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Impacts of Remittance and FDI on Economic Growth in South Asian Countries: A Panel Data Analysis

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Abstract
The current study looks at the short- and long-term effects of foreign direct investment (FDI) and remittances on gross domestic product (GDP) in South Asian nations, particularly Bangladesh, India, Sri Lanka, and Pakistan. Utilizing annual panel data from several secondary sources spanning the period from 1981 to 2023, the research applies multiple econometric techniques, including LLC and IPS tests, Johansen Fisher type cointegration test, and panel Vector Error Correction Model (VECM), along with several diagnostic tests to ensure model reliability. The findings reveal a substantial long-term relation between the variables. Remittances and total reserves have a notable optimistic impact on GDP in both the long and short term, while FDI negatively impacts GDP. To enhance remittance flow and promote sustainable economic growth, the study suggests exporting a skilled labor force abroad. Consequently, the study recommends that South Asian countries develop policies, programs, and institutional reforms to encourage the productive use of remittances.

***Keywords**: Economic growth, Foreign direct investment, Remittance VECM, LLC, IPS.*

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1. Introduction
Remittance involves migrant workers sending money to their families in their home countries while living and working abroad. In emerging countries, it has grown to be an essential and dependable source of capital accumulation and outside finance (Al-Assaf & Al-Malki, 2014). According to Comes et al. (2017), remittances from abroad improve national revenue by stimulating investment, boosting consumption, creating jobs, and indirectly raising the income of non-recipient households. As a result, remittance inflows often lead to poverty reduction, skill and technique acquisition, health improvements, and better access to education and other benefits (Khathalan, 2012). Remittances deliver vital foreign exchange earnings and affect the recipients' balance of payments (Barajas, 2010). These economic benefits also extend to host countries, enhancing productivity, fostering skill development, promoting innovation and entrepreneurship, and increasing tax revenues.

The neoclassical migration theory holds that labor migrates from low to high wage nations as a result of pay disparities (Kurekova, 2011). Through a number of ways, the almost 281 million individuals who will migrate globally in 2023 will have a significant influence on emerging nations' economy. The Global Knowledge Partnership on Migration and Development (KNOMAD, 2023) noted in a thematic report that remittances are a vital macroeconomic factor, contributing $786 billion to the global economy, with $450 billion directed towards developing or underdeveloped economies. In some of these nations, remittances surpass FDI and make up a considerable portion of the GDP (Adenutsi, 2010). Remittances help growth national savings, decrease balance of payments and foreign exchange constraints, and support development budgets. They are particularly beneficial for developing countries in addressing challenges related to insufficient foreign exchange reserves needed to cover import costs.

Globally, remittances have been rising quickly, making them the source of foreign exchange revenues for poor nations that is expanding the quickest, especially in South Asia. Nations such as Sri Lanka, India, Bangladesh, Pakistan, and Nepal are among the largest beneficiaries of remittances globally, receiving billions of dollars annually from their expatriate workers. According to a World Bank report, remittance flows to South Asia are appraised to have grown up by 7.2% in 2023, reaching $189 billion. India received $125 billion, Pakistan $26.3 billion, Bangladesh $21.82 billion, Nepal $11 billion, and Sri Lanka $5.4 billion (World Bank, 2023). Regarding GDP from remittances, Nepal ranked highest among all South Asian countries in 2023, with 22.8%. Following Nepal were Pakistan with 7.1%, Sri Lanka with 7%, Bangladesh with 5.2%, and India with 3.4%. This indicates that the share of remittances as a percentage of GDP in these high remittance-receiving countries in South Asia is relatively low. Consequently, the low share of remittances to GDP in these countries prompted the current study to inspect the consequence of remittances on economic development in South Asia.

Like foreign remittances, foreign exchange reserves have a vital role in stabilizing economies, promoting trade and investment, and enabling sustainable economic growth. Chowdhury (2023) found that foreign exchange reserves positively impact investment in both the short and long term in Bangladesh. Similarly, a study by Osigwe *et al*. (2015) demonstrated the positive effect of foreign exchange reserves on economic growth in Nigeria. Vacaflores and Kishan (2014) observed the positive impact of remittances on international reserves in five Latin American countries, identifying international reserves as potential transmission channels. Additionally, Suman Bindu *et a*l. (2024) revealed a significant and positive influence of remittances and financial development on international reserves in Brazil, Russia, India, China, and South Africa (BRICS) from 1960 to 2022, both in the short run and long run. Similarly, Kashif *et al*. (2017) argue that economic growth positively influences international reserves, showing a dynamic relationship between the two. Their findings indicate that a 1 percent increase in economic growth results in a 0.16 percent increase in international reserves.

The aim of our study is to assess the influence of remittances on economic growth in certain South Asian nations employing a panel cointegration approach. The study focuses on four emerging economies that receive significant remittances globally. Additionally, the mixed conclusions on the association between remittances and economic development in South Asia underscore a significant research gap. This study offered many valuable insights for financial policymakers, aiding in the implementation and design of remittance-related policies and understanding their both direct and indirect belongings on economic growth. Following is the outline for the research paper: A review of the literature and theoretical framework are covered in Section 2, data and variables are explained in Section 3, methodology is explained in Section 4, findings and discussion are presented in Section 5, and suggestions are concluded and provided in Section 6.

