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Employing the ARDL Model to Predict the GDP of Iraq Through the Years (2005 to 2023)

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Abstract: This study investigates the economic indicators of Iraq, specifically focusing on Gross Domestic Product (GDP), Interest Rate (IR), and Foreign Direct Investment (FDI) from 2005 to 2023. The dataset reveals a complex interplay of these variables, influenced by post-conflict recovery, fluctuating oil prices, and political stability. To analyze the relationships among these indicators, an Autoregressive Distributed Lag (ARDL) model is estimated. Initial stationarity tests confirm that the variables achieve stationarity upon differencing, enabling the application of the ARDL framework. Through rigorous model selection criteria, ARDL (1, 0, 2) is identified as the optimal model, highlighting significant short-term and long-term dynamics, particularly the negative impact of lagged FDI on GDP. Diagnostic tests further affirm the robustness of the model, indicating no issues with multicollinearity, autocorrelation, and heteroskedasticity. The findings contribute to understanding Iraq's economic landscape and the critical role of FDI in shaping GDP trajectories, providing valuable insights for policymakers and stakeholders.

Keywords: GDP, IR, FDI, ARDL, Long-term and Short-term.

توظيف نموذج ARDL للتنبؤ بالناتج المحلي الإجمالي للعراق خلال السنوات (٢٠٠٥ إلى ٢٠٢٣)

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المستخلص: تبحث هذه الدراسة في المؤشرات الاقتصادية للعراق، مع التركيز بشكل خاص على الناتج المحلي الإجمالي، وسعر الفائدة، والاستثمار الأجنبي المباشر من عام ٢٠٠٥ إلى عام ٢٠٢٣. وتكشف مجموعة البيانات عن تفاعل معقد بين هذه المتغيرات،وتقلب أسعار النفط، والاستقرار السياسي لها تأثير في تحليل العلاقات بين هذه المؤشرات، لقد تم تقدير نموذج الانحدار الذاتي إبطاء الموزع.(ARDL)تؤكد اختبارات الإستقرارية الأولية أن المتغيرات تحقق الثبات عند الاختلاف الأول، مما يتيح تطبيق النموذج المذكور.من خلال معايير اختيار النموذج ، تم تحديد (ARDL(1,0,2))باعتباره النموذج الأمثل، مما يسلط الضوء على ديناميكيات قصيرة الأجل وطويلة الأجل الهامة، وخاصة التأثير السلبي للاستثمار الأجنبي المباشر المتأخر على الناتج المحلي الإجمالي. يشيرالنتائج إلى عدم وجود مشاكل في التعدد الخطي، والارتباط الذاتي، وعدم تجانس التباين. تساهم النتائج في فهم الاقتصادي في العراق والدور الحاسم للاستثمار الأجنبي المباشر في تشكيل مسارات الناتج المحلي الإجمالي، مما يوفر رؤى قيمة لصناع السياسات وأصحاب المصلحة.

الكلمات المفتاحية: الناتج المحلي الإجمالي، الاستثمار الأجنبي المباشر، ARDL، الأمد البعيد والقصير.

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Introduction

The Autoregressive Distributed Lag (ARDL) model, introduced by Pesaran and Shin (1998) and further refined by Pesaran, Shin, and Smith (2001), is a prominent econometric tool designed for analyzing dynamic relationships between variables in time series data. Unlike traditional models that impose the strict requirement of stationarity on all variables, the ARDL model accommodates a mix of stationary (I(0)) and non-stationary (I(1)) variables, thus offering significant flexibility. This capability allows researchers to avoid the often complex and restrictive need for pre-testing variables for stationarity, making the ARDL model particularly valuable for empirical studies involving variables with different integration orders (Pesaran et al., 2001). One of the key strengths of the ARDL model is its ability to conduct cointegration analysis through bounds testing. This feature enables the model to test for the presence of a long-term equilibrium relationship among variables, even when the variables have mixed orders of integration. The bounds testing approach, as developed by Pesaran et al. (2001), involves comparing the computed F-statistic against critical values to determine whether the variables are cointegrated. This method provides a clear and straightforward way to assess long-term relationships, which is crucial for understanding economic and financial dynamics over time. The practical applications of the ARDL model are broad and encompass various fields such as economics, finance, and policy analysis. Researchers and policymakers utilize the ARDL model to explore both short-term dynamics and long-term equilibrium relationships among key economic indicators. For instance, Narayan (2005) demonstrated the utility of the ARDL model in analyzing the saving and investment nexus in China, highlighting its effectiveness in capturing both immediate and lasting effects of economic policies. By allowing for simultaneous estimation of short-term adjustments and long-term relationships, the ARDL model offers a comprehensive analytical framework that supports informed decision-making and policy development (Pesaran et al., 2001; Narayan, 2005).

