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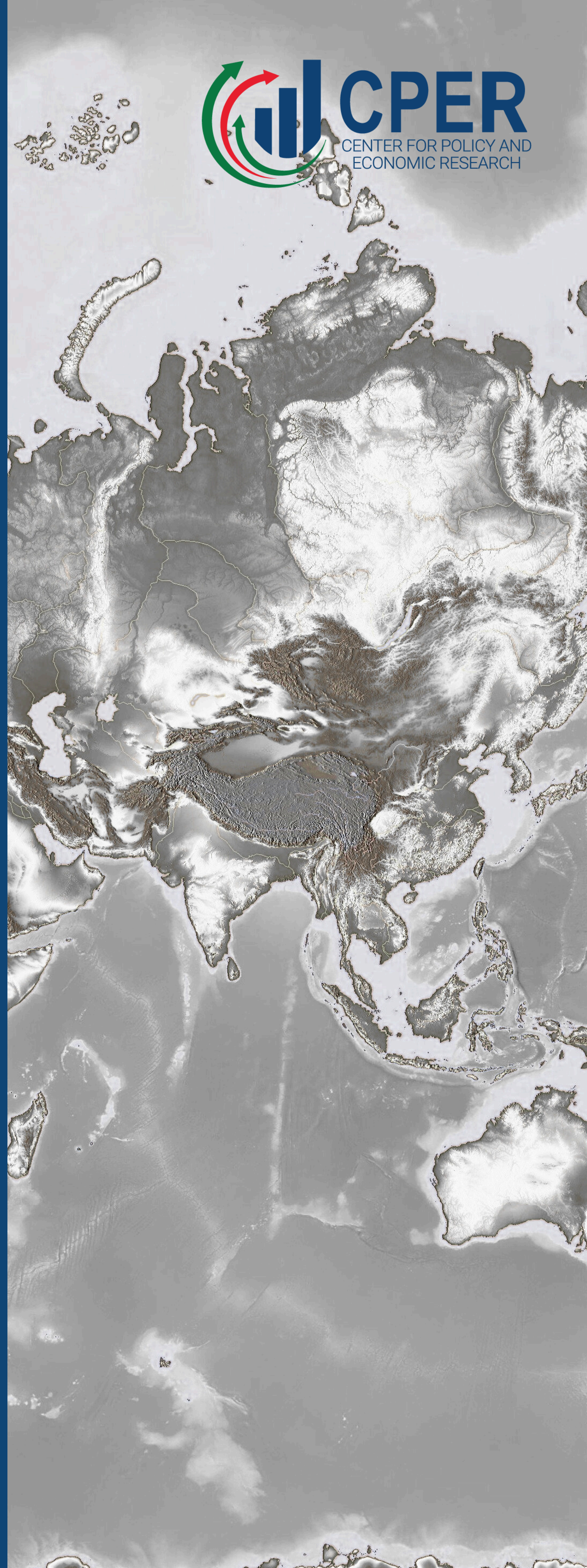

Nexus Between Exports, Remittances, FDI, and Economic Growth in Bangladesh

A Structural Break ARDL Bounds Test Approach

Al Mamun

Center for Policy and Economic Research (CPER)

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Abstract

This study examines the dynamic relationship between exports, remittances, foreign direct investment (FDI), and economic growth in Bangladesh from 1976 to 2019, incorporating structural breaks into the empirical framework. Applying the Autoregressive Distributed Lag (ARDL) bounds testing approach, along with structural break dummies and interaction terms, the analysis identifies a stable long-run cointegrating relationship among the variables. The results demonstrate that both exports and remittances have a significant and positive impact on economic growth, highlighting their central role in sustaining Bangladesh's development trajectory. By contrast, FDI is found to have a negative association with growth, reflecting persistent structural and institutional constraints that have limited its effectiveness as a driver of growth. The inclusion of a structural break around 2010 captures shifts in the growth process, underscoring the importance of policy reforms and external shocks in shaping macroeconomic outcomes. The findings suggest that Bangladesh's long-term growth prospects depend on export diversification, productive utilization of remittances, and targeted reforms to attract efficiency-enhancing FDI. These results carry important policy implications as the country navigates post-COVID-19 recovery and external uncertainties such as the Russia–Ukraine war, and seeks to consolidate its transition toward sustainable, export-led economic growth.

Keywords: Economic growth, Exports, Remittances, FDI, Structural break, ARDL

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1. Introduction

Since its independence, Bangladesh has made sustained efforts to achieve long-term economic growth, a goal shared by many developing economies. These efforts have enabled the country to attain lower-middle-income status in 2015 and place it on track to graduate from the United Nations' Least Developed Countries (LDC) list by 2026, accompanied by notable growth and poverty reduction (World Bank, 2021). Nonetheless, in an era marked by both globalization and rising anti-globalization tendencies, identifying the key determinants of economic growth has become increasingly complex. As emphasized in the economic literature, growth is shaped by multiple interrelated factors. Domestic determinants—such as human capital, savings, democracy, political stability, governance quality, and sound macroeconomic policies—are critical for sustaining growth (Mamun & Arfanuzzaman, 2020; Narayan & Smyth, 2005; Roubini & Wachtel, 1999). Similarly, external drivers—including workers' remittances and foreign direct investment (FDI)—alongside internal factors such as exports, are equally vital for the economic progress of developing countries (Almfraji & Almsafir, 2014; Azman-Saini et al., 2010; Chen & Jayaraman, 2016). Ultimately, sustainable economic growth is instrumental in reducing unemployment, expanding access to quality education and health services, and improving living standards. Moreover, economic growth fosters human development, which remains the overarching goal of economic activity worldwide (Nourzad & Powell, 2003).

This study examines the influence of both internal and external factors on Bangladesh's economic growth. Specifically, it offers an empirical examination of the effects of personal remittances, FDI, and exports on GDP, thereby contributing to and extending the existing body of literature. For this purpose, annual data covering the period 1976–2019 are analyzed using the Autoregressive Distributed Lag (ARDL) approach, a widely applied econometric technique suitable for time-series analysis with mixed orders of integration.

Remittances have been a critical external resource for Bangladesh since the 1980s. The country is currently the sixth-largest source of migrant workers globally, with an estimated 7.8 million citizens working abroad (UNDESA, 2019). Remittance inflows reached $18.21 billion (6.6% of GDP) in FY2020, rising further to $24.78 billion in FY2021, despite the challenges posed by the COVID-19 pandemic (Bangladesh Bank, 2021). By contrast, FDI inflows have remained relatively weak. According to UNCTAD (2021), FDI declined from $3.6 billion in 2018 to $2.9 billion in 2019, followed by a further 11% fall to $2.6 billion in 2020. This decline reflects both the global investment slowdown triggered by the COVID-19 crisis and the recent Russia-Ukraine conflict, as well as structural domestic constraints, including inadequate infrastructure, unreliable energy supplies, bureaucratic inefficiencies, corruption, and political uncertainties. These issues are reflected in Bangladesh's poor performance in the World Bank's Ease of Doing Business Index, where the country ranked 168th out of 190 economies in 2020, placing it ahead of only Afghanistan in South Asia (World Bank, 2020).

Exports, particularly in the ready-made garment (RMG) sector, have been another primary growth driver. Since 2001, Bangladesh has experienced an average annual growth rate of approximately 11% in exports, primarily driven by the expansion of RMG production. In FY2019, export earnings totaled $41.32 billion, but then fell by 10.6% to $36.92 billion in FY2020, as global trade contracted amid the pandemic (Bangladesh Bank, 2021). Nevertheless, the World Bank projected that continued export performance, alongside robust domestic consumption, would help Bangladesh sustain a GDP growth rate of 6.4% in FY2021–22 (World Bank, 2021). Despite the increase in exports in recent years, there is a high likelihood that Bangladesh's export prospects could be affected due to the Russia-Ukraine war.

Given these dynamics, it is essential to examine the long-run relationships between remittances, FDI, exports, and economic growth, considering the impact of the COVID-19 pandemic and the Russia-Ukraine war. Such an analysis can provide policymakers in Bangladesh and other developing economies with valuable insights, enabling them to formulate targeted strategies that balance internal and external growth determinants to achieve sustainable development. However, considering all the issues, this article's core objective was to scrutinize the effects of external factors (remittances and FDI) and internal factors (exports) on economic growth.

The remainder of this study is structured as follows. Section 2 reviews the relevant literature. Section 3 outlines the methodological framework. Section 4 describes the data and methodology. Section 5 presents the empirical results and discussion. Finally, Section 6 concludes with a discussion of policy implications.

2. Literature Review

The existing literature has extensively examined the impact of external (remittances and foreign direct investment) and internal (exports) determinants on economic growth. Scholars have applied diverse econometric techniques and variable combinations, producing mixed evidence regarding their effects.

For instance, using annual data from 1976 to 2005, Ahmed and Uddin (2009)employed a Vector Error Correction Mechanism (VECM) to analyze the causal nexus among exports, imports, remittances, and GDP growth in Bangladesh. Their findings suggest that exports, imports, and remittances have no significant long-term influence on GDP, but instead exert short-term effects. Similarly, Zobair and Uddin (2019), applying the ARDL approach with data spanning 1976–2017, identified FDI as a key external determinant of growth, while foreign aid and remittances appeared to have adverse effects. They recommended policy reforms to create a more investment-friendly environment, ensure effective use of foreign aid, and channel remittances toward capital formation. Hussain and Haque (2016), using a VECM and data from 1973 to 2014, reported that trade and FDI have a significant impact on per capita GDP and maintain long-run relationships. Uddin and Sjö (2013) also found that remittance inflows and financial sector expansion contribute positively to long-run GDP growth, while remittances act as short-run shock absorbers.