2. Literature Review

The goal of this research is to examine how FDI and remittances touch the economic development of four South Asian nations. Scholars globally have examined several research to explore the influence of remittances on economic expansion. Since the theme of the article is remittances and economic growth, only pertinent and related research will be reviewed in this part to deliver a profounder understanding of the chosen subject. In their analysis of panel data (1980-2004) spanning 25 years and 39 developing nations, Pradhan et al. (2009) found that remittances had an optimistic and large influence on economic development. The impact of remittances on economic growth in 23 Latin American and Caribbean nations, both those with higher and lower incomes, was also examined by Ramirez and Sharma (2008), who used panel data spanning from 1990 to 2007. The researchers also found that remittances significantly and positively impacted the increase in real per capita GDP. Finding an optimistic correlation between remittances and economic growth, Fayissa and Nsiah (2010) studied 36 African states from 1980 to 2004. Similarly, Cooray (2012) found a strong positive correlation in South Asia using panel data from 1970 to 2008. The impact of remittances on economic growth in six countries that received large amounts of them was investigated by Meyer and Shera (2017). These countries were: Romania, Bosnia and Herzegovina, Bulgaria, Macedonia, Albania, and Moldova. Panel data collected from 1999 to 2013 showed that remittances meaningfully and absolutely affect economic growth.

Examining panel data from seven European nations between 2010 and 2016, Comes et al. (2018) sought to understand the linking between remittances, economic progress, and FDI. Their research proved that these countries' economies benefited from both FDI and remittances. Jawaid and Raza (2010) looked at five South Asian countries from 1975 to 2009 and found that remittances hurt Pakistan but helped India, Nepal, Sri Lanka, and Bangladesh in the long run. Azam claims that remittances boost economic growth in four countries: Sri Lanka, Bangladesh, Pakistan, and India (2015). Chand and Singh (2024) examined the belongings of remittances on 52 emerging and rising nations from 1996 to 2021 and found that they accelerated sustainable economic growth. However, after looking at data from 113 countries over 39 years (1970–1998), Chami et al. (2005) showed that remittances actually hinder economic progress. The influence of remittances on GDP development is negative. The association between worker remittances and economic development in Turkey was examined by Karagoz (2009) using time series data from 1970 to 2005. The study found a negative connection between the two variables. Sutradhar (2020) follows a similar line of thinking by examining the value of worker remittances in the economic growth of South Asian nations using balanced panel data from 1977– 2016. The research demonstrates that remittances hinder economic growth in all countries except India. With balanced panel data spanning 1994–2013, Pradhan (2016) studied five developing economies—Russia, Brazil, India, China, and South Africa—to see if remittances had any impact on economic growth. He found that there is a favorable association between remittances and China's economic progress. However, studies showed that remittances hit Russia, India, and Brazil particularly hard, stunting their economic growth. The effect was positive in South Africa, even if it was statistically insignificant. Tolcha and Rao (2014) found that remittances had a adverse effect on GDP in the long run, despite having a huge optimistic consequence on economic development in the short term, in their study of Ethiopia from 1981 to 2012. It was determined by Barjas et al. (2009) using panel data from 84 nations spanning 1970–2004 that remittances did not pay to economic growth in developing nations. No obvious influence of remittances on the country's economic progress was found by Shaikh et al. (2015) in their research of 35 years of time series data (1980-214) for Pakistan. Moreover, between 1976 and 2010, Khathalan (2012) investigated the short- and long-term correlations between worker remittances and economic development in Pakistan using the ARDL and ECM methods. Worker remittances are positively correlated with both short-term and long-term economic growth, according to the data. Ali and Ismail (2024) conducted a study that utilized the ARDL bound test to analyze the consequence of remittances on Pakistan's foreign reserves. The study covered the years 1976–2022. The research shows that FDI, GDP, exports, and remittances all have a constructive and extensive effect on foreign exchange reserves. Using data from Bangladesh, Pakistan, and Sri Lanka, Nasrin Jui (2024) analyses how inflation, FDI, and remittances affect GDP. While FDI, inflation, and remittances do affect GDP in Pakistan, the study found no such relationship in Sri Lanka or Bangladesh. The literature reviewed predominantly examines the impacts of remittances on developing or developing economies, showing diverse outcomes. Studies have identified positive, negative, mixed, and neutral effects of remittances on economic development in these counties. Most research has focused on either individual countries or groups of countries outside of South Asia. This paper, however, investigates the combined influence of remittances on four emerging South Asian nations.

3. Data and Variables

This research utilizes secondary data to discover the impacts of remittances and FDI on GDP in South Asian countries. Our dependent variable is GDP, while the independent variables include remittances, FDI, and total reserves. GDP is considered a proxy for economic growth in this analysis. To achieve the study's objectives, panel data from various secondary sources spanning the period from 1980 to 2023 have been gathered. A summary of the study's variables and their sources is presented in Table 1

Table 1. Variables with source of data

Variables	Type	Explanation	Data source
GDP	Dependent Variable	GDP per capita growth	WDI, World Bank
FDI	Independent Variable	Net FDI inflows (% of GDP)	WDI, World Bank
REM	Independent Variable	Remittance inflows (% of GDP)	WDI, World Bank
TR	Independent Variable	Total Reserve (% of total External debt)	WDI, World Bank

Here, WDI = World Development Indicator; GDP =Gross Domestic Product; REM= Remittance; FDI= Foreign Direct Investment; TR= Total Reserve

