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Macroeconomic Determinants of FDI Inflow in Bangladesh: Univariate and Multivariate Time Series Econometrics

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Abstract:

Foreign Direct Investment (FDI) inflows in Bangladesh have exhibited a declining trend in recent years despite the steady expansion of the national economy. This study employs both univariate and multivariate time series econometric techniques, including ARIMA, ARDL, and ECM models, to analyze the macroeconomic determinants of FDI inflows from 1972 to 2020. The results indicate that exchange rate, GDP growth, trade openness, stock market capitalization, and inflation significantly influence FDI inflows, while the impact of foreign exchange reserves and interest rates varies across the short and long run. The estimated models demonstrate robust predictive capabilities, with the ARIMA (1,1,0) model providing reliable forecasts for FDI trends. Additionally, the ARDL bounds test confirms a long-run equilibrium relationship, with the error correction term suggesting a rapid speed of adjustment of 92.43%. Policy implications derived from these findings underscore the need for maintaining exchange rate stability, enhancing trade openness, and strengthening financial markets to attract sustained FDI. Additionally, fostering macroeconomic stability through inflation control and prudent interest rate policies can improve investor confidence. The results advocate for targeted policy interventions, including investment-friendly regulations and infrastructure development, to position Bangladesh as a more attractive destination for foreign investment. This research contributes to the broader literature by offering empirical insights into the dynamic relationship between macroeconomic variables and FDI inflows, aiding policymakers in crafting data-driven strategies for long-term economic growth.

Keywords: Foreign Direct Investment, ARDL, ARIMA, ECM, Exchange Rate, Trade Openness, Macroeconomic Stability.

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1.0 Introduction

Foreign Direct Investment (FDI) has long been recognized as a critical driver of economic growth, particularly in developing economies. By facilitating the transfer of capital, technology, and managerial expertise, FDI not only enhances productivity but also fosters employment creation and infrastructure development. For Bangladesh, a country with a rapidly growing economy and a strategic geographic location, attracting FDI is essential to sustain its economic momentum and achieve long-term development goals. However, despite its potential, Bangladesh has historically lagged behind its regional peers in attracting FDI inflows. This raises important questions about the macroeconomic factors that influence FDI decisions and how policymakers can create a more conducive environment for foreign investors.

The relationship between macroeconomic variables and FDI inflows has been extensively studied in the context of both developed and developing countries. However, the unique economic, political, and institutional landscape of Bangladesh necessitates a tailored examination of these determinants. Previous studies have highlighted factors such as market size, trade openness, infrastructure quality, political stability, and labor costs as key drivers of FDI. Yet, the relative importance of these factors in the context of Bangladesh remains underexplored, particularly in light of the country's evolving economic policies and global integration efforts.

This study aims to fill this gap by employing both univariate and multivariate time series econometric techniques to analyze the macroeconomic determinants of FDI inflows in Bangladesh. By utilizing advanced econometric methods, including cointegration analysis and vector error correction models (VECM), this paper seeks to uncover the long-run and short-run dynamics between FDI inflows and key macroeconomic indicators. The variables under consideration include gross domestic product (GDP), exchange rates, inflation, trade openness, infrastructure development, and political stability, among others.

The findings of this study are expected to provide valuable insights for policymakers in Bangladesh, offering evidence-based recommendations to enhance the country's attractiveness to foreign investors. Moreover, the methodological approach adopted in this research contributes to the broader literature on FDI determinants by demonstrating the applicability of time series econometrics in understanding the complex interplay between macroeconomic variables and investment flows.

In the following sections, we provide a comprehensive review of the literature on FDI determinants, outline the theoretical framework guiding this study, describe the data and methodology, present the empirical results, and discuss their implications for policy and future research.

2.0 Literature Review

Nunnenkamp & Spatz (2002) have examined the relationship between the inflows of foreign direct investment and its determinants for a sample of around 28 developing countries. For this research study, the authors have chosen the time scale from 1987 to 2000. In this research study, the authors have used comprehensive survey data which have been collected and gathered by the European Round Table of Industrialists (ERTI) for those 28 developing countries from late 1980s. For examining the true relationship between the inflows of foreign direct investment in those 28 developing countries and their determinants, the authors have applied Spearmen coefficients of correlation. In addition, the authors have also implemented different models of panel data regression mechanism.

Otieno & Njuguna (2016) have investigated the macroeconomic effect of different variables on the inflows of foreign direct investment in Kenya. For this research, the authors have chosen the time frame from 2002 to 2013 for the collection of the required data set. In addition, the authors have implemented the correlation analysis and the linear regression model for finding the effect of macroeconomic variables on the inflows of foreign direct investment in Kenya.

Şahbudak, Şahin & Şengün (2016) have analyzed the crucial determinants of the inflows of foreign direct investment for Turkey. For this research study, the researchers have chosen a timescale from 1975 to 2014. To find the determinants of the inflows of foreign direct investment of Turkey, the researchers have used the Autoregressive Distributed Lag method or ARDL method. The long-run result in this research study has shown that the inflation rate of Turkey has a significant relationship with the inflows of foreign investment but has negative sign. In addition, it has been shown that the trade openness of the economy and the gross fixed capital formation of Turkey have a positive and very significant relationship with the inflows of foreign direct investment in Turkey. In addition, it has been revealed that though the growth rate of the GDP per capita of Turkey has a positive relationship with the inflows of foreign direct investment, this macroeconomic variable is not statistically significant.

Bangladesh Perspective

Some research studies have focused on analyzing the determining factors of the inflows of foreign direct investment in Bangladesh. Aziz, Sarkar & Mahmud (2014) have examined different macroeconomic factors which might have an impact on the determination of the inflows of foreign investment in the Bangladeshi economy. For this research purpose, the authors have used the time scale from 1972 to 2010. In this research study, the authors have implemented the mechanism of lock linear regression. In addition, the authors have also implemented the ordinary least square method or OLS regression mechanism so that they can be able to estimate the effects of the determinants on the inflows of foreign direct investment in Bangladesh. To conduct this research study, the authors have used the natural log of the real inflows of foreign direct investment as the dependent variable. The independent variables that have been used to conduct this research study include the market size of the economy which has been proxied by taking the natural log value of real GDP, labour productivity indicator which has been expressed by taking the natural log value of the productivity indexes of labour industry in some selected industries like (Cement, Steel, Paper, Fertilizer, Jute, and Cotton), the Trade balance of Bangladesh. From the results of the econometric models, it has been found that the market size of Bangladesh has a positive impact on the inflows of foreign direct investment, and this variable is also statistically significant (Aziz, Sarkar & Mahmud, 2014). In addition, the trade balance amount is also found to have a positive indicator for the inflows of foreign direct investment, and it is also statistically significant.

