statistic (p-value):	2.665 (0.051)			

From Table 4, we can see that the coefficients of the 4^{th} lag of remittance are significant at 5% level of significance. Which implies that this variable was playing an important role for the response variable $\Delta\sqrt{Remittance_t}$. So, we can consider this variable for our forecasting purpose.

The R-squared value of this model is 0.727 which implies that almost 73% of the total variation of our response variable can be explained by a linear relationship with the predictors. Finally the *p*-value of the F-statistic is greater than 0.005 which reveals that, at the 5% significance level, the model is not significant. But this *p*-value is less than 0.1, that means the model is significant at 10% level of significance.

Table 5. VAR model output for Equation-2

Variable	Estimate	S. E	t-value	*p*-value
$\Delta\sqrt{Remittance_1}$	0.267	0.295	0.904	0.384
$\Delta^2\sqrt{GDP_1}$	-0.345	0.185	-1.869	0.086
$\Delta\sqrt{Remittance_2}$	0.398	0.365	1.091	0.297
$\Delta^2\sqrt{GDP_2}$	-0.304	0.220	-1.377	0.194
$\Delta\sqrt{Remittance_3}$	-0.296	0.330	-0.897	0.387
$\Delta^2\sqrt{GDP_3}$	-0.146	0.225	-0.649	0.528
$\Delta\sqrt{Remittance_4}$	0.656	0.326	2.010	0.067
$\Delta^2\sqrt{GDP_4}$	-0.332	0.222	-1.496	0.161
$\Delta\sqrt{Remittance_5}$	-1.231	0.485	-2.538	0.026*
$\Delta^2\sqrt{GDP_5}$	-0.204	0.236	-0.864	0.405
$\Delta\sqrt{Remittance_6}$	0.972	0.448	2.170	0.051
$\Delta^2\sqrt{GDP_6}$	-0.892	0.216	-4.134	0.002 **
Constant	0.404	2.225	0.182	0.859
Multiple R-Squared:		0.825		
F-statistic (p-value):		4.715 (<0.01)		

From Table 5, we can see that the coefficients of the 5*th* lag of $\Delta sqrt$ remittance and 6*th* lag of $\Delta^2\sqrt{GDP_t}$are statistically significant at 5% level of significance. Some other lags of $\Delta\sqrt{Remittance_t}$ are marginally significant for the model, which implies that these variables were playing an important role for the response variable $\Delta^2\sqrt{GDP_t}$. Although some lagged coefficients were negative, this might be due to the sampled data. So, we can consider this variable for our forecasting purpose.

The R-squared value of this model is 0.825 which implies that almost 83% of the total variation of our response variable can be explained by a linear relationship with the predictors. Finaly the *p*-value of the F-statistic is less than0.05 reveals that, at the 5% significance level, the model is significant.

Granger Causality Test

From Table 6, it is evident that the impact of remittances on GDP has a *p*-value below the significance level of 0.05 which provides enough evidence to reject the null hypothesis. Therefore, we state that GDP is granger caused by remittance. In contrast, the *p*-value for the GDP's impact on remittances is higher than the 0.05 significance level. So, we don't have sufficient evidence to reject the null hypothesis and conclude that remittances are not granger caused by GDP.

Table 6. Granger causality test result

Null hypothesis	Def.	F test statistic	*p*-value	Conclusion
Remittance does not granger cause GDP	12	4.541	≤ 0.050	Null is rejected
GDP does not granger cause Remittance	12	0.917	0.517	Null is not rejected

VAR Model Diagnosis

A few diagnostic tests and their findings are outlined below.

Table 7. Breush-Godfrey test results for checking autocorrelation

Variable	LM test	*p*-value	Decision
Remittance	2.375	0.882	Null is not rejected
GDP	3.884	0.692	Null is not rejected

From Table 7, it has been observed that the *p*-value is greater than the pre-specified level of significance (0.05). Therefore, we do not reject the null hypothesis, i.e., it can be said that there is no autocorrelation existed in the residuals of the model.