Source: Author

4. Methodology and Data Analysis

4.1 Model Specification

The current research employs the ordinary least squares (OLS) method to examine the association between GDP, REM, FDI, and TR. Employing a multiple regression model based on Mankiw, Romer, and Weil's (1992) theoretical framework, the function posits that GDP in South Asian countries is influenced by remittances, FDI, and total reserves. The relationship can be expressed as:

$$DP = f(REM, FDI, TR) \quad (1)$$

Since we acquire our data at discrete intervals, we may formulate the model as follows:

$$GDP_{it} = f(REM_{it}, FDI_{it}, TR_{it}) \quad (2)$$

The logarithmic form of variables is commonly used in regression models to handle situations when there is a non-linear connection between the independent and dependent variables. When the data are transformed into logarithmic form, the model looks like this:

$$LGDP_{it} = L\alpha + \beta_1 LREM_{it} + \beta_2 LFDI_{it} + \beta_3 LTR_{it} + \varepsilon_{it} \quad (3)$$

If we assume $L\alpha = \beta_0$, the model is simplified as:

$$LGDP_{it} = \beta_0 + \beta_1 LREM_{it} + \beta_2 LFDI_{it} + \beta_3 LTR_{it} + \varepsilon_{it} \quad (4)$$

Where,

$LGDP_{it}$ = Natural logarithm of GDP at time t and country i

$LREM_{it}$ = Natural logarithm of remittance at time t and country i

$LFDI_{it}$ = Natural logarithm of FDI at time t and country i

LTR_{it} = Natural logarithm of total reserve at time t and country i

e = Base of natural log

ε_{it} = Error term

$\beta_0 =$ Intercept/ Slope coefficient

$\beta_1, \beta_2, \beta_3 =$ coefficient parameters to be estimated.

4.2 Panel Unit Root Test

In panel data, unit root tests (URT) are crucial for determining whether data series are non-stationary, which is vital for accurate econometric analysis. Non-stationary data can produce spurious regression results, leading to unreliable statistical inferences. By detecting unit roots, researchers can choose appropriate modeling techniques, such as differencing non-stationary data or applying cointegration methods for long-term relationship analysis. This approach ensures robust and valid conclusions, avoids misleading results, and enhances the reliability of forecasts and policy recommendations. To recognize the order of incorporation of the study's variables, two standard panel unit root tests, Levin, Im-Pesaran and Shin, and Lin and Chu are used. The following section discusses these tests.

4.2.1 Levin, Lin and Chu (LLC) Unit Root Test

Using a pooled regression model that incorporates lagged differences of the panel series as explanatory variables, the LLC test is applied to panel data. It examines the two hypotheses, one proposing panel stationarity and the other positing a unit root in the panel data. Should the test statistic surpass the critical threshold, we may conclude that the panel is stationary and reject the null hypothesis. Assuming cross-sectional independence and homogeneity in the autoregressive coefficient dynamics across all panel units, the LLC panel unit root test is based on the Augmented Dickey-Fuller (ADF) test. Here is the basic ADF definition that the test follows:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{i,j-1} \Delta y_{i,t-j} + e_{i,t} \tag{5}$$

Here, Δ represents the first difference operator $y_{i,t}$ (is a vector) represents the variables, α_i, β and $\gamma_{i,j}$ are the coefficient to be assessed, $e_{i,t}$ is normally distributed random variable (independently) for all i and t with finite heterogeneous variances and zero means, $e_{i,t} : IID(0, \sigma_i^2)$. p_i represents the number of lags selected for the ADF regression. Levin et al. (2002) suggests that this unit root test may not provide reliable estimates when the sample size exceeds 250 cross-sectional units.

4.2.2 Im-Pesaran and Shin (IPS) Unit Root Test

The IPS test is a widely used first-generation unit root test for panel data, renowned for its effectiveness in handling cross-sectional independence, where residuals are correlated across individuals in the panel model. It employs a pooled regression model that includes lagged differences of the panel series and lagged dependent variables as explanatory variables. The test evaluates the null hypothesis of a unit root in the panel data against the alternative hypothesis of panel stationarity. If the test statistic surpasses the critical value, the null hypothesis is rejected, indicating panel stationarity. Introduced by Im, Pesaran, and Shin (2003), this test is based on the Augmented Dickey-Fuller principle, represented by the following equation:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \sum_{j=1}^{p_i} \gamma_{i,j-1} \Delta y_{i,t-j} + e_{i,t} \tag{6}$$

Here, $y_{i,t} (i = 1,2,..., N; t = 1,2,..., T)$ represents the time series for country i across the period *t*; β_i denotes the number of lags included in the ADF regression, and $e_{i,t}$ indicates that the error terms are serially correlated. The hypotheses for the IPS test are outlined as follows:

$H_0 : \beta_i = 0$ for all $i = 1,..., N$

$$H_1 : \begin{cases} \beta_{i \leq 0} \\ \beta_{i = 0} \end{cases} \quad \text{for } i = 1,..., N_1 \text{ for } i = N_1 + 1, N_1 + 2,..., N$$

The IPS test-statistic is assessed by; $t_{IPS} = \frac{\sqrt{N}[\bar{t} - E(\bar{t})}{\sqrt{Var(\bar{t})}}$ (7)

The terms $Var(\bar{t})$ and $E(\bar{t})$ are produced by tabulated and simulations by IPS.

4.3 The Cointegration Test

In 1987, Engle and Granger proposed the idea of cointegration, which implies a link between two time series over the long run. A cointegration test can be used when the integration orders of the variables are same. The Johansen Fisher-type cointegration technique (1988) is used to test for long-term equilibrium connections among the variables in this study since panel data is used. In order to carry out the tests, this technique makes use of two statistics.