Beyond Bangladesh, Shahid et al. (2013) and Tahir et al. (2015) demonstrated that remittances and FDI have a positive influence on Pakistan's growth, while imports have an adverse effect. A related study on Fiji, covering the period from 1980 to 2015, found that remittances and FDI promote economic growth in both the short and long term, whereas imports hurt growth. The authors suggested that governments should adopt policies to attract FDI and remittances while reducing import dependency (Makun, 2018). In the Middle East and North Africa (MENA) context, Kalai and Zghidi (2019) employed ARDL and VEC models using data from 1999 to 2012. They confirmed a long-run unidirectional relationship between FDI and economic growth, highlighting positive spillover externalities.

Several studies emphasize the strong role of remittances in Bangladesh's growth process. Islam (2020) Islam (2020) argued that rising remittances are a major driver of GDP growth. Using annual data from 1972 to 2013, Wadood and Hossain (2015) found a significant long-run relationship between remittances and growth, a result consistent with Kumar and Stauvermann (2014), who applied the ARDL approach to data from 1979 to 2012.

By contrast, the evidence on FDI is less consistent. Ali, Rukunujjaman, and Alam (2015) observed no robust link between FDI and growth, attributing this to Bangladesh's unfavorable investment climate. Khatun and Ahamad (2015), however, reported positive short-run causal relationships from FDI to energy use and growth, with long-run causalities in the energy equation. Rahman (2015) instead identified a negative correlation between FDI and growth, underscoring the mixed nature of the evidence.

Regarding exports, Islam and Hossain (2015) utilized time-series data from 1971 to 2011 and found that exports have a significant influence on growth in both the short and long run. Mamun and Nath (2005) analyzed quarterly data from 1976 to 2003 and reported cointegration between industrial production and exports, with long-run causality running from exports to GDP. Earlier, Begum and Shamsuddin (1998) employed a two-sector growth model and annual data (1961–1992) to conclude that export growth significantly enhances GDP by increasing total factor productivity. Their findings also revealed that investment shares in GDP boost growth in stable periods but have negligible effects during times of conflict or instability. Similarly, Hossain and Dias Karunaratne (2004) identified significant positive effects of total and manufacturing exports on growth in both the short and long run using VECM and quarterly data (1974–1999).

Overall, the empirical evidence is inconclusive. While some studies report that exports, remittances, and FDI have a positive influence on economic growth, others suggest that these relationships are either negative or insignificant. Moreover, earlier studies may not fully capture Bangladesh's current economic dynamics. This inconsistency underscores the need for further empirical investigation into the long-term and short-term effects of internal and external determinants on Bangladesh's economic growth.

3. Methodological Framework

Following the review of existing studies, it is evident that the multivariate analysis of time-series data requires several sequential steps. This study adopts the following procedure: (i) identification of structural breaks in the data; (ii) selection of optimal lag length; (iii) determination of stationarity; (iv) selection of appropriate econometric methods for time-series analysis; (v) testing for cointegration; and (vi) conducting diagnostic checks to ensure robustness of the estimated model.

3.1 Structural Break in Time Series

A structural break refers to a sudden shift in an economic time series caused by regime changes, policy interventions, or external shocks (Shrestha & Bhatta, 2018). Such breaks may occur in the intercept, the trend, or both simultaneously. Structural breaks complicate conventional unit root testing, since standard procedures may incorrectly classify a stationary series as non-stationary (Perron, 1989). To address this issue, Perron (1989) proposed a modified unit root test that incorporates a known structural break in the time series.

Subsequently, several advanced methods have been developed that enable the detection of single or multiple unknown breakpoints. In this context, Gregory and Hansen (1996) introduced a cointegration framework with regime shifts, offering three distinct models:

a. Level Shift (Break in the Constant): A change occurs in the intercept while slope coefficients remain constant. The equilibrium shifts in parallel form:

$$Y_t = \alpha_1 + \alpha_2 \Upsilon_{t\sigma} + \beta^T X_t \tag{1}$$

where Y_t is the dependent variable, and X_t is the vector of regressors, t the time index, σ the break date, and $\Upsilon_{t\sigma}$ a dummy variable ($\Upsilon_{t\sigma} = 0\ if\ t \leq \sigma\ and\ \Upsilon_{t\sigma} = 1\ if\ t > \sigma$). Here, α_1 represents the intercept before the break, while α_2 captures the shift at the break.

b. Level Shift with Trend (Break in Constant and Trend): Gregory and Hansen extended the model by adding a deterministic time trend:

$$Y_t = \alpha_1 + \alpha_2 \Upsilon_{t\sigma} + \mu t \ + \beta^T X_t \tag{2}$$

c. Regime Shift (Break in Constant and Slope): In this specification, both the intercept and slope coefficients are subject to change, allowing the equilibrium relation to rotate as well as shift:

$$Y_t = \alpha_1 + \alpha_2 \Upsilon_{t\sigma} + \beta_1^T \beta^T X_t + \ \beta_2^T \beta^T X_t \Upsilon_{t\sigma} \tag{3}$$

where β_1 denotes slope coefficients prior to the regime shift, and β_2 represents changes in the slope coefficients after the shift.

3.2 Lag Length Selection

Following the detection of a structural break, the next step is to determine the lag length. Selecting an appropriate lag order is crucial: too few lags may omit relevant dynamics, whereas too many can inflate estimation errors and reduce efficiency.

Several criteria have been developed for lag selection, with the most widely used being Schwarz's Bayesian Information Criterion (SBIC), Akaike's Information Criterion (AIC), and the Hannan–Quinn Information Criterion (HQIC). These criteria strike a balance between model fit and parsimony. As noted in Lütkepohl (2013), their general forms are:

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2\mathrm{t}_p}{T} \tag{4}$$

$$SBIC = -2\left(\frac{LL}{T}\right) + \frac{\ln(T)}{T}\mathrm{t}_p \tag{5}$$

$$HQIC = -2\left(\frac{LL}{T}\right) + \frac{2ln\{\ln(T)\}}{T}\ \mathrm{t}_p \tag{6}$$

where T is the number of observations, LL is the log-likelihood value, and t_p is the number of estimated parameters.

The log-likelihood function can be expressed as: $LL = -\left(\frac{LL}{T}\right)\left\{\ln\left(\left|\hat{\Sigma}\right|\right) + K\ln(2\pi) + K\right\}$, where K is the number of equations, and $\left|\hat{\Sigma}\right|$ is the maximum likelihood estimate of the residual covariance matrix.

Since the constant term does not affect inference, Lütkepohl (2013) recommends dropping it, yielding the following adjusted forms:

$$AIC = \ln(|\textstyle\sum_u|) + \frac{2pK^2}{T} \tag{7}$$

$$SBIC = \ln(|\textstyle\sum_u|) + \frac{\ln(T)}{T}pK^2 \tag{8}$$

$$HQIC = \ln(|\textstyle\sum_u|) + \frac{2ln\{\ln(T)\}}{T}\ pK^2 \tag{9}$$

where $\sum_u$ denotes the estimated residual covariance matrix and p the lag order.

3.3 Determining Stationarity in Time Series

Following the identification of structural breaks and the selection of optimal lag lengths, the next critical step in time series econometrics is to assess the stationarity of the variables. Stationarity implies that a series exhibits a constant mean and variance over time, and its autocovariance depends only on the lag between observations, not on the specific point in time. Non-stationary series, by contrast, often display trends, seasonality, or stochastic drift, which may lead to spurious regression results if not adequately addressed.

In applied macroeconomics, ensuring stationarity is essential because most econometric models (such as OLS, VAR, or ARDL) require the underlying variables to be either stationary or cointegrated. If a variable is found to be non-stationary, it must be differenced or otherwise transformed before estimation.

Stationarity can be examined using both graphical and statistical techniques. Initially, plotting the series over time can provide a visual indication of whether the mean and variance appear to be constant. However, graphical inspection is subjective and insufficient for inference. Therefore, formal unit root tests are employed to determine whether a time series is statistically stationary.

3.3.1 Unit Root Test Methods

Unit root tests are designed to assess whether a series possesses a unit root, i.e., whether it is non-stationary. Several tests have been developed in the literature, among which the most widely used are:

- The Augmented Dickey–Fuller (ADF) test
- The Phillips–Perron (PP) test

- The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

These tests differ in their assumptions regarding the error term, trend components, and null hypotheses.

3.3.1.1 Augmented Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test is a widely used extension of the Dickey–Fuller test that accounts for higher-order serial correlation by including lagged differences of the dependent variable. The ADF regression model is typically specified as:

$$\Delta y = \mu + \sigma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} \tag{10}$$

where:

- $\Delta y_t = y_t - y_{t-1}$ denotes the first difference of the series,
- μ is a constant (drift term),
- $\sigma = \alpha - 1$, with α being the coefficient on y_{t-1},
- k is the number of lagged differences included to ensure white-noise residuals, and

The null hypothesis of the ADF test is that the series has a unit root $(\sigma = 0)$, implying non-stationarity. Rejection of the null indicates stationarity.

3.3.1.2 Phillips-Perron Test

The Phillips–Perron (PP) test is an alternative non-parametric test for unit roots that corrects for serial correlation and heteroskedasticity in the error term without requiring the addition of lagged difference terms. The general form of the PP regression is:

$$\Delta y = \sigma y_{t-1} + \beta_i R_{t-i} \tag{11}$$

where R_{t-i} represents deterministic trend components, such as a constant or linear trend, the PP test has the same null hypothesis as the ADF test (presence of a unit root). However, it uses a different method to compute the test statistic, relying on robust estimators of the variance.

3.3.1.3 Kwiatkowski-Phillips-Schmidt-Shin Test for Stationarity

While both the ADF and PP tests assume non-stationarity as the null hypothesis, the KPSS test reverses this logic, taking stationarity as the null and unit root (non-stationarity) as the alternative (Kwiatkowski et al., 1992). This test is often used in conjunction with ADF or PP to strengthen inference.

The KPSS model can be represented as:

$$Y_t = X_t \tag{12}$$

where, $X_t = X_{t-1}$.