1. Time Series and its Components

Time series data consist of observations collected sequentially over time, providing insights into how variables evolve and interact over a specified period. The fundamental components of a time series include the trend, seasonality, cyclicality, and random variation. The trend represents the long-term movement or direction in the data, indicating whether the series is generally increasing or decreasing over time. Seasonality captures regular and predictable patterns that recur at specific intervals, such as monthly or quarterly, often driven by external factors like weather or holidays. Cyclicality refers to fluctuations that occur over longer periods, are influenced by economic cycles or business conditions, and are not of fixed length like seasonality. Finally, random variation encompasses irregular, unpredictable fluctuations or noise that cannot be attributed to the other components, often resulting from random events or measurement errors. Understanding these components is crucial for effective time series analysis, as it helps in modeling, forecasting, and making informed decisions based on historical data patterns.

A. Stationary and Non-Stationary Time series

In time series analysis, stationary and non-stationary time series are fundamental concepts determining the applicability of various statistical models and methods. A stationary time series exhibits consistent statistical properties over time, including a constant mean, variance, and autocovariance that depend only on the time lag between observations rather than the actual period. This stability allows for more reliable model estimation and forecasting. Conversely, a non-stationary time series displays changes in its statistical properties over time, often characterized by trends, seasonality, or structural breaks. Non-stationary series can lead to misleading results if analyzed without appropriate transformation, such as differencing or detrending, to achieve stationarity. Understanding whether a time series is stationary or non-stationary is crucial, as it impacts the choice of modeling techniques and the validity of inference drawn from the data.

B. Autoregressive Distributed Lagged Model

The Autoregressive Distributed Lag (ARDL) model is a versatile and widely used approach in time series econometrics for analyzing the relationships between variables. It is beneficial for examining short-term and long-term dynamics within a time series dataset. Here’s a detailed overview of the ARDL model, including its components, estimation methods, and applications.

(1) Components of the ARDL Model

(A) Autoregressive Terms: The model includes lagged values of the dependent variable. These terms capture the influence of past values of the dependent variable on its current value. For example, if Y_t is the dependent variable, Y_{t-1} and Y_{t-2} would be autoregressive terms representing past values.

(B) Distributed Lag Terms: The model incorporates lagged values of independent variables. These terms help capture the delayed effects of the independent variables on the dependent variable. For instance, if X_t is an independent variable, terms like X_{t-1} and X_{t-2} would represent the distributed lags.

(C) Error Term:The error term u_t accounts for the variability in Y_t that cannot be explained by the model. It represents random fluctuations or noise.

C. Types of ARDLM

The ARDLM according to the lagged values of the variables in the structure of the model consists of three types:

(1) Lagged values of explanatory variable ARDL (0, q).
(2) Lagged values of response variable ARDL (p, 0).
(3) Lagged values of both ARDL (p, q).

In this section, the simple ARDLM (1, 1) is explained that contains lagged values of both (X_t, Y_t)

$Y_t = m + \alpha_1 Y_{t-1} + B0 X_t + B_1 X_{t-1} + u_t$ ……………….. (1)

Where:

Y_t: is a stationary response variable.
X_t: is a stationary explanatory variable.
u_t: is a white noise process.

u_t is a white noise process if each value in the sequence is distributed normally with zero mean and constant variance with uncorrelated serially.

$E(u_t) = E(u_{t-1}) = \ldots = E(u_{t-p}) = 0; \quad p = 0, 1, 2, \ldots.$

$E(u_{t2}) = E(u_{t-12}) = \ldots = E(u_{t-p2}) = \sigma^2$

$E(u_t\, u_{t-s}) = E(u_{t-j}\, u_{t-j-s}) = 0$ for all ut

Under the above conditions, one can say that u_t is a white noise process.