Trace Test Statistic: $\lambda_{trace}(r) = -T\sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i)$ (8)

Null Hypothesis: There are less than or equal to r cointegrating vectors.

Alternative Hypothesis: More than r integrands are cointegrating.

Test Statistics for Max-Eigen Value: $\lambda_{\max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{r+1})$ (9)

Null Hypothesis: Vectors that are cointegrating have a count of r.

Alternative Hypothesis: There are (r+1) cointegrating vectors.

Here, r = the number of cointegrating vectors , T = the sample size, and $\hat{\lambda}$ = assessed eigenvalue. Rejecting the null hypothesis in favor of the alternative suggests a long-run relationship between the independent and dependent variables if the estimated statistic (trace or Max-Eigen value) exceeds the critical value. When the results from the maximum eigenvalue test differ from the trace statistic, the maximum eigenvalue result is given priority.

4.4 Panel Vector Error Correction Model

VECM is an extension of the vector autoregressive (VAR) model designed for variables with consistent differences in their starting values. After confirming cointegration among the variables through a cointegration test, the VECM is employed to estimate both long-run and short-run causal relationships within the time series. The ECM model that is commonly used for cointegrated series: $\Delta y_{it} = \beta_0 + \sum_{i=1}^{n} \beta_i \Delta y_{it-1} + \sum_{i=0}^{n} \delta_i \Delta x_{it-1} + \lambda ECT_{it-1} + \mu_{it}$ (10)

Where, $y_{it} = \beta_0 + \beta_1 x_{it} + \varepsilon_{it}$ (11)

(cointegrating regression for long-run) and

$$ECT_{it-1} = y_{it-1} - \beta_0 - \beta_1 x_{it-1} \quad (12)$$

(long-run model and cointegrating equation)

Reflecting the short-run dynamics of the dependent variable, the error correction term (ECT) indicates deviations from the long-run equilibrium in the previous period. As a result, the coefficient of ECT measures how soon y reaches equilibrium following a change in x, and it so characterizes the speed of adjustment. Equation (1) may be used to express the VECM model as follows:

$$\begin{aligned} \Delta LGDP_{it} &= \alpha + \beta(LGDP_{it-1} + \gamma_0 + \gamma_1 LREM_{it-1} + \gamma_2 LFDI_{it-1} + \gamma_3 LTR_{it-1}) \\ &+ \lambda \Delta LGDP_{it-1} + \sigma \Delta LREM_{it-1} + \delta \Delta LFDI_{it-1} + \varphi \Delta LTR_{it-1} + \varepsilon_{it} \end{aligned} \quad (13)$$

The error correction equation is the one above, where Δ demonstrations the fluctuations of the variables, β is the adjusted parameter.

4.5 Dumitrescu-Hurlin Causality Test

The Dumitrescu-Hurlin panel Granger causality test determines if one-time series can predict another in panel data. This method extends the traditional Granger causality test to handle panel data's complexities, which include multiple cross-sectional units observed over time. Introduced by Dumitrescu and Hurlin in 2012, the test allows for heterogeneity among individual units, meaning the causal relationship can differ across entities in the panel. The procedure involves estimating a panel regression for each variable pair and testing the null hypothesis that there is no causality from the predictor to the dependent variable in any cross-sectional unit. Rejecting the null hypothesis indicates that the predictor variable Granger causes the dependent variable in at least some panel units. A straightforward Granger (1969) test based on heterogeneous panel data sets is proposed by Dumitrescu and Hurlin (2012). Examine the linear model that follows:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{k} \gamma_{i,k} y_{i,t-1} + \sum_{k=1}^{k} \beta_{i,k} x_{i,t-1} + \varepsilon_{i,t} \tag{14}$$

where x and y are two stationary variables observed for N individual for T periods, k is the lag order and α_i is the fixed effect. In order to evaluate the homogeneous non-causality test hypothesis, Dumitrescu and Hurlin (2012) suggest taking into account both the causal links and the heterogeneity of the regression model. The following is the definition of the homogeneous non-causality test's null hypothesis: $H_0 : \beta_i = 0 \quad \forall_i = 1,..., N$ (15)

with $\beta_{i,1}..., \beta_{i,k}$. β_i may differ across the countries under the alternative hypothesis. Further, the panel granger causality test assumes that under H_a there are $N_1 < N$ individual processes with no causality from x to y. The alternative hypothesis is defined as follows:

$$H_a : \beta_i = 0 \quad \forall_i = 1,..., N \qquad \beta_i \neq 0 \quad \forall_i = N_1 + 1, N_1 + 2,..., N \tag{16}$$

where N_1 is unknown but satisfies the condition $0 \le N_1 / N < 1$. If $N_1 = N$ there is no causality for any individuals in the panel, hence the null hypothesis is not rejected and if $N_1 = 0$ there is causality for all of the individuals in the panel (Dumirescu & Hurlin, 2012). The panel statistics is the cross-sectional average of the individual Wald statistics.

4.6 Various Residual Diagnostic Tests

Tests for residuals are conducted using the following experiments: (i) Serial correlation $\rightarrow$ Breusch-Godfrey Test; (ii) Heteroscedasticity $\rightarrow$ Breusch- Pagan Test; and (iii) Normality $\rightarrow$ Jarque-Bera Test

4.6.1 Breusch-Godfrey Test

An experiment to determine serial correlation in regression model mistakes is the Breusch-Godfrey test. With the use of this test, we may simultaneously assess the correlation between an error term and many lag error terms to determine whether they are associated.
Null hypothesis: The absence of serial correlation.
Alternative Hypothesis: Serial correlation exists.
Consequently, our model exhibits serial correlation if the p-value is 0.05 or below.