The test statistic is derived from a Lagrange Multiplier (LM) principle and requires estimation of the long-run variance of the residuals. The long-run variance is typically computed using either the Bartlett kernel (as in the original KPSS paper) or the Quadratic Spectral kernel, which has been shown by Andrews (1991) and Newey and West (1994) to yield more accurate estimates in finite samples.

3.4 Methods for Time Series Analysis

Selecting an appropriate econometric methodology for time series data is essential, as model misspecification or the use of an unsuitable technique can yield biased and unreliable estimates. Method selection generally begins with unit root testing, which establishes whether variables are stationary. Models designed for stationary series cannot be applied to non-stationary series without risking spurious regression results.

If all variables are stationary, methods such as Ordinary Least Squares (OLS) or Vector Autoregression (VAR) can provide consistent and efficient estimates. Conversely, if all variables are non-stationary and integrated of the same order, cointegration techniques such as the Johansen test or the Autoregressive Distributed Lag (ARDL) model are more appropriate. In cases where variables are integrated of mixed order, i.e., a combination of I(0) and I(1), the ARDL approach provides the most suitable framework (Shrestha & Bhatta, 2018). It is worth noting, however, that this classification represents the basic model selection criteria, and additional econometric considerations often guide the final choice of methodology.

3.4.1 ARDL Models

OLS, VAR, and Johansen cointegration methods are not suitable when variables have mixed integration orders. In the context of Bangladesh, where macroeconomic variables (e.g., exports, remittances, FDI, and GDP growth) rarely exhibit uniform integration, the Autoregressive Distributed Lag (ARDL) model emerges as the most appropriate choice (Zobair & Uddin, 2019).

The ARDL approach, initially developed by Pesaran and Shin (1995) and further advanced by Pesaran (1999), is based on OLS estimation and applies to series that are either stationary, non-stationary, or of mixed order of integration (I(0) and I(1)). The ARDL framework incorporates sufficient lags to capture the data-generating process within a dynamic specification, thereby reducing omitted variable bias and improving robustness.

A key advantage of the ARDL approach is that a dynamic Error Correction Model (ECM) can be derived through a linear transformation. The ECM formulation integrates short-run dynamics with long-run equilibrium relationships without losing information on long-run behavior. Importantly, it mitigates issues such as spurious regression that typically arise from non-stationary data.

The general ARDL specification can be expressed as:

$$y_t = \alpha + \beta x_t + \gamma z_t \tag{13}$$

The error correction representation of the ARDL model is given as:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + \sum_{i=1}^{p} \gamma_i \Delta x_{t-i} + \sum_{i=1}^{p} \delta_i \Delta z_{t-i} + \theta_1 y_{t-1} + \theta_2 x_{t-1} + \theta_3 z_{t-1} \tag{14}$$

The first part of the equation with β, γ, and δ represents the short-run dynamics of the model, and the second part with θs represents the long-run relationship. The null hypothesis of the equation is $\theta_1 + \theta_2 + \theta_3 = 0$, which indicates the non-existence of a long-run relationship.

3.5 Diagnostic Tests of the Time Series Model

Every time-series analysis must assess the model's adequacy through goodness-of-fit statistics and a series of diagnostic tests. These procedures ensure that the estimated model is econometrically valid, robust, and unbiased.

3.5.1 Goodness of Fit

The first indication of model robustness comes from assessing how well the regression line fits the data, whether residuals exhibit serial correlation, and whether the overall model is statistically significant.

The coefficient of determination (R^2) provides a measure of explanatory power but can be upwardly biased as the number of regressors increases. Hence, the adjusted R^2, which accounts for degrees of freedom, is a more reliable indicator. Nonetheless, extremely high or low R^2 values may signal specification issues: a very high R^2 may indicate overfitting, while a low R^2 can still yield meaningful results if supported by valid diagnostic tests.

The F-statistic tests the joint significance of the regressors. A p-value close to zero suggests that the model is well-specified, while a higher p-value raises concerns about its validity.

The Durbin–Watson (DW) statistic assesses first-order autocorrelation in residuals. A DW value close to two implies the absence of serial correlation. However, in models including lagged dependent variables, the DW statistic is not an appropriate diagnostic, and alternative tests such as the Breusch–Godfrey LM test should be applied.

3.5.2 Diagnostics Tests

Diagnostic testing depends on the chosen econometric specification but generally covers four critical dimensions:

1. **Lag Structure:** Appropriate lag length is verified using lag length criteria and autoregressive (AR) root tests to ensure model stability.
2. **Coefficient Diagnostics:** Techniques such as Variance Inflation Factors (VIF) detect multicollinearity, while Wald tests evaluate the joint significance of parameters.
3. **Residual Diagnostics:** This is the most crucial component, as valid inference requires residuals to be independently and identically distributed (i.i.d.), resembling white noise. Standard tests include the Lagrange Multiplier (LM) test for serial correlation, correlogram analysis, and heteroskedasticity tests (e.g., Breusch–Pagan or White tests).
4. **Stability Diagnostics:** Stability of estimated coefficients across sub-samples is typically assessed using CUSUM and CUSUMSQ tests, ensuring that model parameters remain stable over time.

4. Data and Methodology

4.1 Data and Variables

This study utilizes 44 annual observations spanning the period from 1976 to 2019, subject to data availability. The data were obtained from the World Bank's World Development Indicators (WDI) database (https://data.worldbank.org/country/BD). The variables of interest include Gross Domestic Product (GDP), Personal Remittances, Foreign Direct Investment (FDI), and Exports, which are used to examine the influence of internal and external determinants on Bangladesh's economic growth.

Table 1 reports the descriptive statistics of the selected variables. Over the sample period, the average GDP at current prices amounted to $75.1 billion. The mean inflow of personal remittances was approximately $4.77 billion, which is more than 155% higher than the average FDI inflow, yet around 79% lower than average export earnings. Thus, exports appear to be the most substantial contributor among the selected determinants of economic growth in Bangladesh.

The average value of exports stood at $11 billion, which was approximately 79% higher than remittances and more than 179% higher than FDI inflows. In contrast, FDI registered the lowest average inflow, at approximately $600 million, which is significantly lower than both remittances and exports.

For consistency and to facilitate econometric estimation, all variables were transformed into their natural logarithmic (log) form. This transformation reduces heteroskedasticity, allows interpretation of estimated coefficients as elasticities, and makes the time series more suitable for cointegration analysis. Graphical plots of the data series are presented in Figure 1, which illustrate the upward trend in all variables across the study period.

Table 1. Summary Statistics

Variable	Observation	Mean	SD
GDP	44	75,100,000,000	74,900,000,000
Remittances	44	4,770,000,000	5,700,000,000
FDI	44	600,000,000	884,000,000
Export	44	11,000,000,000	13,200,000,000

Figure 1 illustrates the time-series plots of the variables in both their raw and logarithmic forms. All variables exhibit an upward trend, reflecting the overall expansion of the Bangladeshi economy during the sample period. In particular, Figure 1a (GDP) provides the most unambiguous indication of structural changes, as GDP is the dependent variable in this study. A sharp and persistent increase after 2010 suggests the presence of a structural break around that period.