Table 8. Breush-Pagan test for heteroscedasticity

Variable	Test statistic	*p*-value	Decision
Remittance	2.282	0.131	Null is not rejected
GDP	2.747	0.097	Null is not rejected

From Table 8, it is evident that the null hypothesis is not rejected as the *p*-value is higher than the pre-specified level of significance (0.05). It can be said that there exists no heteroscedasticity.

Table 9. Jarque-Bera test for normality

Variable	Test statistic	*p*-value	Decision
Remittance	1.935	0.380	Null is not rejected
GDP	1.266	0.531	Null is not rejected

From Table 9, it has been observed that the *p*-value for the test of normality for both remittance and GDP are greater than the pre-specified level of significance (0.05). It indicates that the null hypothesis is true, i.e., that the residuals for GDP and remittance in our fitted model have a normal distribution.

Forecasting of Remittance Using VAR Model

The following Table 10 shows the forecasted values of Remittance series by using a VAR model.

Table 10. Forecasted values of Remittance using VAR model

Year	Forecasted values	95% lower CI	95% upper CI
2023	26522.61	23493.50	29735.33
2024	19701.04	14490.55	25710.21
2025	28547.39	19184.86	39764.36
2026	34182.39	20454.04	51416.46
2027	24108.54	10041.22	44239.79

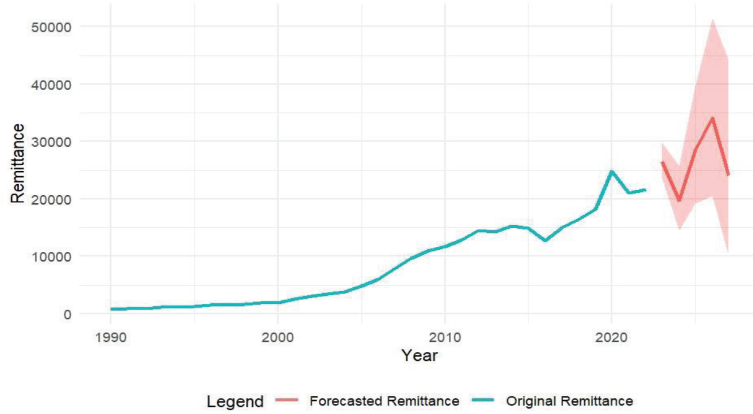

Fig. 1. Plot of the forecasted values of remittance using VAR model with 95% CI

From Table 10 and Figure 1, it has been found that the forecasted values of the remittances for the years 2023 to 2027 indicate significant variation in the expected figures, with the values for each year falling within a wide confidence interval. Although the forecast suggests possible growth in the coming years, the broad confidence intervals underscore the inherent uncertainty in economic predictions. These variations in the projected values highlight the importance of careful planning and ongoing monitoring of economic trends.

Diagnosis of the Residuals

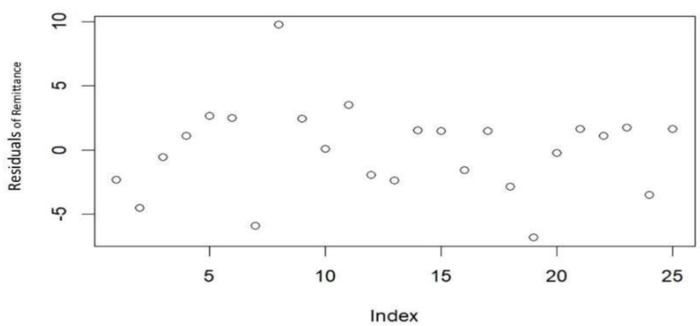

Fig. 2. Plot of the residual values of remittance using VAR model

In Figure 2, the random scatter and constant spread of the residuals observed in the above plot suggest that the model assumptions are likely met.