A research study has been conducted by Islam et al. (2015) who have examined the determinants of the inflows of foreign investment in Bangladesh. For this research study, the authors have used the time frame from 1972 to 2010. In addition, the researchers have used the log-linear regression mechanism in this research study. The empirical analysis of this research study has indicated that the market size of the Bangladeshi economy had a positive impact on the inflows of foreign direct investment, and it is truly statistically significant. In addition, it has also been found that the trade balance of the Bangladeshi economy has a positive impact on the inflows of foreign investment, and it is also a statistically significant variable.

Islam & Sahajalal (2019) have also tried to find out the true relationship between some selected macroeconomic variables and the inflows of foreign direct investment as a percentage of the GDP for the Bangladeshi economy. In this research study, the authors have selected the inflows of foreign direct investment as a dependent variable. For the independent variables, the authors have included the real foreign exchange rate, inflation rate, real GDP, and interest rate of the economy. For this research study, the authors have used the time frame from 1976 to 2018. The time series econometrics model has been implemented in this research study. From the empirical analysis, it has been revealed that there is a negative impact of the real GDP, the real foreign exchange rate and the inflation rate on the inflows of foreign direct investment. On the other hand, it has been found that the interest rate of the economy has a positive impact on the inflows of foreign direct investment in Bangladesh (Islam & Sahajalal, 2019). In addition, the authors have used the CSUSM square and the CUSUM test. From those tests, in the research period, the model was not stable.

The summary of some major macroeconomic variables used in the previous literature is tabulated below as follows –

Table 1: Summary of Literature

Variables	Found Significant in Previous Literature	Found Insignificant in Previous Literature
GDP Growth Rate	Faeth (2005); Li & Liu (2005); Fosu & Magnus (2006); Ang (2008); Ang (2008); Kholdy & Sohrabian (2008); Faras & Ghali (2009); Khrawish & Siam (2010); Samimi et al. (2010); Sun (2011); Sichei & Kinyondo (2012); Alavinasab (2013); Shahzad & Al-Swidi (2013); Onuorah & Nnenna (2013)	Şahbudak, Şahin & Şengün (2016)
GDP Per Capita	Khrawish & Siam (2010), Jaspersen et al. (2000)	
Exchange Rate	Hara & Razafimahefa (2005); Tsen (2005); Faeth (2005); Ahmed (2008); Ang (2008); Adam & Tweneboah (2009); Khrawish & Siam (2010); Vijayakumar et al. (2010); Pradhan et al. (2011); Uwubanmwen & Ajao (2012); Mushtaq et al. (2012); Malik & Malik (2013); Onuorah & Nnenna (2013); Minhas & Ahsan (2015); Otieno & Njuguna (2016); Islam & Sahajalal (2019)	
Inflation Rate	Tsen (2005); Faeth (2005); Asaolu & Ogunmuyiwa (2010); Khrawish & Siam (2010); Almsafir et al. (2011); Pradhan et al. (2011); Uwubanmwen & Ajao (2012); Imoudu (2012); Malik & Malik (2013); Onuorah & Nnenna (2013); Bekhet & Al-Smadi (2015); Otieno & Njuguna (2016); ŞAHBUDAK, ŞAHİN & ŞENGÜN (2016); Islam & Sahajalal (2019)	Vijayakumar et al. (2010); Mangır et al., (2012); Mushtaq et al. (2012)

Real Interest Rate	Almsafir et al. (2011); Otieno & Njuguna (2016)	
Forex Reserve	Asaolu & Ogunmuyiwa (2010); Khachoo & Khan (2012)	
Capitalisation of the Stock Market	Ahmed (2008); Adam & Tweneboah (2009); Asaolu & Ogunmuyiwa (2010); Mushtaq et al. (2012); Bekhet & Al-Smadi (2015); Kariuki (2015)	
Trade to GDP Ratio	Asiedu (2001); Nunnenkamp & Spatz (2002); Fosu & Magnus (2006); Sahoo (2006); Ang (2008); Faras & Ghali (2009); Samimi et al. (2010); Anyanwu (2011); Kiran (2011); Uwubanmwen & Ajao (2012); Imoudu (2012); Mangır et al., (2012); Sattarov (2012); Alavinasab (2013); Shahzad & Al-Swidi (2013); Bekhet & Al-Smadi (2015); Minhas & Ahsan (2015); ŞAHBUDAK, ŞAHİN & ŞENGÜN (2016); Dellis et al. (2017)	Vijayakumar et al. (2010)
Total Tax Revenue	Faeth (2005); Solomon et al., (2015); Dellis et al. (2017)	
Remittances Received	Basnet & Upadhyaya (2014)	
Budget Size	Khrawish & Siam (2010); Sufian, et al. (2010); Anyanwu (2011)	Uwubanmwen & Ajao (2012)

3.0 Research Methodology

3.1 Data Sources and Variable Selection

This study employs annual time series data spanning from 1972 to 2020 to analyze the macroeconomic determinants of Foreign Direct Investment (FDI) inflows in Bangladesh. The data is sourced from reputable institutions, including the UNCTAD (United Nations Conference on Trade and Development) Database, World Bank's World Development Indicators (WDI), the Bangladesh Bank, and the International Monetary Fund's (IMF) International Financial Statistics (IFS). The selection of variables is guided by both theoretical considerations and empirical evidence from prior studies on FDI determinants. The key variables under investigation include:

Table 2: Research Variables

Variable Indicators	Variables
LFDI	Log of FDI Inflows
GGR	GDP Growth Rate
LGPP	Log of GDP Per Capita
LER	Log of Exchange Rate
IR	Inflation Rate
RIR	Real Interest Rate
LFR	Log of Forex Reserve
LMC	Log of Stock Market Capitalization
TGR	Trade to GDP Ratio
LTR	Log of Total Tax Revenue
LRM	Log of Remittances Received
LBS	Log of Budget Size

3.2 Univariate Time Series Analysis

For this univariate time series analysis, I have used the Box-Jenkins Methodology to find the determinants of LFDI based on its own past values or moving averages. This B-J methodology has mainly 4 steps (Box & Jenkins, 1970). They are being described below as follows –

Step 1: Identification

One approach is graphical approach. Another one is a statistical test. It includes mainly two types of tests – Augmented Dicky Fuller Test (ADF Test) (Dickey & Fuller, 1979; 1981) and Phillips Perron Test (PP Test) (Phillips & Perron, 1988). We have conducted all three approaches to check for stationarity of LFDI. The hypotheses for the stationarity checking are –

H_0: The series is non-stationary, or it has a unit root.