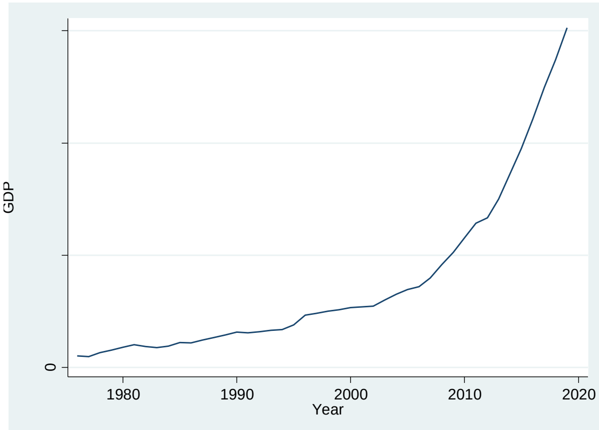

Figure 1a: GDP

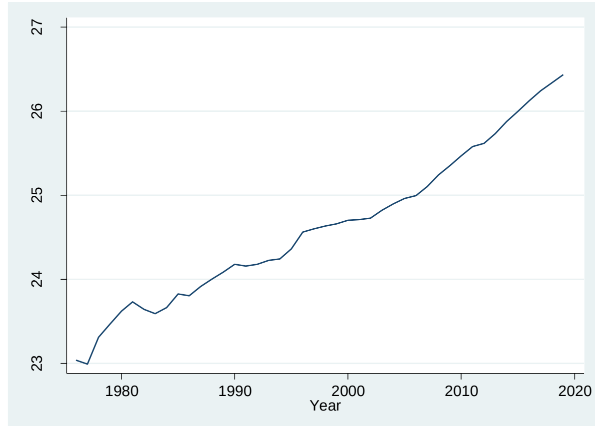

Figure 1b: ln GDP

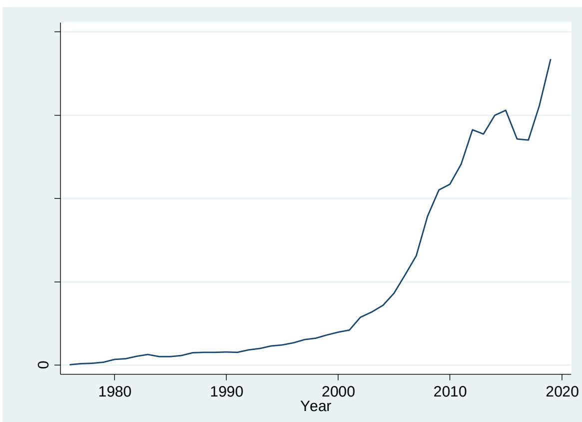

Figure 1c: Remittance

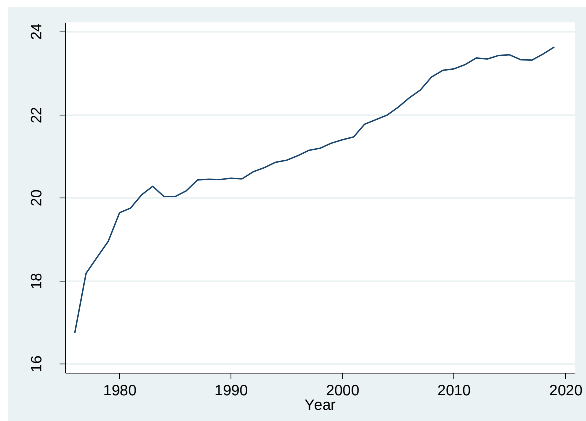

Figure 1d: ln Remittance

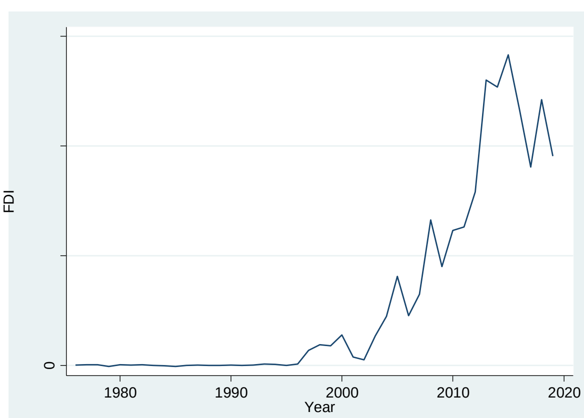

Figure 1e: FDI

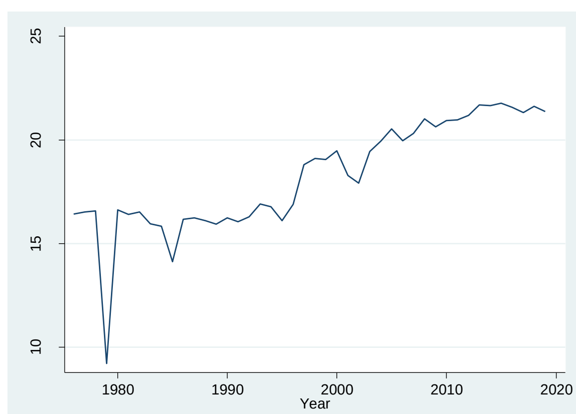

Figure 1f: ln FDI

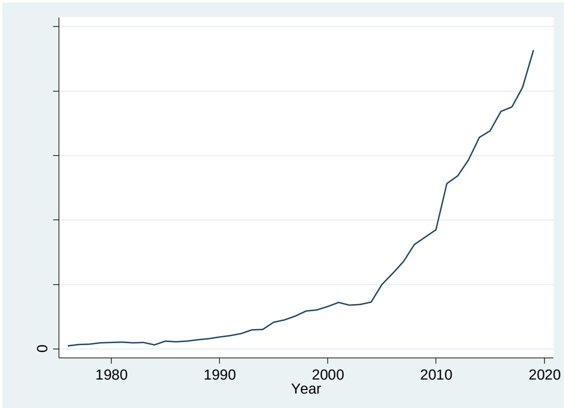

Figure 1g: Export

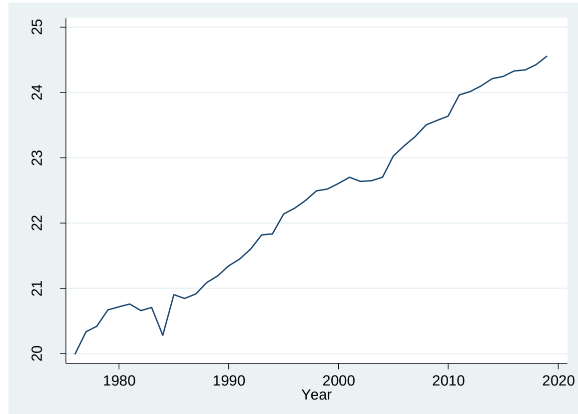

Figure 1h: ln Export

Figure 1. Graphical Plots of the Incorporated Series

Structural breaks are crucial to identify because they can distort traditional unit root tests and lead to misleading inferences regarding stationarity and cointegration. To account for this issue, the study applies Gregory and Hansen's (1996) cointegration test with regime shifts, which explicitly incorporates potential breaks in the long-run relationship. The test evaluates the null hypothesis of no cointegration at the breakpoint against the alternative hypothesis of cointegration with a structural break. Specifically, three variants of the Gregory–Hansen test are employed: (i) level shift, (ii) level shift with trend, and (iii) regime shift, allowing for different forms of structural change in the cointegrating equation.

The first specification (Table 2a), which allows for a break in the constant, shows that the Zt statistic fails to reject the null hypothesis of no cointegration, since the test statistic is less than the 1%, 5%, and 10% critical values. This outcome indicates that no cointegrating relationship exists at the breakpoint of 2012 under this model.

Similarly, the second specification (Table 2b), which allows for a break in both the constant and the deterministic trend, also fails to reject the null hypothesis. Again, the results suggest the absence of cointegration at the 2012 breakpoint.

In contrast, the third specification (Table 2c), which incorporates a regime shift (break in both the constant and slope coefficients), indicates a statistically significant rejection of the null hypothesis. Specifically, the Zt statistic exceeds the critical values at the 2010 breakpoint, implying that the variables are cointegrated in the long run but with evidence of a structural break around that year. The sharp increase in GDP after 2010 can be attributed to the robust macroeconomic policies and structural reforms implemented by the government.

Since the ADF and Za statistics fail to reject the null hypothesis of no cointegration, whereas the Zt statistic rejects it under the regime shift model, this study adopts 2010 as the year of the structural break. Accordingly, a break dummy variable (Dummy2010) was constructed, taking the value of 1 for years 2010 and later and 0 otherwise. In addition, interaction terms were generated between this dummy and the key regressors (lnRemittances, lnFDI, and lnExports) to capture the potential heterogeneous effects of the break on different explanatory variables, following the approach of Gregory and Hansen (1996).

4.2 Econometric Model

4.2.1 Model Specification

The primary objective of this study is to examine the impact of external determinants—namely, remittances and foreign direct investment (FDI)—and an internal determinant—exports—on Bangladesh's economic growth. The analysis is based on annual data spanning 1976–2019 (44 observations), constrained by data availability.

Table 2. Gregory-Hansen Test for Cointegration with Regime Shifts

Table 2a: Break in the Constant

Testing Procedure	Test Statistic	Breakpoint	Date	Asymptotic Critical Values		
				1%	5%	10%
ADF	-3.40	37	2012	-5.77	-5.28	-5.02
Zt	-5.06	37	2012	-5.77	-5.28	-5.02
Za	-32.40	37	2012	-63.64	-53.58	-48.65

Note: The level shift (break in the constant) equation, including the error term, can be written as $Y_t = \alpha_1 + \alpha_2 \Upsilon_{t\sigma} + \beta^T X_t + e_t$, using the equation (1); where Y is ln GDP, X is the ln of remittances, FDI, and export, t is time subscript ($t = 1, 2, \dots, n$), σ is the break date, and $\Upsilon_{t\sigma}$ is a dummy variable ($\Upsilon_{t\sigma} = 0 \; if \; t \le \sigma \; and \; \Upsilon_{t\sigma} = 1 \; if \; t > \sigma$). Similarly, α_1 represents the intercept before the shift, and α_2 represents the change in the intercept at the time of the shift. Finally, the slope coefficients β are held constant, and e_t is an *I*(0) process.

Table 2b: Break in the Constant and Trend

Testing Procedure	Test Statistic	Breakpoint	Date	Asymptotic Critical Values		
				1%	5%	10%
ADF	-4.47	37	2012	-6.05	-5.57	-5.33
Zt	-4.48	37	2012	-6.05	-5.57	-5.33
Za	-28.36	37	2012	-70.27	-59.76	-54.94

Note: The level shift with the trend (break in the constant and trend) equation, including the error term, can be written as $Y_t = \alpha_1 + \alpha_2 \Upsilon_{t\sigma} + \mu t + \beta^T X_t + e_t, \quad t = 1, 2, \dots, n$, using equation (2), where μt indicates a trend.

Table 2c: Break in the Constant and Slope

Testing Procedure	Test Statistic	Breakpoint	Date	Asymptotic Critical Values		
				1%	5%	10%
ADF	-4.87	27	2002	-6.51	-6.00	-5.75
Zt	-7.51	35	2010	-6.51	-6.00	-5.75
Za	-47.73	35	2010	-80.15	-68.94	-63.42

Note: The regime shift (break in the constant and slope) equation, including the error term, can be written as $Y_t = \alpha_1 + \alpha_2 \Upsilon_{t\sigma} + \beta_1^T \beta^T X_t + \beta_2^T \beta^T X_t \Upsilon_{t\sigma} + e_t, t = 1, 2, \dots, n$, using the equation (3); where α_1 and α_2 areas in the level shift model, β_1 denotes the cointegrating slope coefficients before the regime shift, and β_2 denotes the change in the slope coefficients.

Accordingly, the following econometric model is specified:

$$lnGDP_t = \alpha_0 + \beta_1 lnREM_t + \beta_2 lnEXP_t + \beta_3 lnFDI_t + \beta_4 D2010_t + \beta_5 IBDlnREM_t + \beta_6 IBDlnEXP_t + \beta_7 IBDlnFDI_t + e_t \quad (15)$$

where:

- $lnGDP_t$ = natural logarithm of real GDP, the dependent variable representing economic growth.
- $lnREM_t$ = natural logarithm of personal remittance inflows.
- $lnEXP_t$ = natural logarithm of aggregate exports.
- $lnFDI_t$ = natural logarithm of foreign direct investment inflows.
- $D2010_t$ = structural break dummy, equal to 1 for years ≥ 2010, and 0 otherwise.
- $IBDlnREM_t + IBDlnEXP_t$, and $IBDlnFDI_t$ = interaction terms between the 2010 break dummy and the respective regressors, capturing possible shifts in their long-run effects after the structural break.
- α_0 = constant term, β_i = slope parameters, and e_t = error term assumed to be independently and identically distributed.