4.6.2 Breusch-Pagan Test

To determine if a linear regression model has heteroscedasticity, apply the Breusch-Pagan test. It determines if the values of the independent variables have an impact on the variance of the regression errors. Heteroscedasticity is evident in the situation.
Null Hypothesis: No heteroscedasticity in the residuals.
Alternative Hypothesis: Heteroscedasticity exists in the residuals.

When the p-value of the test statistic falls below a predetermined threshold, such as p<0.05, the null hypothesis is rejected and heteroscedasticity is presumed. Converting the variables to logarithms is one way to address this problem, since it can reduce the impact of extreme data values. Using heteroscedasticity-consistent standard error estimate is an additional technique.

4.6.3 Jarque-Bera Test

A crucial presumption for many statistical tests is normality. To determine if a sample's skewness and kurtosis match those of a normal distribution, apply the Jarque-Bera test. The test statistic is always non-negative, and it suggests that the data most likely do not follow a normal distribution if it deviates considerably from zero. Reliability of residuals is assumed to be normal, Alternative hypothesis is that residuals are not regularly distributed. If the p-value is less than 0.05, it indicates that the model does not follow a normal distribution

5. Results and Discussion

5.1 Descriptive Statistics

All of the variables in Table 2 have reasonable ranges of values and small standard deviations. If the skewness coefficient for the LGDP variable is less than 1, then the distribution is severely skewed. On the other hand, LREM, LFDI, and LTR all have moderately skewed distributions, as shown by skewness coefficients ranging from -1.5763 to 0.3384. Furthermore, all variables have a leptokurtic distribution, as the kurtosis coefficients are non-zero.

Table 2. Descriptive Statistics

Measures	LGDP	LREM	LFDI	LTR
Mean	1.0959	1.3966	-0.8760	2.9409
Median	1.2029	1.5390	-0.3682	2.9174
Maximum	2.1017	2.3599	1.2868	4.9127
Minimum	-1.5141	-0.3011	-6.9078	1.1972
Std. Dev.	0.6878	0.6181	1.6737	0.8187
Skewness	-1.0748	-0.6840	-1.5763	0.3384
Kurtosis	4.0869	2.8903	4.8747	2.8395
Jarque-Bera	41.5848	13.4987	96.4187	3.4664
Probability	0.0000	0.0012	0.0000	0.1767

Source: EViews output

5.2 Results of Multicollinearity Test

A common technique for identifying multicollinearity is to look at the predictor variables' bivariate correlation. As a general rule, multicollinearity is indicated by a correlation coefficient of 0.80 or above. It appears that multicollinearity is not an issue in this model, since the correlation matrix in Table 3 reveals that there is no strong link between any two independent variables.

Table 3. Correlation Matrix

Variables	LGDP	LREM	LFDI	LTR
LGDP	1.0000			
LREM	0.2067	1.0000		
LFDI	0.3435	0.4851	1.0000	
LTR	0.5305	0.0445	0.4569	1.0000

Source: EViews output

5.3 Cross-Section Dependence Test

Firstly, it's essential to test for cross-sectional dependence in our data to ensure accurate coefficient estimates in panel data analysis (Pesaran, 2021). Identifying cross-sectional dependency is crucial for the validity of models, reliability of results, accurate statistical inference, robust policy recommendations, and meeting academic standards. This study employs the Breusch-Pagan LM test, Pesaran scaled LM test, and Pesaran CD test to detect cross-sectional dependence among variables. Table 4 shows the test results, indicating no cross-sectional dependency as the probability values exceed the 5% significance level. Consequently, a first-generation panel unit root test, which assumes cross-sectional independence, is used to verify the unit root specification of the series.

Table 4: Determination of Residual Cross-Section Dependence

Test	Statistics	d.f	Probabilities
Breusch-Pagan LM	11.39223		0.0770
Pesaran scaled LM	1.556602	6	0.1196
Pesaran CD	0.956751		0.3387

Source: EViews output

5.4 Outcomes of Panel Unit Root Test

According to Table 5, all of the variables are non-stationary at their initial level but become stationary when the first difference is taken into account. At the 5% significance level, the null hypothesis of a unit root is decisively rejected by the computed LLC and IPS test statistics at the first difference, together with their related p-values. Therefore, both the tests indicate the need for co-integration analysis to explore the long-term relationships among the variables.

Table 5: Outcomes of Panel Unit Root Test

Variable	Statistics	At level		At First Difference		Inference
		C	C and T	C	C and T	
LGDP	LLC	3.49325	0.33476	-6.09112	-6.77065	I(1)
	IPS	4.40155	0.21115	-7.58972	-9.10387	I(1)
LREM	LLC	0.87805	0.08791	-8.19150	-7.09861	I(1)
	IPS	3.67446	-0.07329	-8.78424	-7.81120	I(1)
LFDI	LLC	-2.37861	-3.35724	-9.14478	-7.68031	I(1)
	IPS	-2.17333	-3.02211	-10.1956	9.38328	I(1)
LTR	LLC	-0.68762	-0.49474	-10.5161	-9.73347	I(1)
	IPS	-0.56049	-0.71042	-10.4186	-9.60534	I(1)

Source: EViews output; **Note:** C indicates Constant, and C and T denote Constant and Trend

5.5 Johansen Fisher Type Cointegration Result

The initial step in conducting a co-integration test is to determine the optimal lag order. Several methods can be used to identify the ideal lag period for the VAR model. Table 6 shows that four out of five methods recommend a lag order of 1. Therefore, the optimal lag order for the VAR model is 1.