H_1: The series is stationary, or it has no unit root.

For the ADF test, we have used the mathematical approaches for finding the stationarity. The ADF test requires including the trend and the significant lags to check the stationarity for the time series model. The regression equation for ADF regressions –

$$\Delta LFDI_t = \phi_0 + \delta LFDI_{t-1} + \sum_{j=1}^{p} \delta_j \, \Delta LFDI_{t-j} + b * time$$

Here, Δ represents the 1st difference.

For the optimal lag length "p", the rule of thumb is to use this formula –

$$Lag\ length\ =\ \sqrt[3]{(Number\ of\ observations)}$$

If it is the case that the variable LFDI is not stationary at its raw level, then the variable would be used for 1st difference and then it would be named as 1st difference of LFDI (d.LFDI). Then the same regression process would be conducted for the ADF and PP test along with the graphical representations. The regression equation for ADF regressions of d.LFDI is –

$$\Delta^2 LFDI_t = \phi_0 + \delta \Delta LFDI_{t-1} + \sum_{j=1}^{4} \delta_j \, \Delta^2 LFDI_{t-j} + b * time$$

Here, Δ^2 represents the 2nd difference.

If it is found that the variable LFDI is stationary at 1st difference, then the univariate model would be ARIMA Model or the Autoregressive Integrated Moving Average Model. Here, the parameters for AR, integrating factor and MA would be found out for the values of "p", "d", and "q", and the model would be known as ARIMA (p,d,q). If the variable is stationary at 1st difference, then the value of "d" parameter would be 1.

For other parameters (p and q), the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plot would be used. ACF determines the correlation between the dependent variable and its lag values. On the other hand, PACF determines the partial correlation between the dependent variable and its own past values including the consideration that both observations are correlated with other time's observation. PACF is used for finding "q" parameter and ACF is used for finding "p" parameter.

Hence, the AR (p) equation –

$$LFDI_t = \alpha + \sum_{j=1}^{p} \delta_j \, LFDI_{t-j} + \varepsilon_t$$

The MA (q) equation –

$$LFDI_t = \alpha + \sum_{j=1}^{q} \delta_j \, \varepsilon_{t-j} + \varepsilon_t$$

Finally, the ARIMA (p,d,q) equation is –

$$\Delta LFDI_t = \alpha + \sum_{j=1}^{p} \delta_j \, \Delta LFDI_{t-j} + \sum_{j=1}^{q} \delta_j \, \varepsilon_{t-j} + \varepsilon_t$$

Step 2: Estimation

After the estimation of the ARIMA (p,d,q) models, the best model would be chosen based on the values of significant coefficients, volatility measured by the Square of Sigma, Log Likelihood Statistics, AIC (Akaike's Information Criterion), and BIC (Bayesian Information Criterion)

Step 3: Diagnostics Checking

Residual diagnoses were performed using descriptive statistics and drawing graphs. Furthermore, the residuals were formally checked for white noise via the Portmanteau Test (Ljung & Box, 1978; Box & Pierce, 1970). Serial correlation was thoroughly examined through an analysis of the ACF and PACF Plot (Li & McLeod, 1981) and formally tested using the Durbin Watson test or DW test (Durbin & Watson, 1950; 1951; 1971) and the Breusch-Godfrey Serial Correlation LM Test (Breusch, 1978; Godfrey, 1978). For checking Heteroskedasticity, or non-constant residual variance, the Breusch-Pagan / Cook-Weisberg test (Breusch & Pagan, 1979; Cook & Weisberg, 1983) and the White Test (Cameron & Trivedi's decomposition) (White, 1980) were utilized, along with the ARCH Heteroskedasticity Test (Engle, 1982). Finally, the Stability Diagnostics of the estimated ARIMA model were assessed by examining the Root of the Model (Hamilton, 1994) and performing the Ramsey RESET Test (Ramsey, 1969).

Step 4: Forecasting

Finally, the fitted values have been estimated through the best-chosen model of ARIMA (p,d,q). And then the fitted values have been plotted against the actual values.

Multivariate Time Series Analysis

Multivariate time series analysis means there will be more than one independent variable for modelling the dependent variable over time. There are different models in multivariate time series analysis based on the order of integration or I (d) of each variable.

Order of Integration, I (d) for Each Variable

For determining the I (d) of each variable, the unit root test has been conducted based on the Graphical approach, ADF test and PP Test (same explanation and steps as mentioned in the above section of univariate analysis). If the variables are integrated of different orders – some variables are I (1), and some are I (0), but no variable is I (2), then the ARDL or Autoregressive Distributed Lag Model will be used for multivariate time series analysis (Pesaran & Shin, 1999).

Optimal Lag Order Selection

For determining the optimal lag length for multivariate analysis, different criteria have been used – LR (Log Likelihood Ratio), FPE (Final Prediction Error), AIC (Akaike Information Criterion), HQIC (Hannan–Quinn Information Criterion), and SBIC (Schwarz-Bayesian Information Criterion).