In this specification, GDP serves as the dependent variable, while remittances, exports, FDI, the structural break dummy, and the interaction dummies act as independent variables. All monetary variables (GDP, remittances, exports, and FDI) are expressed in millions of U.S. dollars and transformed into natural logarithms to reduce heteroskedasticity and facilitate interpretation of coefficients as elasticities.

4.2.2 Estimating Methodology

Estimating an appropriate model using time series data requires careful attention, as such data often exhibit unique characteristics that must be addressed prior to analysis. Time series data frequently contain a unit root and are typically non-stationary. Therefore, it is essential to examine potential non-stationarity and determine the integration order of each series. Failing to account for issues of stationarity or unit roots can lead to spurious regression results. As Gujarati et al. (2012) emphasize, ensuring stationarity is critical to avoid inconsistencies in coefficient estimation.

When time series variables are non-stationary, the recommended approach is either to apply cointegration techniques or to transform the data by differencing according to the series' order of integration, and then use the differenced data in the analysis instead of the original series (Tahir et al., 2015). Before conducting stationarity tests, it is essential to determine an appropriate lag length, as selecting too many lags can lead to increased forecasting errors. In this study, three widely used criteria are employed to identify an optimal lag structure: Schwarz's Bayesian Information Criterion (SBIC), Akaike's Information Criterion (AIC), and the Hannan-Quinn Information Criterion (HQIC). Lütkepohl's formulations for these criteria are discussed in Section 3.

To assess potential non-stationarity, this study applies the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit-root tests. The three tests can be expressed, including the error term (e_t), as follows:

First, the Augmented Dickey-Fuller (ADF) test, rewritten using equation (10), is specified as follows:

$$\Delta y_t = \mu + \sigma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + e_t \tag{16}$$

where $\sigma = \alpha - 1$, α is the coefficient of y_{t-1}, and Δy_t represents the first difference of y_t, i.e., $y_t - y_{t-1}$.

The null hypothesis of the ADF test is $\sigma = 0$ (the series is non-stationary), whereas the alternative hypothesis is $\sigma < 0$ (the series is stationary). A rejection of the null hypothesis indicates that the series is stationary; failure to reject the null suggests non-stationarity.

Second, the Phillips-Perron (PP) test, rewritten using equation (11), is specified as follows:

$$\Delta y_t = \sigma y_{t-1} + \beta_i R_{t-i} + e_t \tag{17}$$

where e_t is an I(0) process with zero mean, and R_{t-i} represents a deterministic trend component.

The hypothesis testing procedure of the PP test is similar to that of the ADF test. The null hypothesis is $\sigma = 0$ (the series is non-stationary), while the alternative hypothesis is $\sigma < 0$ (the series is stationary). The key distinction between the ADF and PP tests lies in their treatment of serial correlation. The Phillips-Perron test is non-parametric, meaning it does not require specifying the functional form of serial correlation in Δy_t under the null hypothesis (Shrestha & Bhatta, 2018). Consequently, the computation of the t-statistic and corresponding p-values differs from the ADF test.

Moreover, the PP test modifies the test statistics to account for potential autocorrelation and heteroskedasticity in the error term. While the ADF test is generally considered more reliable than the PP test, both tests suffer from issues such as size distortion and low power, which may reduce their effectiveness in small samples (Maddala & Kim, 1999). Nonetheless, the PP test is often recommended when dealing with large datasets, particularly in the context of financial time series.

The classical unit-root testing framework may sometimes be biased toward accepting the null hypothesis of non-stationarity. To address this concern, Kwiatkowski, Phillips, Schmidt, and Shin (1992) introduced the KPSS test, which instead takes stationarity as the null hypothesis. The KPSS test is commonly applied in conjunction with the ADF and PP tests to provide a more robust inference about the time series properties. In particular, it is useful for detecting whether a series is fractionally integrated, i.e., it lies between I(0) and I(1), rather than fitting neatly into either category.

Finally, the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test, using equation (12), is specified as follows:

$$Y_t = X_t + e_t \tag{18}$$

where e_t is an error term, and $X_t = X_{t-1} + u_t$.

In the KPSS framework, the hypothesis concerns the process u_t. The null hypothesis (H_0) states that the series is stationary, whereas the alternative hypothesis (H_1) implies non-stationarity. The critical values for the KPSS test are obtained from the Lagrange Multiplier (LM) test statistic.

4.2.3 Choice of Estimation Approach

There exists a wide range of econometric techniques for analyzing time series data, including Fully Modified Ordinary Least Squares (FMOLS), Hendry's General-to-Specific (GETS) modeling approach, Johansen Maximum Likelihood (JML), the Engle-Granger (EG) test, the Johansen multivariate cointegration test, and the more recently developed Autoregressive Distributed Lag (ARDL) framework (Makun, 2018; Tahir et al., 2015).

Among these, the ARDL approach, developed by Pesaran, Shin, and Smith (2001), has gained particular popularity. The ARDL model is highly effective because it can handle variables with different integration orders (i.e., a mix of I(0) and I(1)), address potential endogeneity issues, and perform well in both small and large sample contexts (Pesaran et al., 2001; Tahir et al., 2015).

In contrast, Shrestha and Bhatta (2018) argue that if all variables are stationary, traditional methods such as Ordinary Least Squares (OLS) or Vector Autoregression (VAR) are sufficient. However, when all variables are non-stationary, the Johansen cointegration test is more appropriate. In cases where some variables are stationary while others are non-stationary, the ARDL framework provides the most suitable approach.

Accordingly, this study employs the ARDL procedure to test for cointegration and examine the long-run relationship among variables, given the possibility that the dataset comprises a combination of stationary and non-stationary series.

4.3 Cointegration Analysis (ARDL)

The Autoregressive Distributed Lag (ARDL) approach to cointegration, introduced by Pesaran, Shin, and Smith (2001), is a widely applied step-by-step procedure for testing long-run relationships among variables. The first step involves examining the existence of long-run cointegration by reformulating equation (15) into an Unrestricted Error Correction Model (UECM) within the ARDL framework as follows:

$$\begin{aligned}\Delta lnGDP_t = \alpha_0 &+ \beta_1(lnGDP)_{t-1} + \beta_2(lnREM)_{t-1} + \beta_3(lnEXP)_{t-1} + \beta_4(lnFDI)_{t-1} + \beta_5(D2010)_{t-1} \\ &+ \beta_6(IBDlnREM)_{t-1} + \beta_7(IBDlnEXP)_{t-1} + \beta_8(IBDlnFDI)_{t-1} + \sum_{i=1}^{n}\beta_9\Delta(lnGDP)_{t-1} \\ &+ \sum_{i=1}^{n}\beta_{10}\Delta(lnREM)_{t-1} + \sum_{i=11}^{n}\beta_9\Delta(lnEXP)_{t-1} + \sum_{i=1}^{n}\beta_{12}\Delta(lnFDI)_{t-1} \\ &+ \sum_{i=1}^{n}\beta_{13}\Delta(D2010)_{t-1} + \sum_{i=1}^{n}\beta_{14}\Delta(IBDlnREM)_{t-1} + \sum_{i=1}^{n}\beta_{15}\Delta(IBDlnEXP)_{t-1} \\ &+ \sum_{i=1}^{n}\beta_{16}\Delta(IBDlnFDI)_{t-1} + e_t \qquad (19)\end{aligned}$$

Here, (Δ) denotes the first-difference operator, capturing short-run dynamics, while coefficients attached to lagged levels of the variables $(\beta_1, \beta_2, \ldots, \beta_8)$ represent the long-run relationship.

The null hypothesis of no long-run relationship is:

$$H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$$

against the alternative:

$$H_1: \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq \beta_8 \neq 0$$

Rejecting the null hypothesis implies the existence of a long-run cointegrating relationship, while failure to reject suggests otherwise. The coefficients $\beta_9, \beta_{10}, \ldots, \beta_{16}$ capture the short-run dynamics of the model.

Pesaran, Shin, and Smith (2001) introduced the bounds F-test procedure, which evaluates cointegration by imposing restrictions on the long-run coefficients through a Wald test. The calculated F-statistic is then compared with two sets of critical values: a lower bound (assuming all variables are I(0)) and an upper bound (assuming all are I(1)). Three possible outcomes arise:

1. If the calculated F-statistic exceeds the upper bound, cointegration is confirmed (H_0 rejected).
2. If the F-statistic falls below the lower bound, no long-run relationship exists (H_0 accepted).
3. If the F-statistic lies between the two bounds, the result is inconclusive.

Narayan (2005) and Narayan (2017) later recalculated critical values for small samples (30–80 observations), arguing that the Pesaran et al. (2001) values were designed for large samples and may lead to misleading inferences in small datasets. Since this study employs 44 annual observations, Narayan's small-sample critical values are considered more appropriate. Nevertheless, both sets of critical values are reported to ensure robustness.

In the second step, once cointegration is established, the ARDL model is estimated to obtain both short-run and long-run coefficients. Duasa (2007) emphasizes that the ARDL method allows for flexible optimal lag selection. Long-run coefficients are derived from the unrestricted ARDL estimates by dividing the coefficient of each explanatory variable by the negative of the lagged dependent variable's coefficient (Khatun & Ahamad, 2012). For instance, the long-run coefficients of remittances, exports, foreign direct investment, and the included dummy variables are computed as:

$\left({}^{\beta_2}/_{\beta_1}\right) - 1$, $\left({}^{\beta_3}/_{\beta_1}\right) - 1$, $\left({}^{\beta_4}/_{\beta_1}\right) - 1$, $\left({}^{\beta_5}/_{\beta_1}\right) - 1$, $\left({}^{\beta_6}/_{\beta_1}\right) - 1$, $\left({}^{\beta_7}/_{\beta_1}\right) - 1$, and $\left({}^{\beta_8}/_{\beta_1}\right) - 1$.