Table 6: Criteria for Selecting VAR Lag Orders

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-713.3523	NA	0.115940	9.196825	9.275026	9.228587
1	-232.2995	931.2689	0.000298*	3.234609*	3.625616*	3.393419*
2	-220.8640	21.55148	0.000317	3.293128	3.996941	3.578987
3	-205.4771	28.20932*	0.000319	3.300989	4.317607	3.713895
4	-199.4085	10.81450	0.000364	3.428315	4.757739	3.968269
*shows the lag order chosen according to the criteria						

Source: EViews output

Table 7 shows the trace test and Table 8 shows the maximum eigenvalue test; both tests reject the null hypothesis that no co-integration exists at the 5% significance level, and they both indicate four co-integration equations. Therefore, the independent and dependent variables are strongly related to one another over the long run.

Table 7: Rank Test (Trace) for Unrestricted Cointegration

Hypothesized No of CE(s)	Eigenvalue	Trace Statistic	Critical Value (at 0.05 level)	Probability
None *	0.174610	64.75636	47.85613	0.0006
At most 1 *	0.110182	34.81998	29.79707	0.0121
At most 2 *	0.076153	16.60882	15.49471	0.0339
At most 3 *	0.026890	4.252296	3.841465	0.0392
*Signifies that the hypothesis is rejected at the 0.05 level; a trace test uncovers many cointegrating equations.				

Source: EViews output

Table 8: Maximum Eigenvalue Unrestricted Cointegration Rank Test

Hypothesized No of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value (at 0.05 level)	Probability
None *	0.174610	29.93638	27.58434	0.0245
At most 1	0.110182	18.21116	21.13162	0.1221
At most 2	0.076153	12.35652	14.26460	0.0980
At most 3 *	0.026890	4.252296	3.841465	0.0392
*Denotes rejection of the hypothesis at the 0.05 level; a trace test reveals one or more cointegrating equations.				

Source: EViews output

Table 9: Cointegration Equation (Long-run Equation)

LGDP	LREM	LFDI	LTR
1.00000	-0.383417 (0.10573)	0.035229 (0.04467)	-0.557687 (0.07923)

Source: EViews output

5.6 Results of Panel Vector Error Correction Model

From the panel vector error correction estimates (Table 9), we derive the co-integration long-run equation:

$$ETC_{it-1} = 1.0000LGDP_{it-1} - 0.3834LREM_{it-1} + 0.0352LFDI_{it-1} - 0.5577LTR_{it-1} + 1.1258 \ldots \text{(17)}$$

Where, ECT is the error correction term. We get from equation (17),

$$LGDP_{it-1} = ECT_{it-1} + 0.3834LREM_{it-1} - 0.0352LFDI_{it-1} + 0.5577LTR_{it-1} - 1.1258 \ldots \text{(18)}$$

Equation (18) closely resembles the co-integrating equation obtained through the Johansen method (Table 9). This equation can be interpreted as follows: a one-unit increase in remittances results in a 0.3834-unit rise in GDP for South Asian countries. Conversely, a one-unit increase in FDI causes a 0.0352-unit decrease in GDP, while a one-unit increase in TR leads to a 0.5577-unit increase in GDP. The lower section of Table 10 features four columns presenting the error correction estimates for four dependent variables: D(LGDP), D(LREM), D(LFDI), and D(LTR). Our primary focus is on the variable D(LGDP). Thus, we derive the estimated VECM with D(LGDP) as the target variable:

$$\Delta LGDP_{it} = -0.7152ECT_{it-1} - 0.0297\Delta LGDP_{it-1} + 0.0210\Delta LREM_{it-1} + 0.0027\Delta LFDI_{it-1} - 0.2376\Delta LTR_{it-1} + 0.0041 \quad \text{(19)}$$

Where, ECT_{it-1} is defined in equation (17). Equation (17) provides the numerical representation of the vector error correction model described in equation (13). In terms of interpretation, a one-unit increase in GDP at lag 1 is associated with an average decrease of 0.0297 units in GDP. Additionally, the coefficient for REM at lag 1 is 0.0210, indicating that a one-unit increase in REM leads to a 0.0210-unit increase in GDP. Conversely, the coefficient for TR at lag 1 is -0.2376, suggesting that a one-unit decrease in TR results in a 0.2376-unit decrease in GDP.

Table 10 shows that the GDP error correction element has a coefficient of -0.715155, which means that annual increases in GDP correct around 71.52% of the disequilibrium. Thus, the system's stability is confirmed, since the current period adjusts the prior period's departures from long-run equilibrium at a rate of 71.52%. This period's modest adjustment speed towards equilibrium is shown by the fact that the error correction term coefficient for remittance is 0.083428, which suggests that any departure from equilibrium owing to changes in remittance is corrected at a rate of 8.34%. Equilibrium adjustment speeds for FDI are 15.34% and for TR they are 8.39%.