ARDL Specification

First of all, the ARDL model would be specified. The equation for this specified ARDL model according to Pesaran & Shin (1999) would be –

$$\begin{aligned} LFDI_t = \phi_0 &+ \sum_{i=1}^{p} \phi_{1_i} LFDI_{t-i} + \sum_{i=0}^{q1} \phi_{2_i} GGR_{t-i} + \sum_{i=0}^{q2} \phi_{3_i} LGPP_{t-i} + \sum_{i=0}^{q3} \phi_{4_i} LER_{t-i} \\ &+ \sum_{i=0}^{q4} \phi_{5_i} IR_{t-i} + \sum_{i=0}^{q5} \phi_6 RIR_{t-i} + \sum_{i=0}^{q6} \phi_{7_i} LFR_{t-i} + \sum_{i=0}^{q7} \phi_{8_i} LMC_{t-i} \\ &+ \sum_{i=0}^{q8} \phi_{9_i} TGR_{t-i} + \sum_{i=0}^{q9} \phi_{10_i} LTR_{t-i} + \sum_{i=0}^{q10} \phi_{11_i} LRM_{t-i} + \sum_{i=0}^{q11} \phi_{12_i} LBS_{t-i} + \varepsilon_t \end{aligned}$$

ARDL Bounds Cointegration Test

There might be long-run co-integration between LFDI and other variables. This co-integration test is known as the ARDL Bounds Co-integration Test (Pesaran et al., 2001). The equation –

$$\Delta LFDI_t = \Omega_0 + \Omega_1\, LFDI_{t-1} + \Omega_1\, GGR_{t-1} + \Omega_1\, LGPP_{t-1} + \Omega_1\, LER_{t-1} + \Omega_1\, IR_{t-1} + \Omega_1\, RIR_{t-1} + \Omega_1\, LFR_{t-1} + \Omega_1\, LMC_{t-1} + \Omega_1\, TGR_{t-1} + \Omega_1\, LTR_{t-1} + \Omega_1\, LRM_{t-1} + \Omega_1\, LBS_{t-1} + \sum_{i=1}^{p} \Omega_{1_i}\, \Delta LFDI_{t-i} + \sum_{i=0}^{q1} \Omega_{2_i}\, \Delta GGR_{t-i} + \sum_{i=0}^{q2} \Omega_{3_i}\, \Delta LGPP_{t-i} + \sum_{i=0}^{q3} \Omega_{4_i}\, \Delta LER_{t-i} + \sum_{i=0}^{q4} \Omega_{5_i}\, \Delta IR_{t-i} + \sum_{i=0}^{q5} \Omega_6\, \Delta RIR_{t-i} + \sum_{i=0}^{q6} \Omega_{7_i}\, \Delta LFR_{t-i} + \sum_{i=0}^{q7} \Omega_{8_i}\, \Delta LMC_{t-i} + \sum_{i=0}^{q8} \Omega_{9_i}\, \Delta TGR_{t-i} + \sum_{i=0}^{q9} \Omega_{10_i}\, \Delta LTR_{t-i} + \sum_{i=0}^{q10} \Omega_{11_i}\, \Delta LRM_{t-i} + \sum_{i=0}^{q11} \Omega_{12_i}\, \Delta LBS_{t-i} + \varepsilon_t$$

The determination of the co-integration would be based on F-statistics and t-statistics. If they are more than the upper bound of I (0), then there is a long-run relationship and co-integration exists between LFDI and its independent variables.

ARDL and ECM Estimation

If it is found that there is a long-run relationship between LFDI and other variables, then it is required to perform the Error Correction Model or ECM for short-run dynamics and speed of adjustment factor determination. The long-run level equation –

$$LFDI_t = \lambda_1 GGR_t + \lambda_2 LGPP_t + \lambda_3 LER_t + \lambda_4 IR_t + \lambda_5 RIR_t + \lambda_6 LFR_t + \lambda_7 LMC_t + \lambda_8 TGR_t + \lambda_9 LTR_t + \lambda_{10} LRM_t + \lambda_{11} LBS_t + \varepsilon_t$$

The error term from this equation would be –

$$ECT_t = \varepsilon_t = LFDI_t - (\lambda_1 GGR_t + \lambda_2 LGPP_t + \lambda_3 LER_t + \lambda_4 IR_t + \lambda_5 RIR_t + \lambda_6 LFR_t + \lambda_7 LMC_t + \lambda_8 TGR_t + \lambda_9 LTR_t + \lambda_{10} LRM_t + \lambda_{11} LBS_t)$$

Finally, the Error Correction Model (ECM) would be –

$$\Delta LFDI_t = \theta_0 + \sum_{i=1}^{p} \theta_{1_i} \Delta LFDI_{t-i} + \sum_{i=0}^{q1} \theta_{2_i} \Delta GGR_{t-i} + \sum_{i=0}^{q2} \theta_{3_i} \Delta LGPP_{t-i} + \sum_{i=0}^{q3} \theta_{4_i} \Delta LER_{t-i} + \sum_{i=0}^{q4} \theta_{5_i} \Delta IR_{t-i} + \sum_{i=0}^{q5} \theta_{6} \Delta RIR_{t-i} + \sum_{i=0}^{q6} \theta_{7_i} \Delta LFR_{t-i} + \sum_{i=0}^{q7} \theta_{8_i} \Delta LMC_{t-i} + \sum_{i=0}^{q8} \theta_{9_i} \Delta TGR_{t-i} + \sum_{i=0}^{q9} \theta_{10_i} \Delta LTR_{t-i} + \sum_{i=0}^{q10} \theta_{11_i} \Delta LRM_{t-i} + \sum_{i=0}^{q11} \theta_{12_i} \Delta LBS_{t-i} + \theta_2\, ECT_{t-1} + \varepsilon_t$$

ARDL and ECM Diagnostics

Then the estimated ARDL model would undergo some diagnostic checking to assess whether the model is significant and stable for the determination of LFDI.

A comprehensive battery of diagnostic tests was administered to evaluate the fitted model's adequacy, covering both Residual Diagnostics and Model Stability Diagnostics. Initially, the residuals were scrutinized using both a Descriptive Statistics Approach and a Graphical Approach. The crucial assumption of independence was assessed using the Portmanteau Test for White Noise (Ljung & Box, 1978; Box & Pierce, 1970). The distribution of the residuals was then checked for Normality through the Jarque-Bera test (Jarque and Bera, 1987) and visual inspection of a Histogram Plot (Pearson, 1895). Serial Correlation was rigorously tested using the Durbin Watson Test or DW Test (Durbin & Watson, 1950; 1951; 1971), the Breusch-Godfrey Serial Correlation LM Test (Breusch, 1978; Godfrey, 1978), and a Correlogram Test (Friendly, 2002). Furthermore, the residuals were examined for Heteroskedasticity utilizing the Breusch-Pagan / Cook-Weisberg test (Breusch & Pagan, 1979; Cook & Weisberg, 1983), the White Test (Cameron & Trivedi's decomposition) (White, 1980), and the ARCH Heteroskedasticity Test (Engle, 1982). Finally, the structural integrity of the model was confirmed through Model Stability Diagnostics, which included the Ramsey RESET Test (Ramsey, 1969), the CUSUM Test (Royston, 1992; Brown et al., 1975), and the CUSUM of Squares Test (Brown et al., 1975).