ACF Plot of Residuals for Remittance

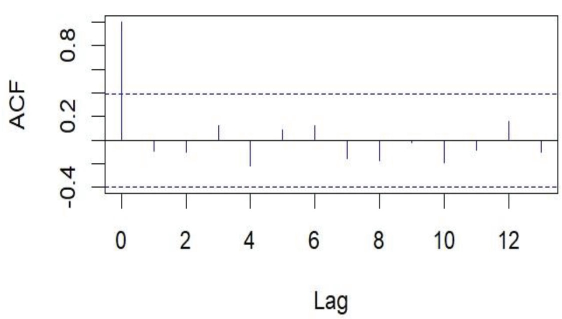

Fig. 3. ACF plot of the residual values of Remittance using VAR model

From Figure 3, it has been observed that the residuals are closed to zero and within the confidence bands. So, it can be concluded from the plot that the residuals are uncorrelated.

Forecasting of GDP Using VAR Model

Table 11. Forecasted values of GDP using VAR model

Year	Forecasted value	95% lower CI	95% upper CI
2023	460742.6	447324.4	474359.1
2024	486762.2	458310.9	516070.2
2025	438863.9	397133.8	482678.4
2026	482202.9	422438.4	545920.0
2027	481016.2	404074.3	564659.4

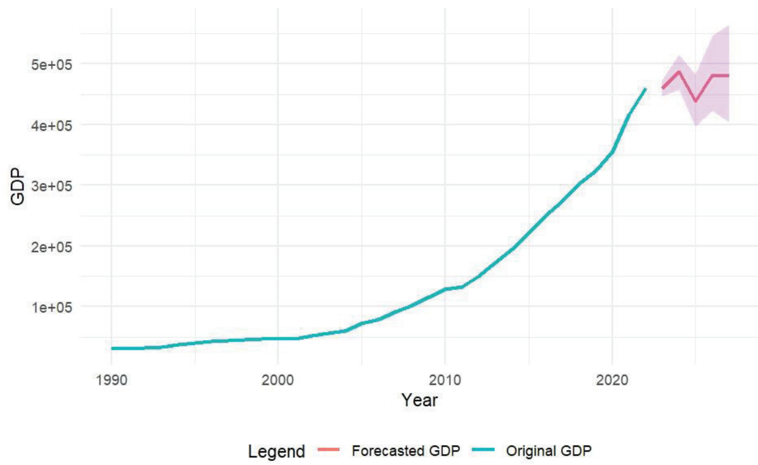

Fig. 4. Plot of the forecasted values of GDP using VAR model

From Table 11 and Figure 4, the forecasted values of GDP for the years 2023 to 2027 reflect a generally stable trend, with some variation in the projected figures, as indicated by the confidence intervals. In summary, while the forecast shows overall growth with some fluctuations over the next few years, the wide confidence intervals emphasize the uncertainty in these projections. These variations suggest the need for careful consideration and flexibility in planning for future developments.

Residual Plot of GDP

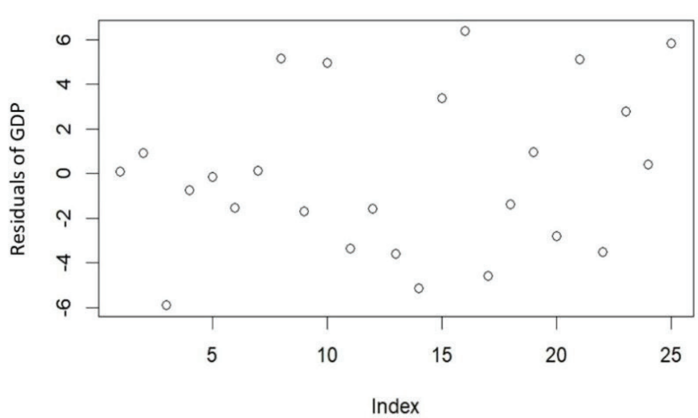

Fig. 5. Plot of the residual values of GDP using VAR model

From Figure 5, the random scatter and constant spread of the residuals observed in the above plot suggest that the model assumptions are likely met.