Table 10: Vector Error Correction Estimations

Coitegration Eq.	CointEq1			
D(GDP(-1))	1.000000			
D(REM(-1))	-0.383417			
D(FDI(-1))	0.035229			
D(TR(-1))	-0.557687			
C	1.125829			
Error Correction	D(GDP)	D(REM)	D(FDI)	D(TR)
CointEq1	- 0.715155	0.083428	0.153360	0.083921
D(GDP(-1))	- 0.029688	- 0.060484	0.064215	0.014200
D(REM(-1))	0.020979	0.067876	- 0.273678	0.250016
D(FDI(-1))	0.002729	0.028033	- 0.177699	0.016751
D(TR(-1))	- 0.237560	0.051493	0.405239	-0.060557

Source: EViews output

5.7 Long-run Causality

In Table 10, C(1) represents the error correction term, which indicates the speed at which the model returns to long-run equilibrium. For C(1) to be economically significant, it must be negative and statistically significant. A negative value means that any deviation in one direction will be corrected in the opposite direction, maintaining equilibrium. Conversely, a positive error correction coefficient suggests that the model fails to converge to long-run equilibrium, potentially indicating instabilities, specification issues, or data problems. In our model, C(1) is -0.715155 with a p-value of 0.0000, indicating that it is both negative and statistically significant. This demonstrates a long-run causality from the independent variables to the dependent variable, GDP. The value of C(1) also shows that about 71.52% of the disequilibrium is corrected annually through changes in GDP, meaning that the previous period's deviation from long-run equilibrium is adjusted in the current period at an adjustment speed of 71.52%. This confirms the stability of our system and demonstrates that the model effectively converges towards equilibrium.

Table 11: Results of Ordinary Least Square Estimates

	Coefficient		Std. Error	t-statistic	Prob.
ECT	C(1)	-0.715155	0.096230	-7.431471	0.0000
D(LGDP(-1))	C(2)	0.389291	0.062198	6.258938	0.0000
D(LREM(-1))	C(3)	-0.158532	0.042388	-3.740051	0.0003
D(LFDI(-1))	C(4)	0.739121	0.111991	6.599804	0.0000
D(LTR(-1))	C(5)	-0.526751	0.410634	-1.282773	0.2013
R^2		0.598210	Akaike info criterion		2.449423
Adjusted R^2		0.591035	Schwarz criterion		2.522620
F-statistic		83.37622	Hannan-Quinn criterion		2.479121
Prob.(F-statistic)		0.000000	Durbin-Watson stat		0.184260

Source: EViews output

5.8 Short-run Causality

In Table 11, the coefficients C(3), C(4), and C(5) represent the short-run impacts of LREM, LFDI, and LTR, respectively. To determine if LREM, LFDI, and LTR exhibit short-run causality with LGDP, it is necessary to perform the Wald test on these coefficients.

Table 12 shows that the p-value of the chi-square test for the null hypothesis C(3) = 0 is 0.0000, and for C(4) = 0 is 0.0002, both of which are less than 5%. Thus, we reject the null hypothesis, indicating short-run causality from remittances to LGDP and from LFDI to LGDP. In other words, LREM and LFDI significantly explain short-run changes in LGDP. Conversely, the Wald test result shows that the p-value of the chi-square test for the null hypothesis C(5) = 0 is 0.1996, which is greater than 5%. Therefore, we fail to reject the null hypothesis, indicating no short-run causality from total reserves to LGDP.

Table 12: Wald Test Results

Null Hypothesis	Test Statistic	Value	Probability	Inference
C(3) = 0	t-statistic	6.258938	0.0000	Rejected
	F-statistic	39.17430	0.0000	
	Chi-square	39.17430	0.0000	
C(4) = 0	t-statistic	-3.740051	0.0003	Rejected
	F-statistic	13.98798	0.0003	
	Chi-square	13.98798	0.0002	
C(5) = 0	t-statistic	-1.282773	0.2013	Accepted
	F-statistic	1.645507	0.2013	
	Chi-square	1.645507	0.1996	

Source: EViews output

5.9: Outcomes of Residual Diagnostic Tests

The chi-square produced a p-value of 0.1311, as shown in Table 13, which is greater than the 5% criterion. Consequently, the null hypothesis, which indicates that the model does not include serial correlation, cannot be rejected.

Table 13: Results of Breusch-Godfrey Serial Correlation LM Test

F-statistic	1.641312	Prob. F(10,158)	0.0995
Obs* R-squared	16.18604	Prob. Chi-Square(9)	0.0944

Source: EViews output

Table 14: Results of Breusch-Pagan-Godfrey Heteroscedasticity Test

F-statistic	1.894879	Prob. F(3,168)	0.1324
Obs*R^2	5.629500	Prob.Chi-Square(1)	0.1311

Source: EViews output

From Table 14, we observe that the chi-square p-value is 0.0995, which exceeds 5%. Consequently, we are unable to reject the null hypothesis, indicating that the model does not exhibit heteroscedasticity.