4.0 Data Analysis

4.1 Univariate Time Series Analysis

We have identified 3 models based on the ACF, PACF functions of d.LFDI. These 3 models are –

Table 3: Model Selection

Models	Significant Coefficients	Sigma Square Value	Log Likelihood Statistics	AIC Statistics	BIC Statistics
ARIMA (0,1,1)	**1**	0.19	-27.69	61.39	67.00
ARIMA (1,1,0)	**1**	0.18	**-27.43**	**60.86**	**66.47**
ARIMA (1,1,1)	0	**0.18**	-27.43	62.86	70.34

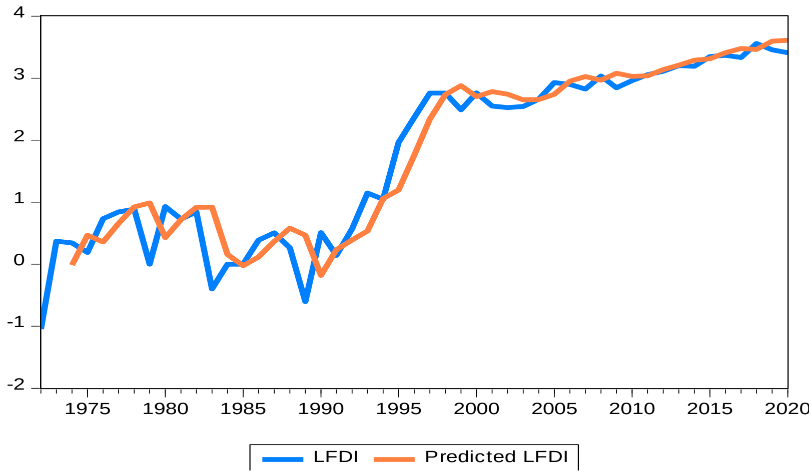
From Table 3, it can be seen that the ARIMA (1,1,0) model has the largest number of green colour signals as it has the highest number of significant coefficients, the highest log likelihood statistics, the lowest AIC and the lowest BIC. That means the final estimated model would be –

Diagnostic Checking

Table 4: Diagnostic Test Results

Diagnostics	Tests	Statistic	Significance	Result
White Noise	Portmanteau Test	13.7867	0.9089	Error series follows the process of white noise
Serial Correlation	Durbin Watson Test	2.0836	-	No Autocorrelation
	Breusch-Godfrey LM Test	2.695	0.7469	No Autocorrelation
Heteroskedasticity	Breusch-Pagan/ Cook-Weisberg	1.7	0.1921	Residuals are homoscedastic
	White Test	0.75	0.6857	Residuals are homoscedastic
	ARCH Heteroskedasticity Test	3.6	0.6082	No ARCH effect in the residual series
Model Stability	Root of the Estimated Model	-0.3535	-	Model is covariance stationary
	Ramsey RESET Test	2.37	0.0844	No omitted variables

Figure 1: Forecasting



From Figure 1, it can be seen that there is a much lower level of variance between the actual and the fitted. Both the LFDI and the predicted LFDI are moderately the same. Hence, we can conclude that the univariate time series model of ARIMA (1,1,0) for the determination of the Log of Foreign Direct Investment in Bangladesh is valid, significant, and stable.

4.2 Multivariate Time Series

Table 5: Order of Integration

Variable Indicator	Variables	Order of Integration, I (d)	
LFDI	Log of FDI Inflows		I (1)
GGR	GDP Growth Rate	I (0)	
LGPP	Log of GDP Per Capita		I (1)
LER	Log of Exchange Rate	I (0)	
IR	Inflation Rate	I (0)	
RIR	Real Interest Rate	I (0)	
LFR	Log of Forex Reserve		I (1)
LMC	Log of Stock Market Capitalisation		I (1)
TGR	Trade to GDP Ratio		I (1)
LTR	Log of Total Tax Revenue		I (1)
LRM	Log of Remittances Received		I (1)
LBS	Log of Budget Size		I (1)

ARDL Specification

Table 6: Regression Output for ARDL Specification

ARDL(2,1,2,2,2,2,1,2,2,2,2,2) regression

Variables	Coefficients	Std. Error	t-Statistic
$LFDI_{t-1}$	-0.1267	0.0923	-1.3721
$LFDI_{t-2}$	0.2023**	0.0692	2.9251
GGR_t	7.0542**	2.3722	2.9737
GGR_{t-1}	3.5144	2.4058	1.4608
$LGPP_t$	-7.1129***	2.3411	-3.0382
$LGPP_{t-1}$	-6.7037**	2.2635	-2.9617
$LGPP_{t-2}$	-1.5747	1.7799	-0.8847
LER_t	7.6452**	2.6041	2.9359
LER_{t-1}	-11.5346***	3.3570	-3.4360
LER_{t-2}	12.5114***	2.6449	4.7304
IR_t	-0.4831	0.7805	-0.6190
IR_{t-1}	4.0017***	0.7093	5.6416
IR_{t-2}	1.9259***	0.4758	4.0475
RIR_t	-3.1413***	0.7228	-4.3458
RIR_{t-1}	-3.0835***	0.9122	-3.3804
RIR_{t-2}	-3.5671***	0.6824	-5.2274
LFR_t	-0.6669**	0.2925	-2.2802
LFR_{t-1}	1.2736**	0.4324	2.9457
LMC_t	0.5188***	0.1490	3.4821
LMC_{t-1}	0.2627**	0.1111	2.3644
LMC_{t-2}	0.4079***	0.1322	3.0853
TGR_t	-0.1052	0.7454	-0.1411
TGR_{t-1}	-0.9600	0.8361	-1.1482
TGR_{t-2}	6.6516***	0.8319	7.9960
LTR_t	-2.4997***	0.6086	-4.1070