D. Estimation

To estimate the parameters of ARDLM ordinary least squares (OLS) can be used in one condition that satisfies the assumptions of the OLS method, that the $E(X_t u_t) = E(Y_t u_t) = 0$ and $E(u_{t2}) = \sigma^2$ for $(t = 0, 1, 2, \ldots)$ in another word if the variables (X_t, Y_t) are uncorrelated with the residuals then OLS estimators are consistent (assuming that multicollinearity is not existed) estimators, also it provides that the model is not suffering from heteroscedasticity problem, it is obvious that there are some problems with finite and infinity lag model in case we have finite lag model we should focus on choosing the lag length and then treat the collinearity in the results of the model, in case we have polynomial distributed lag (PDL) lag weights are required to treat the collinearity and falls it on a smooth curve.

The ARDL model is an infinite lag model that is both flexible and parsimonious, recall the eq(1) which is the ARDL (1, 1) model then the generalized of this equation is the ARDL(p, q) model as it is shown below:

$$Y_t = m + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-p} + B_0 X_t + B_1 X_{t-1} + \ldots + B_q X_{t-q} + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The above equation contains p lags of the response variable and q lags of the explanatory variable.

(1) Estimation and interpretation of finite ARDLM

The decreasing to zero of the explanatory effect on the response variable gives the capability of estimating the parameters of eq(3) directly.

$$Y_t = \alpha + \sum_{s=0}^{q} B_s X_{t-1} + u_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Assuming that X_t strictly exogenous then the parameters can be estimated by using OLS or GLS.

E. Multicollinearity

Despite of the stationary of variable X the lagged can be auto-correlated strongly and these highly auto-correlation leads to multicollinearity which caused unreliable estimates with large values of V-COV (B) and gives logically meaningless results. In econometric estimating the parameters should be empty of any significant correlation or auto-correlation of explanatory variables or their lags, in case the sequence of lag coefficients excludes around between large and small and sometimes positive and negative values which are not consistent with econometric theory, the estimation of coefficients should be restricted to satisfy the previously assumptions of smoothness.

F. Koyck Transformation

The lags may cause a multicollinearity problem to overcome this problem Koyck transformation should be used where it assumes a geometric decline and some sign coefficients (Bs) that transform the finite DLM with geometrically declining into the following form:

$$Y_t = \alpha(1 - \lambda) + B_0 X_t + \lambda Y_{t-1} + V_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where:

λ : speed of decline.

B_0: immediate effect.

$\frac{B_0}{1-\lambda}$: Long run effect

$V_t = u_t - \lambda u_{t-1}$

Then ARDLM can be estimated by using OLS method where its results are have a BLUE property as long the residuals do not exhibit auto-correlation.

G. Diagnostic Testing

Diagnostic testing in time series models involves evaluating the model's residuals to ensure that the underlying assumptions of the model are met and to identify potential issues that might affect the model's validity. Proper diagnostic testing helps in improving model specification and ensuring reliable forecasts.

(1) Augmented Dickey-Fuller test

Augmented Dickey-Fuller tests the hypothesis which is stated that the series is not stationary, and can be tested in regression equation.

$\Delta X_t = \beta_0 + a_t + \beta_1 X_{t-1} + \sum_{i=1}^{p} \lambda_i \Delta X_{t-i} + u_t$……………….. (5)

Where a random walk, $a_t = a_{t-1} + a\varepsilon_t$ is allowed.

(2) Durbin-Watson (DW) Test

The Durbin-Watson (DW) test is used to detect the presence of autocorrelation (specifically, first-order autocorrelation) in the residuals of a regression model. Autocorrelation occurs when the residuals (errors) of the model are correlated across observations, which can indicate model specification problems or issues with the data. In order to detect whether the autocorrelation in cross-section time series data exists or not, then we must test the hypothesis :

H_0: There is no first-order autocorrelation in the residuals.

H_1: There is first-order autocorrelation in the residuals.

$$DW = \frac{\sum_{t=2}^{n}(u_t - u_{t-1})^2}{\sum_{t=1}^{n} u_t^2} \quad \text{……………….. (6)}$$

Where:

u_t: is the residuals of the estimated model.

u_{t-1}: is the first lag of the residuals of the estimated model.

(3) The Breusch-Pagan Test

The Breusch-Pagan test is a statistical test used to detect heteroscedasticity in regression models. Heteroscedasticity occurs when the variance of the errors is not constant across all levels of the independent variables, which can lead to inefficient estimates and incorrect conclusions.