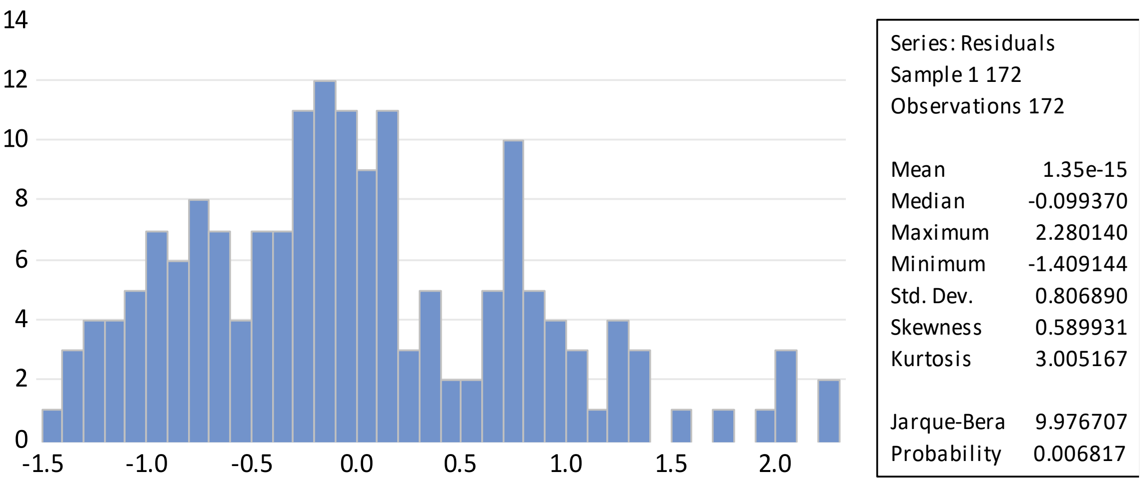

Figure 1: Result of Jarque-Bera Normality Test

The Jarque-Bera test's p-value, which is less than 5%, is shown in Figure 1. Thus, the null hypothesis may be rejected, indicating that the residuals in this model do not follow a normal distribution. Since properly distributed residuals are uncommon in panel data, this result is predicted. The purpose of the diagnostic tests is to assess the model's goodness-of-fit. The model is not normally distributed, but the data imply that there is no serial correlation or heteroscedasticity in it. Furthermore, the F-statistic value of 0.00000 is less than 5%, indicating that the model is doing well. As a result, we may say that there is a reasonably good match for the model.

5.10 Results of Granger Causality Test

In a VEC model, causality can arise from two sources: the error correction term, indicating long-term causality, and the lagged explanatory variables, which show short-run causality. If the series are not cointegrated, short-run relationships are examined using the Granger causality test within a VAR model. For panel data series, the Dumitrescu-Hurlin causality test is commonly used. Therefore, we perform the Dumitrescu-Hurlin Granger causality test (Table 15) to determine whether each independent variable affects the dependent variable or vice versa.

Table 15: Results of Pairwise Dumitrescu Hurlin Causality Tests

Null Hypothesis	W-Stat	Zbar-Stat	Prob.	Inference
LREM does not homogeneously cause LGDP	6.04964	3.46970	0.0005**	Rejected
LGDP does not homogeneously cause LFDI	4.95361	2.50072	0.0124***	Rejected
LGDP does not homogeneously cause LREM	1.47791	-0.57208	0.5673	Accepted
LFDI does not homogeneously cause LGDP	5.00565	2.54673	0.0109***	Rejected
LTR does not homogeneously cause LGDP	8.71176	5.82323	6.E-09	Accepted
LGDP does not homogeneously cause LTR	0.89960	-1.08335	0.2787	Accepted

Source: EViews output. **Note**: ***, **, * denote correspondingly 1%, 5% and 10% level of significance.

Table 15 indicates that for LREM and LGDP, we can reject the null hypothesis that LGDP does not Granger cause changes in LREM, as the p-value is below 0.05. This result indicates a unidirectional short-run Granger causality from remittance to LGDP. Conversely, LFDI shows a bidirectional short-run Granger causality with both LGDP and LREM, meaning each variable influences the other. However, for the remaining variables, the null hypothesis is accepted, indicating no short-run causality with LGDP. Therefore, these variables are independent of LGDP and vice versa.

Conclusion

Using panel data spanning 1980–2022, our study seeks to observe the influence of remittances, FDI, and total reserves on GDP in South Asian nations. An assortment of econometric methods is utilized for estimate, such as the following: the cross-sectional dependency test, the LLC and IPS unit root tests, the Johansen Fisher type cointegration test, the VECM, and the Dumitrescu-Hurlin causality tests. A number of diagnostic tests are also used to evaluate the goodness-of-fit of the model. The empirical results show that South Asian nations' GDP is boosted in the long term by remittances and total reserves, which contribute to GDP growth. FDI has a negative correlation with GDP that is statistically significant over the long and short term. FDI has a bidirectional short-run Granger causation with GDP, but remittances have a unidirectional short-run Granger causality towards GDP, according to the study. Granger causation between total reserves and GDP does not exist, though. Our findings align with those of other researchers who have demonstrated a positive association between remittances and GDP growth, including Ramirez and Sharma (2008), Pradhan et al. (2009), Cooray (2012), Fayissa and Nsiah (2010), Azam (2015), Meyer and Shera (2017), and Chand and Singh (2024). However, our results differ from those of Sutradhar (2020) and Chami et al. (2005), who reached different conclusions. Policymakers in South Asia should take note of the study's conclusions. To facilitate more remittances for economic growth, governments in these nations should center their attention on migration policy and implement appropriate reforms. In conclusion, like other prior studies, this research has certain limits that provide guidelines for future work. First, it focuses on a panel data analysis specific to the South Asian economy. Second, it does not fully explore the impact of workers' remittances on macroeconomic variables in this region. Additionally, due to the limited data available, we could not perform a threshold analysis to investigate the relationships between remittances and other macroeconomic variables. Despite these constraints, the study's findings pave the way for future research opportunities, including examining how remittances impact macroeconomic indicators across various countries and exploring how different types of remittances and financial development influence these indicators.

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