LTR_{t-1}	-1.8173**	0.6114	-2.9722
LTR_{t-2}	0.3948	0.4730	0.8346
LRM_{t}	-1.0832	0.8609	-1.2582
LRM_{t-1}	2.8016***	0.9255	3.0272
LRM_{t-2}	-6.6407***	0.5732	-11.5848
LBS_{t}	-3.8162**	1.4459	-2.6393
LBS_{t-1}	5.4513**	2.1471	2.5389
LBS_{t-2}	12.5939***	2.3148	5.4407
$C\ (\phi_0)$	0.8763	1.0061	0.8709

**** p value < 1%, ** p value < 5%, * p value < 10% significance level*

Hence, the above-specified ARDL model is optimal. From Table 6, the ARDL regression states that around 25 coefficients have been found to be statistically significant from 34 regressors (including constant). From them, 10 coefficients have been found to be statistically significant at 1% significance level. In addition, the Goodness of Fit (R^2) for this optimal ARDL model is around 99.83% and the adjusted R^2 for this optimal ARDL model is around 99.40% This means that 99.40% variations in the LFDI can be explained by the variations of the macroeconomic determinants through this optimal ARDL model.

The critical values for F (33,13) at 5% and 1% significance levels are 2.36 and 3.48 respectively. The calculated F-statistic of the ARDL model is 230.62. This is very much larger than the critical values for 1% and 5% significance levels. That is why I have failed to accept the null hypothesis that all the modelled coefficients are zero. Hence, the overall ARDL model is statistically significant and very highly predictive.

ARDL Bounds Cointegration Test

This ARDL bounds co-integration test has been done for finding out the long-run causal relationship between the macroeconomic variables and the LFDI variable. This ARDL bounds test can be done through two types of statistical tests – the Joint F Test and the Joint t Test. Both the results are shown below as follows –

Table 7: Bounds Test

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
			Asymptotic: n=1000	
F-statistic	24.53508	10%	1.83	2.94
k	11	5%	2.06	3.24
		2.5%	2.28	3.5
		1%	2.54	3.86
Actual Sample Size	47		Finite Sample: n=50	
		10%	-1	-1
		5%	-1	-1
		1%	-1	-1
t-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	**Value**	**Signif.**	**I(0)**	**I(1)**
t-statistic	-9.129751	10%	-2.57	-4.69
		5%	-2.86	-5.03
		2.5%	-3.13	-5.34
		1%	-3.43	-5.68

From the bounds test result shown in Table 7, it can be seen that the F-statistic value (24.535) is way larger than the upper bound critical values at all significant levels of 1%, 2.5%, 5%, and 10%. In addition, the t-statistic value (-9.129751) is also above the upper bound critical values at all significant levels of 1%, 2.5%, 5%, and 10%. That is why I have failed to accept the null hypothesis that there is no co-integration. Therefore, variables are co-integrated with LFDI in the long run, and hence, the Long Run model and short-run dynamics or Error Correction Model would be estimated.

Long Run & Level Relationship Dynamics

As there is co-integration between LFDI and the independent variables, I have estimated Long Run Level dynamics based on this ARDL method. The regression output is shown below –

Table 8: ARDL (2,1,2,2,2,2,1,2,2,2,2,2) regression

Variable	Coefficient	Std. Error	t-Statistic
GGR	11.4333**	4.2933	2.6630
LGPP	-16.6505***	4.1819	-3.9815
LER	9.3273***	0.9753	9.5633
IR	5.8899***	1.5910	3.7021
RIR	-10.5930***	1.9291	-5.4911
LFR	0.6563**	0.2755	2.3824
LMC	1.2867***	0.2838	4.5346
TGR	6.0435***	0.7114	8.4950
LTR	-4.2431***	1.3360	-3.1760
LRM	-5.3250***	0.6741	-7.8995
LBS	15.3930***	3.8259	4.0233

**** p value < 1%, ** p value < 5%, * p value < 10% significance level*

Short Run Dynamics (Error Correction Model)

Table 9: ARDL Error Correction Regression

Variables	Coefficient	Std. Error	t-Statistic
$C\,(\theta_0)$	0.8763***	0.0581	15.0777
$\Delta LFDI_{t-1}$	-0.2023***	0.0383	-5.2765
ΔGGR_t	7.0542***	0.9121	7.7345
$\Delta LGPP_t$	-7.1129***	0.8354	-8.5142
$\Delta LGPP_{t-1}$	1.5747**	0.7050	2.2338
ΔLER_t	7.6452***	1.2189	6.2719

ΔLER_{t-1}	-12.5114***	1.4171	-8.8291
ΔIR_t	-0.4831	0.3176	-1.5209
ΔIR_{t-1}	-1.9259***	0.1810	-10.6427
ΔRIR_t	-3.1413***	0.3298	-9.5245
ΔRIR_{t-1}	3.5671***	0.3872	9.2129
ΔLFR_t	-0.6669***	0.1253	-5.3205
ΔLMC_t	0.5188***	0.0647	8.0177
ΔLMC_{t-1}	-0.4079***	0.0613	-6.6526
ΔTGR_t	-0.1052	0.3594	-0.2925
ΔTGR_{t-1}	-6.6516***	0.4720	-14.0929
ΔLTR_t	-2.4997***	0.2856	-8.7521
ΔLTR_{t-1}	-0.3948	0.2406	-1.6406
ΔLRM_t	-1.0832***	0.3172	-3.4146
ΔLRM_{t-1}	6.6407***	0.3293	20.1655
ΔLBS_t	-3.8162***	0.6138	-6.2178
ΔLBS_{t-1}	-12.5939***	1.1199	-11.2451
$\boldsymbol{ECT_{t-1}}$	**-0.9244*** **	**0.0396**	**-23.3141**

**** p value < 1%, ** p value < 5%, * p value < 10% significance level*

The error correction model or ECM is the short-run components. From Table 9, it can be said that almost all of the regressors are statistically significant, except for 1st difference of the inflation rate, 1st difference of the trade to GDP ratio, and the differenced lag of the log of tax revenue. All other short-run coefficients are statistically very significant at 1% significance level, except for the differenced lag of the log of GDP per capita which is statistically significant at 5% significance level. For instance, 1% increase in the differenced lag of the Log of Remittances received will increase the log of foreign direct investment by 6.64% in the short run. In addition, the Goodness of Fit (R^2) for this Long Run model is around 98.31% and the adjusted R^2 for this Long Run model is around 94.01% This means that 94.01% variations in the LFDI can be explained by the variations of the macroeconomic determinants through this Long Run model. The value of root MSE is 0.1024 in this Long Run model. That means the standard deviation of the errors is very low, meaning that the model is very predictive and significant.