Finally, the short-run Error Correction Model (ECM) is estimated, which incorporates the error correction term (ECT) obtained from equation (19). The ECM is specified as follows:

$$\begin{aligned} \Delta lnGDP_t = \alpha_0 &+ \sum_{i=1}^{n} \beta_9 \Delta(lnGDP)_{t-1} + \sum_{i=1}^{n} \beta_{10} \Delta(lnREM)_{t-1} + \sum_{i=11}^{n} \beta_9 \Delta(lnEXP)_{t-1} \\ &+ \sum_{i=1}^{n} \beta_{12} \Delta(lnFDI)_{t-1} + \sum_{i=1}^{n} \beta_{13} \Delta(D2010)_{t-1} + \sum_{i=1}^{n} \beta_{14} \Delta(IBDlnREM)_{t-1} \\ &+ \sum_{i=1}^{n} \beta_{15} \Delta(IBDlnEXP)_{t-1} + \sum_{i=1}^{n} \beta_{16} \Delta(IBDlnFDI)_{t-1} + (ECM)_{t-1} \\ &+ e_t \end{aligned} \tag{20}$$

The coefficient of the error correction term (ECM_{t-1}) is expected to be negative and statistically significant, indicating the speed of adjustment toward long-run equilibrium following a short-run shock.

5. Results and Discussion

This section presents and interprets the study's empirical findings in a sequential order. First, the optimal lag length for each variable is determined, followed by the results of the stationarity tests. Third, the study reports the estimated ARDL model results. Next, the lag structure of the selected variables is discussed, which is critical for conducting the bounds cointegration test and estimating the error correction model. Subsequently, the bounds cointegration test and the error correction model are estimated. The analysis then proceeds with a set of diagnostic tests, and finally, the stability of the estimated model is evaluated.

5.1 Lag Length Selection

Determining the initial lag length is a prerequisite for stationarity tests. An appropriate lag structure is essential because selecting too many lags can reduce forecast efficiency by increasing estimation error, while selecting too few lags can omit relevant dynamic information (Stock & Watson, 2006). Lag order selection also plays a central role in ARDL estimation, as it directly affects the bounds cointegration test and the specification of the error correction model.

Although experience and theoretical guidance are often employed to choose the number of lags, information criteria are generally used as a systematic procedure. The three most commonly applied criteria are Schwarz's Bayesian Information Criterion (SBIC), Akaike's Information Criterion (AIC), and Hannan-Quinn Information Criterion (HQIC). When all three criteria point to the same lag, the choice is straightforward. However, in cases of divergence, the decision becomes less clear.

The CEPR (2001) report recommends relying on SBIC for quarterly and annual data, regardless of sample size, while AIC tends to perform better for monthly data. For quarterly data with large samples (over 120 observations), HQIC is more reliable (Ivanov & Kilian, 2001). A general rule of thumb is to select: 1–2 lags for annual data, 1–8 lags for quarterly data, and 6, 12, or 24 lags for monthly data. Given that this study uses annual data with 43 observations, SBIC is prioritized, with a maximum lag length of 2 considered appropriate.

Accordingly, this study estimates a standard unrestricted VAR model and evaluates the optimal lag length using multiple selection criteria. Table 3 reports the lag-order selection statistics based on the Likelihood Ratio (LR), Final Prediction Error (FPE), AIC, HQIC, and SBIC. The results show that most criteria (LR, FPE, AIC, HQIC) suggest an optimal lag of 2, while SBIC recommends a lag length of 1. Following the CEPR (2001) guideline for annual data, this study adopts the SBIC criterion and selects one lag for subsequent analysis.

Table 3. Lag-Order Selection Statistics

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-124.576	NA	0.00536	6.12266	6.18332	6.28816
1	51.7408	352.63	2.60E-06	-1.51146	-1.20817	**-0.684003***
2	79.5843	55.687*	1.5e-06*	-2.07544*	-1.52951*	-0.58601

Notes: LR = Likelihood ratio, FPE = Final prediction error, AIC = Akaike information criterion, HQIC = Hannan and Quinn information criterion, SBIC = Schwarz's Bayesian information criterion.
*Indicates significance at the 5% level or lower.

5.2 Stationarity Test

5.2.1 Graphically Test for Stationarity

This study first plotted the logarithmic time-series data of the four variables: ln GDP, ln FDI, ln Remittances, and ln Exports. The annual series of all variables exhibits upward trends, indicating non-stationarity in levels (Figure 2). However, after applying the first difference, the series appears stationary (Figure 3).

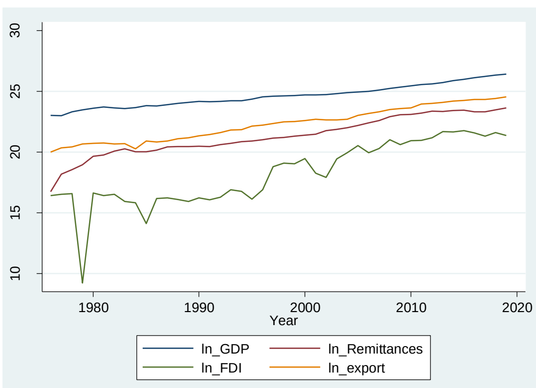

Figure 2. Time Series Plot of Variables in Levels

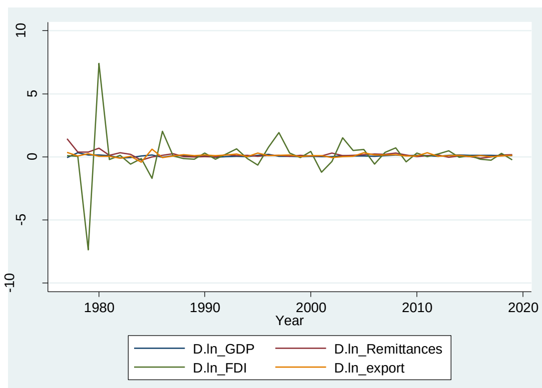

Figure 3. Time Series Plot of First Difference

5.2.2 Unit Root Test for Stationarity

To formally assess stationarity, unit root tests were conducted on the annual series of GDP, Remittances, FDI, Exports, and the constructed dummy variables. The variables were tested in logarithmic form, at levels, and in first differences, under specifications that included an intercept and both trend and intercept. Three widely used tests were applied: The Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

The Augmented Dickey-Fuller (ADF) results (Table 4) confirm that all variables are non-stationary in levels. After first differencing, however, the series becomes stationary. None of the variables exhibit trend stationarity, except for FDI, which is stationary at the 5% level when a trend is included. The ADF test is based on the null hypothesis (H_0) that the variable has a unit root (non-stationary), against the alternative (H_1) that the variable is stationary. Rejection of the null occurs when the absolute test statistic exceeds the absolute critical value.

The Phillips-Perron (PP) test results (Table 5) corroborate the ADF findings. All variables become stationary after first differencing at the 5% significance level. In levels, none of the series are stationary under the intercept specification, although remittances and FDI exhibit trend stationarity at 5%. The null hypothesis in the PP test is that the series contains a unit root, while the alternative suggests stationarity. As with the ADF, rejection of the null requires that the absolute test statistic exceed the critical value.

Table 4. Augmented Dicky Fuller (ADF) Test Results

Variable	Intercept				Trend and intercept			
	Level		First difference		Level		First difference	
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
lnGDP	0.038	0.9615	-4.63	0.0001	-1.716	0.7438	-4.884	0.0003
lnRemittances	-1.411	0.5768	-4.139	0.0008	-2.558	0.2994	-3.955	0.0102
lnFDI	-1.155	0.6927	-7.047	0.0000	-5.328	0.0000	-6.993	0.0000
lnExport	0.068	0.9638	-4.736	0.0001	-2.231	0.4723	-4.7	0.0007
Dummy 2010	-0.488	0.8944	-4.528	0.0002	-1.697	0.7521	-4.631	0.0009
Dummy_lnRemittances	-0.451	0.9013	-4.493	0.0002	-1.671	0.7634	-4.605	0.0010
Dummy_lnFDI	-0.449	0.9017	-4.482	0.0002	-1.659	0.7686	-4.589	0.0011
Dummy_lnExport	-0.436	0.9039	-4.497	0.0002	-1.661	0.7675	-4.616	0.0010

Table 5. Phillips-Perron (PP) Test Results

Variable	Intercept				Trend and intercept			
	Level		First difference		Level		First difference	
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value
lnGDP	0.591	0.9874	-5.734	0.0000	-1.253	0.899	-5.668	0.0000
lnRemittances	-3.855	0.0024	-8.589	0.0000	-6.865	0.0000	-8.207	0.0000
lnFDI	-1.773	0.3941	-10.761	0.0000	-6.371	0.0000	-10.655	0.0000
lnExport	-0.38	0.9133	-9.422	0.0000	-2.843	0.1817	-9.316	0.0000
Dummy 2010	-0.509	0.8902	-6.481	0.0000	-1.737	0.7343	-6.549	0.0000
Dummy_lnRemittances	-0.467	0.8979	-6.457	0.0000	-1.707	0.7477	-6.535	0.0000
Dummy_lnFDI	-0.469	0.8979	-6.479	0.0000	-1.699	0.7511	-6.554	0.0000
Dummy_lnExport	-0.443	0.9026	-9.422	0.0000	-1.688	0.7559	-6.483	0.0000

Results from the KPSS test (Table 6) are broadly consistent. The test assumes the null hypothesis of level or trend stationarity, with non-stationarity as the alternative. At levels, the LM statistics exceed the critical values for most variables, indicating non-stationarity. After first differencing, the series generally falls below the critical values, confirming that the series is stationary.