ACF Plot of Residuals for GDP

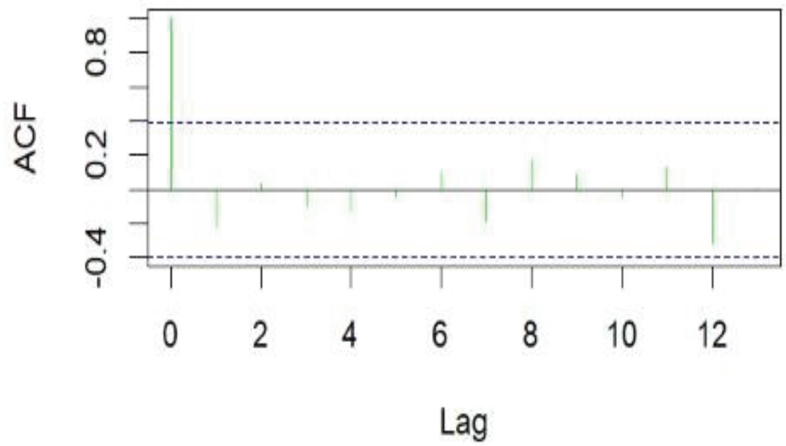

Fig. 6. ACF plot of the residual values of GDP using VAR model

From Figure 6, it has been observed that the residuals are closed to zero and within the confidence bands. So, it can be concluded from the plot that the residuals are uncorrelated.

Forecasting of Remittance Using ARIMA Model

It has been observed that the ARIMA(0,1,1) gives the least AIC. So, we have considered ARIMA(0,1,1) model for forecasting remittance series. As our model is fitted for the first difference of the square root of remittance data, after forecasting from the model, we have taken the inverse transformation of the forecasted values to get the forecast of the original variable.

Table 12. Forecasted values of Remittance using ARIMA model

Year	Forecasted value	95% lower CI	95% upper CI
2023	22721.30	19291.43	26431.65
2024	23859.77	17103.80	31737.65
2025	25026.06	15047.79	37528.65
2026	26220.19	13123.39	43804.65
2027	27442.14	11330.60	50565.67

From Table 12, the forecasted values of remittances for the years 2023 to 2027 show a general upward trend, but with significant variation as indicated by the wide confidence intervals.

Forecasting of GDP Using ARIMA Model

From the Table 12, it has been observed that the ARIMA(0,2,2) gives the least AIC. So, we have considered ARIMA(0,2,2) model for forecasting GDP series.

Table 13. Forecasted values of GDP using ARIMA model

Year	Forecasted value	95% lower CI	95% upper CI
2023	462120.9	440091.6	484688.1
2024	465902.5	401077.9	535580.9
2025	471498.0	345707.7	616766.9
2026	478868.3	277919.9	734149.4
2027	487982.1	203119.9	895722.3

From Table 13, the forecasted values of GDP for the years 2023 to 2027 show a steady upward trend, but the wide confidence intervals suggest significant uncertainty in the projections.

Forecasting of Remittance Using Holt's Smoothing Approach

The following table shows the forecasted values of Remittance series by using Holt's smoothing approach.

Table 14. Forecasted values of Remittance using Holt's smoothing approach

Year	Forecasted value	95% lower CI	95% upper CI
2023	23202.42	19519.16	27203.83
2024	24832.70	17518.26	33419.97
2025	26499.69	15609.82	40254.50
2026	28201.61	13795.59	47703.81
2027	29936.68	12077.37	55765.56

From Table 14, the forecasted values of remittances for the years 2023 to 2027 show a consistent upward trend, with considerable variation indicated by the wide confidence intervals.