Diagnostics Checking

Table 10: Diagnostic Tests

Diagnostics	Tests	Statistic	Significance	Result
White Noise	Portmanteau Test	17.2035	0.6987	Error series follows the process of white noise
Normality Test	Jarque-Bera test	0.4109	0.8143	Residuals are normally distributed
Serial Correlation	Durbin Watson Test	2.476242		No Autocorrelation
	Breusch-Godfrey LM Test	5.385	0.0677	No Autocorrelation
Heteroskedasticity	Breusch-Pagan / Cook-Weisberg	3.78	0.0519	Residuals are homoscedastic
	White Test	47	0.4313	Residuals are homoscedastic
	ARCH Heteroskedasticity Test	16.215	0.3679	No ARCH effect in the residual series
Model Stability	Ramsey RESET Test	3.43	0.0604	No omitted variables

CUSUM and CUSUM of Squares Test

Figure 2, 3: CUSUM and CUSUM of Squares Graph

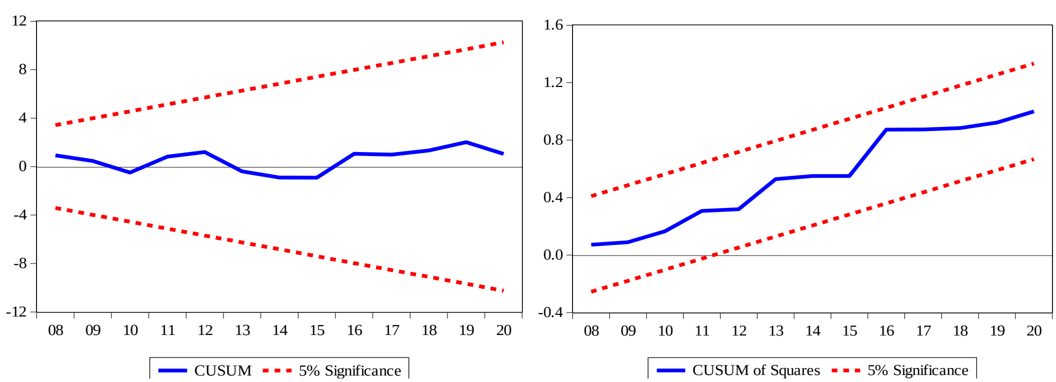
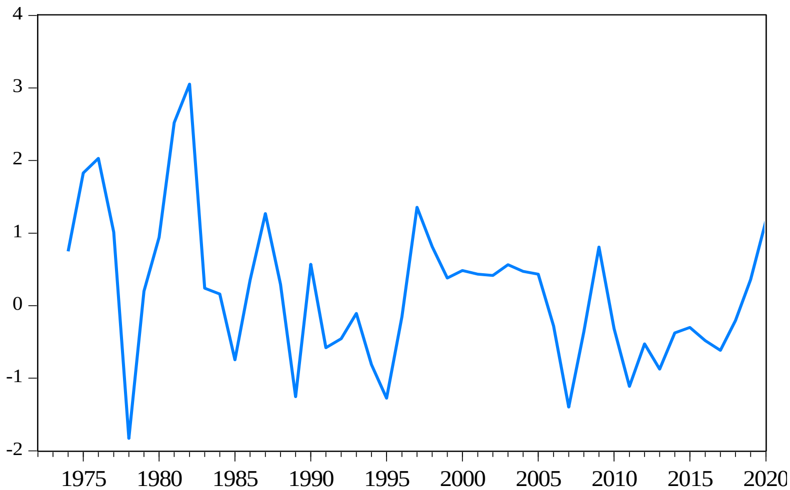


Figure 2 and 3 plot the CUSUM and CUSUM of squares plot. All the CUSUM statistics are lying inside the 5% significance level boundary. That means all the coefficients of the estimated Error Correction Model are significantly stable, and the estimated model is reliable over time. Similarly, all the CUSUM of squares statistics are lying inside the 5% significance level boundary. That means, all the coefficients or parameters of the estimated Error Correction Model would not be departed from the reliability condition. Hence, the estimated model is very robust and significant in estimating the relationship between the macroeconomic variables and LFDI for both the short-run and the long-run associations.

Granger Causality Specifications Model

From the above estimation, it has been found that the ECT_{t-1} term is negative and it is statistically very significant at 1% significance level. This means that there is a high level of long-run equilibrium causal relationship between the LFDI and its macroeconomic determinants, where the speed of long-run adjustment is around 92.43%. In addition, from the ARDL Bounds Co-integration test, it has been found that the F-statistic and t-statistic are statistically very significant at all significant levels of 1%, 2.5%, 5%, and 10%. That means there is a high level of long-run co-integration and causality exists between the LFDI and its determinants. The co-integrating graph is shown below as follows –

Figure 4: Cointegration Graph



From the co-integration graph shown in Figure 4, it can be stated that there is no trend or pattern for the long-run co-integrating relationship. This means the graph follows a random walk or stochastic process which is highly significant for the casual long-run relationship determination. In addition to this co-integration measurement, the Granger Causality model specifies the direction of the causalities between the variables one by one. There are 3 types of Granger causality. I have tabulated the causal directions between LFDI with other variables in Table 11.