Overall, the graphical inspection and the three complementary unit root tests consistently indicate that the variables are integrated of order one, I(1). That is, the series are non-stationary in levels but become stationary after first differencing.

5.3 ARDL Model Estimation

The ARDL model was estimated using the optimal lag length of one, as determined by the Schwarz Bayesian Information Criterion (SBIC). The selected specification is ARDL (1 1 1 0 0 0 1 0), which incorporates a structural break through the inclusion of a dummy variable for the year 2010 (Table 7). The model also includes interaction break dummies for remittances, FDI, and exports, allowing the estimation to account for possible shifts in the relationship following the structural break.

Table 6. KPSS Test Results

Variable	LM Statistics KPSS test			
	Intercept		Trend and intercept	
	Critical value @ 10% = 0.347, 5% = 0.463, 2.5% = 0.574, & 1% = 0.739		*Critical value @ 10% = 0.119, 5% = 0.146, 2.5% = 0.176, 1% = 0.216*	
	Level	**First difference**	**Level**	**First difference**
lnGDP	2.21	0.171	0.335	0.0973
lnRemittances	2.17	0.517	**0.121**	0.208
lnFDI	2.03	0.0401	**0.111**	0.0334
lnExport	2.27	0.0502	**0.155**	0.0515
Dummy 2010	1.36	0.169	0.405	0.0498
Dummy_lnRemittances	1.36	0.176	0.407	0.0499
Dummy_lnFDI	1.36	0.176	0.408	0.0517
Dummy_lnExport	1.36	0.179	0.409	0.0502

The estimation results suggest that GDP growth is significantly influenced by its own lagged value (t_{-1}). Remittances, FDI, and the interaction dummy of FDI also exert effects up to one lag, whereas exports, the 2010 break dummy, and the interaction dummies for remittances and exports exert contemporaneous (t_{-0}) effects. Identifying the structural break enables the detection of the timing and significance of changes in the underlying relationships. The 2010 break dummy is statistically significant, indicating that the structural incident led to a temporary decline in economic growth of approximately 15.43%.

The selected ARDL (1 1 1 0 0 0 1 0) model will subsequently be employed to: (i) test for the existence of cointegration using the bounds testing approach, (ii) estimate both long-run and short-run coefficients, (iii) compute the error correction term (speed of adjustment), and (iv) conduct relevant diagnostic tests to ensure model validity.

5.4 ARDL Bounds Test for Cointegration

This section investigates the presence of a long-run relationship among the variables using the ARDL bounds testing approach, which is derived from the error-correction representation (Pesaran et al., 2001). The bounds test is based on the joint F-statistic, whose asymptotic distribution is non-standard under the null hypothesis (H_0) of no cointegration (no level relationship) against the alternative hypothesis (H_1) of a cointegrating relationship.

The test procedure establishes two sets of critical values corresponding to the lower bound I(0) and the upper bound I(1). At the first level, it is assumed that all variables are integrated of order zero, while at the second level, the variables are assumed to be integrated of order one. The approach involves estimating the equation by ordinary least squares (OLS) and examining the joint significance of the lagged level variables.

Table 7 ARDL Model Estimation

Variable	ARDL Estimation
L.lnGDP	0.291*
	(0.107)
lnRemittances	-0.114
	(0.0633)
L.lnRemittances	0.200***
	(0.0455)
lnFDI	0.00344
	(0.00689)
L.lnFDI	-0.0119
	(0.00615)
lnExport	0.316***
	(0.0459)
Dummy 2010	-15.43**
	(4.322)
Dummy_lnRemittances	-0.278
	(0.240)
Dummy_lnFDI	-0.0413
	(0.0762)
L.Dummy_lnFDI	-0.0149**
	(0.00423)
Dummy_lnExport	0.965***
	(0.206)
Constant	8.740***
	(1.374)
N	43
R-squared	0.998
Adjusted R-squared	0.997
Root MSE	0.0496

Note: Standard errors in parentheses
* $p<0.05$, ** $p<0.01$, & *** $p<0.001$

The decision rule is straightforward: if the calculated F-statistic exceeds the upper bound I(1) critical value, the null hypothesis of no cointegration is rejected, indicating the existence of a long-run relationship. Conversely, if the F-statistic falls below the lower bound I(0), the null hypothesis cannot be rejected. In cases where the statistic lies between the two bounds, the test result remains inconclusive (Belloumi, 2014).

The results of the ARDL bounds test are presented in Table 8. The calculated F-statistic (7.251) exceeds both the lower bound (I(0) = 2.96) and the upper bound (I(1) = 4.26) at the 1% significance level. This clearly rejects the null hypothesis of no cointegration, thereby confirming the existence of a long-run equilibrium relationship between the variables (Narayan, 2005).

Accordingly, this study establishes the presence of a long-run cointegrating relationship between GDP growth and its key determinants—remittances, foreign direct investment (FDI), and exports—in the case of Bangladesh.

Table 8. ARDL Bound Test for Cointegration

Significance level	Critical value		Calculated F statistic
	Lower band I(0)	Upper band I(1)	
1%	2.96	4.26	7.251
2.5%	2.60	3.84	
5%	2.32	3.50	
10%	2.03	3.13	

Note: * The variables lag length (1 1 1 0 0 0 1 0)
** H_0 is accepted if F < critical value for I(0) regressors (Lower band); and reject if F > critical value for I(1) regressors (Upper band)

5.5 ARDL and ECM Results

The preceding section established the existence of cointegration among the selected variables, confirming that they move together in the long run. Building on this finding, the present section employs the log-level ARDL error correction model (ECM) to estimate both the long-run relationships and short-run dynamics between the dependent variable and its determinants.

The long-run estimates of the economic relationship between the dependent variable (economic growth) and the independent variables (exports, remittances, and FDI) in Bangladesh are presented in Table 9. The results indicate that remittances exert a statistically significant and positive effect on Bangladesh's economic growth. Specifically, the estimated coefficient of remittances suggests that a one percent increase in remittance inflows raises GDP growth by approximately 0.121%. This outcome aligns with the findings of Mannan (2017) and Islam (2020).

Remittances serve as a crucial driver of growth by supporting low-income households, supplementing domestic savings, and enhancing the country's foreign exchange reserves. Since remittances arrive in foreign currency, they strengthen the balance of payments, cushion the import bill, and contribute to macroeconomic stability. Between FY2009–10 ($10,987.40 million) and FY2020–21 ($24,777.71 million), remittance inflows more than doubled, enabling Bangladesh to maintain a robust foreign reserve of $46,391.40 million in FY2020–21, despite the COVID-19 pandemic (Bangladesh Bank, 2021). The large labor force, coupled with the country's strong ties to oil-rich Middle Eastern economies and neighboring countries such as India and Pakistan (Tahir et al., 2015), further reinforces this channel. Therefore, policymakers should prioritize developing institutional frameworks to support overseas employment and improve welfare services for migrant workers, ensuring the sustainability of remittance flows.

In contrast, the study finds a negative but statistically insignificant long-run relationship between FDI and economic growth. The estimated coefficient implies that a one percent rise in FDI reduces economic growth by 0.012 percent. This negative association may reflect the model's limitation in excluding human capital—an important mediating factor through which FDI enhances growth (Borensztein et al., 1998; Makun, 2018). A similar outcome was observed by Adnan Hye and Islam (2013), while other studies (Adhikary, 2010; Hussain & Haque, 2016; Sarker & Khan, 2020) report a significantly positive relationship. Although the results here are weak, FDI remains potentially beneficial to Bangladesh through technology transfer, productivity spillovers, and access to global value chains. To realize these benefits, the government should implement policies aimed at improving the investment climate—ensuring political stability, strengthening property rights, enforcing legal protections for investors, and addressing infrastructure bottlenecks, particularly in energy and transportation. Expanding investment in these critical sectors would enhance Bangladesh's attractiveness to foreign investors and contribute to sustainable growth, thereby accelerating the country's transition to middle-income status.

Finally, the findings confirm a strong positive and statistically significant relationship between exports and economic growth in Bangladesh. The estimated coefficient of 0.446, significant at the 1% level, implies that a one percent increase in exports boosts GDP growth by nearly 0.45 percent. This effect is notably larger than that of remittances and FDI. The result is consistent with prior studies such as Begum and Shamsuddin (1998) and Al Mamun and Nath (2005), who also documented a strong export-led growth effect for Bangladesh. Historically, the contribution of exports was particularly pronounced during the period 1982–1990, when trade liberalization and deregulation reforms were pursued. This underscores the critical role of outward-oriented policies in fostering growth and highlights the continuing importance of diversifying and expanding Bangladesh's export base.

On the other hand, the economic reform process continued in the early 1990s, but the contribution of exports to economic growth remained negligible in 1990–91 and 1991–92 due to intense political turmoil (Begum & Shamsuddin, 1998). Nevertheless, Bangladesh is a labor-abundant country that primarily exports ready-made garments (RMG) to the European Union and the United States. By diversifying its export-oriented production and leveraging its comparative advantage in low-cost labor, Bangladesh can significantly expand exports to a broader range of countries. In this context, China may serve as a model, given its success in producing goods tailored to global demand. To achieve this, the government must attract both domestic and foreign investors by providing investment incentives, as well as improving the energy and infrastructure sectors. The aspiration of attaining middle-income and eventually upper-middle-income status depends critically on the government's ability to create an investment-friendly environment and ensure adequate facilities for export-oriented industries.