Forecasting of GDP Using Holt's Smoothing Approach

Table 15. Forecasted values of GDP using Holt's smoothing approach

Year	Forecasted value	95% lower CI	95% upper CI
2023	461344.8	439604.5	483609.7
2024	463601.4	399793.4	532131.5
2025	466943.7	343573.6	609202.2
2026	471347.6	275182.9	719980.2
2027	476792.4	200299.5	871337.8

From Table 15, the forecasted values of GDP for the years 2023 to 2027 demonstrate an upward trend, but the wide confidence intervals suggest significant variability and uncertainty in the projections.

Comparing the Forecasting Adequacy of the Models

We have evaluated each of the three models' predicting accuracy to see which one produces the most accurate predictions. Metrics like Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) has been used to assess the predicted values. The test results are displayed in the table below:

Table 16. MAE, RMSE and MAPE values of the models for forecasting remittance

Model	MAE	RMSE	MAPE
ARIMA	3.813	5.857	98.704
Holt's smoothing	4.002	6.019	163.337
VAR	2.621	3.387	64.890

The Table 16 clearly demonstrates that the VAR model produces the lowest-values for RMSE, MAE and MAPE. Therefore, the VAR model offers the best fit for predicting Bangladesh's remittance data.

Table 17. MAE, RMSE and MAPE values of the models for forecasting GDP

Model	MAE	RMSE	MAPE
ARIMA	5.522	7.817	224.389
Holt's smoothing	5.658	7.712	208.710
VAR	2.879	3.520	194.391

The Table 17 clearly shows that the VAR model delivers the lowest-values for RMSE, MAE and MAPE. As a result, the VAR model offers the best fit for predicting Bangladesh's GDP data.

IV. Conclusion

This study thoroughly examined the dynamic interactions between GDP and remittances in Bangladesh using the Engel-Granger co-integration test, Granger causality test and Vector Autoregressive (VAR) modeling. The results from the Engel-Granger co-integration test indicated no cointegration among the variables in the dataset, motivating the use of the VAR model for further analysis. The VAR model highlighted a significant relationship between remittances and GDP. Additionally, the Granger causality test revealed a unidirectional causality, where remittances Granger cause GDP. This suggests that an increase in foreign remittances has the potential to stimulate GDP growth, thereby contributing to the overall economic performance of Bangladesh. This study used ARIMA model, Holt's smoothing approach and VAR model for forecasting of remittances and GDP. For remittances, the forecast shows a consistent increase, though the significant variation in the confidence intervals highlights the unpredictable nature of remittance flows and the challenges in forecasting them with precision.

Similarly, the forecasted values for GDP also demonstrate a steady upward pathway, but with a degree of uncertainty as indicated by the broad confidence intervals. In order to determine the most effective forecasting method, the study assessed various models, which are the ARIMA model, Holt's exponential smoothing and the VAR model. Based on the performance metrics such as RMSE, MAPE and MAE, the VAR model demonstrated superior accuracy in forecasting both GDP and remittances. The VAR model consistently yielded the lowest-values for RMSE, MAPE and MAE, indicating its robustness and reliability for these predictions.

Recommendations

Since the study reveals a significant unidirectional causality,where remittances Granger cause GDP, the government should focus on creating a advantageous environment for remittance inflows. Given the superior accuracy of the VAR model in forecasting both GDP and remittances, policymakers and researchers should continue utilizing this model for economic forecasting. Its robustness, as evidenced by its consistent low RMSE, MAPE and MAE values, makes it a reliable tool for assessing future economic trends and guiding informed decision-making.The wide confidence intervals in the forecasts for both remittances and GDP indicate significant uncertainty in future projections. Therefore, it is crucial for the government and businesses to engage in continuous monitoring of economic indicators.

Further Study

As the Granger causality test showed that remittances have a unidirectional impact on GDP, further research could explore the reverse causality, i.e., whether economic growth in Bangladesh also leads to higher remittance inflows. While the VAR model has proven effective, further studies could explore hybrid models or advanced machine learning techniques to improve forecasting accuracy. According to this research, it can be said that Bangladesh can more effectively utilize the potential of remittances to drive economic growth, while employing reliable forecasting methods to guide future policy decisions and strategic planning.

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