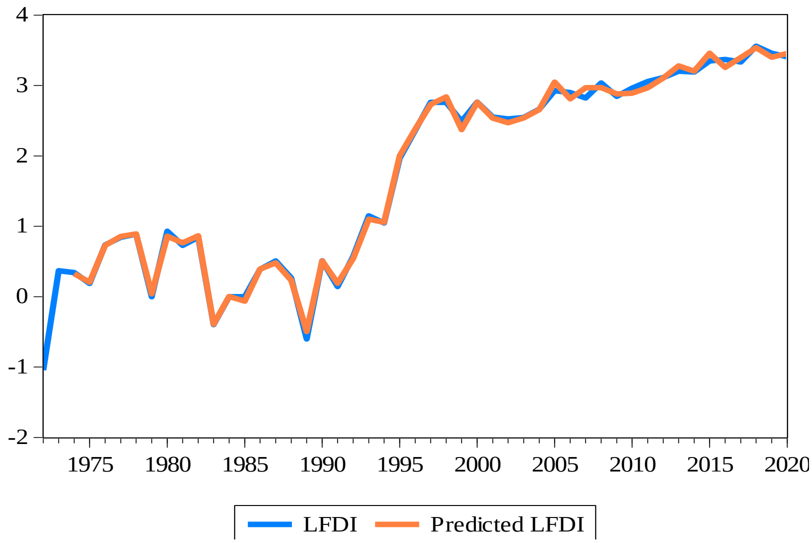
Table 11: Granger Causality

Causal Relations	**F-Statistic**	**Directions**
$GGR_t \rightarrow LFDI_t$	0.4144	Unidirectional
$LFDI_t \rightarrow GGR_t$	18.8378***	
$LGPP_t \rightarrow LFDI_t$	0.5934	Independent
$LFDI_t \rightarrow LGPP_t$	1.3768	
$LER_t \rightarrow LFDI_t$	0.8275	Independent
$LFDI_t \rightarrow LER_t$	1.2778	
$IR_t \rightarrow LFDI_t$	0.0973	Independent
$LFDI_t \rightarrow IR_t$	0.6157	
$RIR_t \rightarrow LFDI_t$	0.9739	Independent
$LFDI_t \rightarrow RIR_t$	0.0168	
$LFR_t \rightarrow LFDI_t$	4.7525**	Unidirectional
$LFDI_t \rightarrow LFR_t$	0.5369	
$LMC_t \rightarrow LFDI_t$	2.6540*	Unidirectional
$LFDI_t \rightarrow LMC_t$	0.0001	
$LBM_t \rightarrow LFDI_t$	1.4907	Independent
$LFDI_t \rightarrow LBM_t$	0.4561	
$TGR_t \rightarrow LFDI_t$	0.4045	Unidirectional
$LFDI_t \rightarrow TGR_t$	3.9462**	
$LTR_t \rightarrow LFDI_t$	1.8754	Independent
$LFDI_t \rightarrow LTR_t$	1.1756	
$LRM_t \rightarrow LFDI_t$	0.1556	Unidirectional
$LFDI_t \rightarrow LRM_t$	3.3661**	
$LBS_t \rightarrow LFDI_t$	2.1751	Independent
$LFDI_t \rightarrow LBS_t$	0.4876	

*** p value < 5%, * p value < 10% significance level*

Table 11 states that there is a significant unidirectional causality exists from the LFDI variable to the GGR variable, and it is statistically significant at 1% significance level. Log of forex reserve Granger causes LFDI at 5% significance level. Log of stock market capitalization Granger causes LFDI at 5% significance level. The other two unidirectional causalities exist from LFDI to the Log of Remittance received and the Trade to GDP ratio. Other variables are related to LFDI independently.

Figure 5: Forecasting



From Figure 5, it can be stated that the estimated ARDL & ECM specified model has predicted the Log of Foreign Direct Investment in Bangladesh almost significantly. There are no significant differences between the LFDI and the predicted LFDI. The predicted LFDI series has fitted well on the actual LFDI graph. It means that the estimated ARDL and ECM specified model is statistically very significant to build a short-run and long-run dynamics for LFDI based on its macroeconomic determinants.

5.0 Conclusion

Based on the Univariate time series modelling, the ARIMA (1,1,0) model has been the best-fitted model for forecasting. It has been seen that one lag of LFDI significantly causes the current LFDI with having p-value of 0.019 which is less than 2.5% significance level. For this ARIMA (1,1,0) modelling, 1st difference of LFDI is used as LFDI is significantly stationary at the 1st difference. There are some differences between the fitted values of LFDI at raw level and the 1st difference level, and the actual values of LFDI at the raw level and 1st difference level. However, overall, the estimated ARIMA (1,1,0) model is significant as it passes all of the diagnostic testing that have been used in this research study. That is why, from this univariate time series model, it can be stated that the current LFDI is significantly dependent on its own 1st lag value. And the estimated ARIMA (1,1,0) process is significant and also reliable as the AR root is located inside the unit circle, meaning that this process is covariance stationary.

For Multivariate time series analysis, ARDL & ECM have been applied to find the significance between the macroeconomic determinants and LFDI of Bangladesh. For this analysis, the maximum lag length has been chosen to be two lags of the variables. After the ARDL specification, the ARDL Bounds Co-integration approach has been conducted to identify the long-run co-integration between the independent variables and LFDI. The test is significant at 1% significance level for both the F-bounds test and the t-bounds test. Hence, the Error Correction Model or ECM has been applied to find the long-run speed of adjustment and short-run dynamics. From the estimated ECM, the speed of adjustment is found to be 92.43%. That means around 92.43% errors of the current period will be adjusted in the long run through this estimated ARDL & ECM. In addition, this long-run speed of adjustment is significant at 1% significance level, meaning that the estimated model is highly significant for the long-run equilibrium relationship and co-integration between macroeconomic variables and LFDI. From the long-run level relationship, all 11 independent variables have been found to be significant for the determination of LFDI in Bangladesh. Except for Log of GDP per capita, Real interest rate, Log of Tax revenue, and Log of Remittance, all other variables have been found to have a positive coefficient. From short-run dynamics, almost all of the regressors have been found to be statistically very significant at 1% significance level, except for the differenced lag of the log of GDP per capita which is statistically significant at 5% significance level.

This study contributes to the broader literature on FDI determinants by offering empirical insights into Bangladesh's investment landscape. The findings suggest that ensuring exchange rate stability, macroeconomic resilience, and trade openness is crucial for attracting sustained FDI inflows in Bangladesh. Policymakers should focus on financial market development, enhancing stock market efficiency, and improving infrastructure to create a more investment-friendly environment. Additionally, targeted fiscal incentives, tax reforms, and streamlined regulatory frameworks can encourage investments in key sectors such as manufacturing, infrastructure, and technology. Political stability and institutional efficiency remain vital in fostering investor confidence and minimizing uncertainty. By implementing these strategic interventions, Bangladesh can strengthen its position as a preferred destination for foreign investment, ultimately driving sustainable economic growth. Future research could incorporate structural breaks, global economic shocks, and firm-level investment behavior to further refine policy recommendations. By implementing strategic reforms, Bangladesh can strengthen its investment climate and sustain long-term economic growth through increased foreign capital inflows.

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