Gregory-Hansen's cointegration test with regime shifts identifies a structural break in 2010, incorporated into the model as a dummy variable. The structural break dummy (Dummy2010) is statistically significant at the 1% level and exhibits a large negative coefficient, indicating that economic growth declined by approximately 21.76% in the long run. However, the interaction terms of remittances (Dummy2010#lnRemittances) and FDI (Dummy2010#lnFDI) with the break dummy are not statistically significant, suggesting that the structural break does not materially affect the long-term relationship between these two variables and economic growth. In contrast, the interaction dummy for exports (Dummy2010#lnExport) is statistically significant at the 1% level, indicating that the structural break has a positive and economically meaningful impact on the export-growth nexus, with exports contributing an additional 1.36 percentage points to growth after the break.

The error correction term (ECT), reported in Table 9 as Adjustment (L.lnGDP), provides evidence of long-run convergence. A non-negative coefficient would indicate no convergence, implying model misspecification. In contrast, a negative and statistically significant coefficient indicates that deviations from long-run equilibrium are corrected over time. The ECT coefficient is estimated at –0.709, statistically significant at the 1% level, confirming that approximately 71% of the disequilibrium from the previous year's shocks is corrected within the current year. This relatively large coefficient (in absolute terms) suggests a rapid adjustment process toward long-run equilibrium following short-run shocks.

Table 9. Long-Run Elasticities and Error Correction Result (Predictand: lnGDP)

Variable	Estimated coefficient
Long-run estimates:	
lnRemittances	0.121**
	(0.0423)
lnFDI	-0.0119
	(0.0128)
lnExport	0.446***
	(0.0469)
Dummy2010	-21.76***
	(5.067)
Dummy2010#lnRemittances	-0.392
	(0.336)
Dummy2010#lnFDI	-0.0791
	(0.105)
Dummy2010#lnExport	1.360***
	(0.202)
Adjustment:	
L.lnGDP	-0.709***
	(0.107)
Short-run estimates:	
D.lnRemittances	-0.200***
	(0.0455)
D.lnFDI	0.0119
	(0.00615)
D.Dummy2010#lnFDI	0.0149**
	(0.00423)
Constant	8.740***
	(1.374)
N	43
R-squared	0.661
Adjusted R-squared	0.541
Root MSE	0.0496

Note: Standard errors in parentheses
* p<0.05, ** p<0.01, & *** p<0.001

The short-run estimates indicate that remittances exert a statistically significant adverse effect on economic growth at the 1% level. This outcome contrasts with their long-run positive contribution, implying that remittance inflows may initially cause consumption-led distortions or exchange rate pressures before yielding growth-enhancing effects. Conversely, FDI shows a positive but statistically insignificant effect on short-run growth. Importantly, the interaction dummy for FDI with the 2010 structural break (D.Dummy2010#lnFDI) is statistically significant, indicating that the structural change had a measurable impact on the short-term growth effect of FDI.

5.6 Diagnostic Test Results

The final step involves assessing the goodness-of-fit of the ARDL error correction model. To this end, a series of diagnostic and stability tests was conducted. Table 10 presents the results of these diagnostic tests, which confirm that the estimated ARDL model is free from major econometric problems and is therefore reliable.

Specifically, the Durbin–Watson statistic indicates that the model is not affected by serial correlation or autocorrelation. Likewise, the Breusch–Godfrey test shows no evidence of higher-order autocorrelation. The White heteroscedasticity test is statistically insignificant at the 5% level, confirming the absence of heteroscedasticity. Furthermore, both the Ramsey RESET test and the Jarque–Bera normality test confirm that the functional form is correctly specified and that the residuals are normally distributed. Overall, the diagnostic checks suggest that the ARDL model is well-specified and robust.

Table 10. Diagnostic Test Results

Specification	chi2	p-Value	Conclusion
Durbin-Watson statistic (autocorrelation)	1.636	1.148	No autocorrelation
Breusch-Godfrey statistic (autocorrelation)	1.617	0.204	No higher-order autocorrelation
Heteroscedasticity	38.17	0.416	No heteroscedasticity
Ramsey RESET test	1.75	0.180	No omitted variables
Jarque-Bera normality test	2.385	0.303	No omitted variables

Note: Significance at the 5% level. The d-statistic is reported for the Durbin–Watson test.

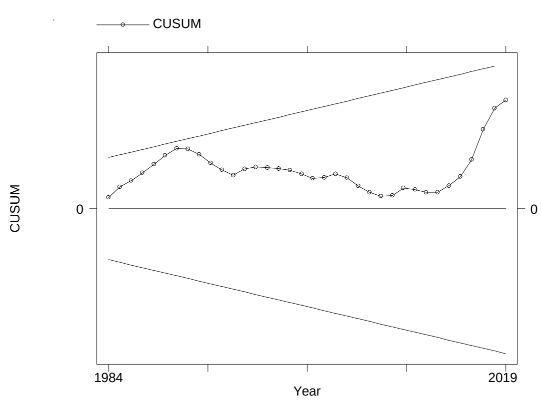

Figure 4. CUSUM Test

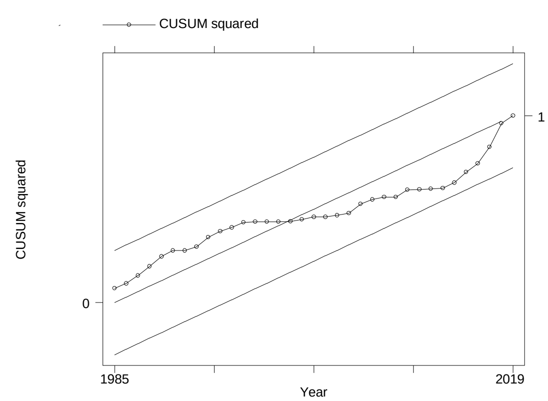

Figure 5. CUSUM-Square Test

5.7 Stability Checking

The stability of the estimated ARDL-error correction model was further examined using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests. Figures 4 and 5 present the plots of these tests, respectively. The results indicate that the CUSUM and CUSUMSQ statistics remain within the 5% critical bounds throughout the sample period. This finding confirms that the model is structurally stable, and its parameters are reliable for inference and policy analysis.

6. Conclusion and Policy Recommendation

The primary objective of this study was to examine the impact of internal (exports) and external (remittances and foreign direct investment, FDI) factors on economic growth in Bangladesh. Using annual data from 1976 to 2019, the study employed the Autoregressive Distributed Lag (ARDL) approach to cointegration. Structural breaks were addressed by incorporating relevant dummy variables into the model.

The findings confirm that both internal and external determinants are critical for sustaining long-run economic growth in Bangladesh. Exports and remittances, in particular, have made significant positive contributions. While this pattern is consistent with other developing countries, Bangladesh is distinctive due to its heavy reliance on remittances and export earnings. The country ranks seventh globally in remittance receipts and second in ready-made garment (RMG) exports (World Bank, 2021b). The RMG sector alone employs around 4.22 million workers (1.72 million men and 2.50 million women) (ACD, 2020) and generated export earnings of $28 billion in 2020, with a global market share of 6.3% (WTO, 2021). Bangladesh is also the sixth-largest exporter of migrant labor, with approximately 7.8 million workers employed abroad, mainly in Gulf countries (UNDESA, 2019), sending home $24.78 billion in remittances in FY 2021 (Bangladesh Bank, 2021).

However, recent shocks such as the COVID-19 pandemic have disrupted labor migration, reduced remittance inflows, and significantly slowed export growth. Since the present study does not cover the COVID-19 period due to data unavailability, the pandemic's full impact remains unexplored. Policymakers therefore need to adopt strategies that diversify the export basket, reduce overdependence on labor exports, and strengthen resilience against external shocks. These steps are crucial as Bangladesh prepares to graduate from its status as a Least Developed Country (LDC) by 2026 and seeks to achieve long-term, sustainable growth.

An important finding of this research is the negative relationship between FDI and economic growth. Although counterintuitive, this outcome may be attributed to Bangladesh's infrastructural deficiencies (roads, electricity, and port facilities), bureaucratic inefficiencies, and weak investment climate. This is reflected in the World Bank's *Ease of Doing Business Index*, where Bangladesh ranked 168th out of 190 countries in 2020—among the lowest in South Asia, ahead only of Afghanistan (World Bank, 2020).

Based on the empirical evidence, several policy recommendations emerge:

1. **Export diversification and upgrading**: While the RMG sector remains the backbone of exports, contributing nearly 84% of merchandise exports, its growth potential may diminish

in the long term. Bangladesh should expand into other competitive sectors such as pharmaceuticals, leather, footwear, seafood, shipbuilding, and processed foods, while also exploring high-value industries such as information technology and defense manufacturing. Export diversification by product and destination, along with a focus on quality enhancement, will be essential.

2. **Attracting foreign direct investment**: To transform into an export-led growth economy, Bangladesh must address structural bottlenecks. Ensuring uninterrupted power and gas supplies, improving transport and port infrastructure, strengthening investor protection laws, and maintaining political stability are vital to creating a business-friendly environment. Moreover, encouraging diaspora investment, as practiced in China, could provide a sustainable source of FDI.
3. **Leveraging remittances**: Skilled labor migration needs to be expanded by aligning vocational training with international labor market demand. Increasing the supply of skilled workers abroad will raise remittance inflows, mitigate unemployment at home, and support long-term growth. Simultaneously, policies must ensure the productive utilization of remittances, such as channeling them into investment and savings rather than only household consumption.
4. **Institutional and governance reforms**: Bureaucratic efficiency, transparency, and the reduction of regulatory barriers are essential to improving the ease of doing business. Such reforms will also complement efforts to enhance FDI inflows and export competitiveness.

Finally, while this study sheds light on the long-run and short-run dynamics of remittances, exports, and FDI with respect to economic growth, it has certain limitations. Specifically, it identifies correlations but does not fully explain the causal mechanisms behind the observed relationships—for instance, the negative long-run association between FDI and growth warrants further investigation. Future research should therefore explore sectoral-level FDI flows, the quality of investments, and their linkages to domestic industries to provide more nuanced policy guidance.

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