H_0: The variance of the errors is constant (homoscedasticity). In other words, there is no relationship between the squared residuals and the independent variables.

H_1: The variance of the errors is not constant (heteroscedasticity). In other words, there is a relationship between the squared residuals and the independent variables.

(A) Breusch-Pagan Test Procedure

The procedure of the mentioned test can be shown as follows:

1. Estimate the original regression model:

$Y_t = B_0 + B_1 X_{t-1} + \ldots + B_q X_{t-q} + u_t$ ……………….. (7)

2. Squaring the residuals of the above-estimated model.

3. Then estimate an auxiliary regression from the squared residuals on the independent variables as shown in equation (8):

$\hat{u}^2_t = \gamma_0 + \gamma_1 X_{t1} + \gamma_2 X_{t2} + \ldots + \gamma_q X_{tq} + v_t$ ……………….. (8)

Where:

$\gamma_0\, \gamma_1 \gamma_2, \ldots, \gamma_q$: are the new coefficients.

v_i: is the new error term in this auxiliary regression.

4. Then the statistical test can be computed according to the below equation:

BP= n.R^2……………….. (9)

Where:

n: is the number of observations.

R^2: is the coefficient of determination from the auxiliary regression.

Under the null hypothesis, the test statistic BP follows a chi-square distribution with q degrees of freedom, where q is the number of independent variables in the auxiliary regression. The computed value of the test is compared to the critical value from the chi-square distribution. If the test statistic exceeds the critical value or if the p-value is below 5%, reject the null hypothesis and conclude that there is evidence of heteroscedasticity.

(4) Bounds Testing for Cointegration

Bounds testing for cointegration, introduced by Pesaran, Shin, and Smith in 2001, is used to determine whether a long-term equilibrium relationship exists between variables in a regression model. This method is particularly useful when dealing with variables of mixed integration orders (i.e., I(0) and I(1) variables) and does not require that all variables be integrated in the same order.
H_0: There is no long-run relationship (cointegration) between the variables. Formally, the coefficients on the lagged levels of the variables in the error correction model are zero.
H_1: There is a long-run relationship (cointegration) between the variables. Formally, at least one of the coefficients on the lagged levels of the variables in the error correction model is non-zero.

(A) Bounds Testing Procedure

The procedure of the mentioned test can be shown as follows:

1) Consider a general form of the autoregressive distributed lag (ARDL) model:

$$Y_t = m + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ldots + \alpha_p Y_{t-q} + B_0 X_t + B_1 X_{t-1} + \ldots + B_q X_{t-q} + u_t \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

2) Rewriting the ARDL model to include the long-term relationship, you form an error correction model:

$$\Delta y_t = б_0 + б_1 \Delta x_t + \lambda(y_{t-1} - л\, x_{t-1}) + \sum_{i=1}^{q-1} \Psi_i \Delta y_{t-i} + \sum_{i=1}^{p-1} ъ_i \Delta x_{t-j} + \mu_t \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

Where:
λ: is the coefficient of the lagged levels and $(y_{t-1} - \theta x_{t-1})$ represents the long-run relationship.

3) The **Bounds Test** follows the F-Distribution and it computes as follows:

$$F = \frac{(R^2_{restricted} - R^2_{unrestricted}) / (k)}{(1 - R^2_{unrestricted}) / (n-k-1)} \ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Where:
$R^2_{restricted}$: is the R-squared from the restricted model (without the lagged levels).
$R^2_{unrestricted}$: is the R-squared from the unrestricted model (with the lagged levels).
k: is the number of restrictions, and n is the sample size.

4) **Compare with Bounds**: Compare the computed F-statistic to critical values from the bounds testing tables. The bounds test provides two critical values: one for the null hypothesis of no cointegration (lower bound) and one for the alternative hypothesis of cointegration (upper bound).
   - **If the F-statistic is above the upper bound**: Reject the null hypothesis of no cointegration.
   - **If the F-statistic is below the lower bound**: Fail to reject the null hypothesis of no cointegration.
   - **If the F-statistic falls between the bounds**: The result is inconclusive, and you may need to gather more evidence or use additional methods.

H. Model evaluators

In statistical modeling, model evaluators are tools or metrics used to assess the quality and performance of a statistical or machine learning model. They help determine how well a model fits the data and generalizes to new, unseen data. Evaluators can be broadly categorized based on the type of model and the specific aspects of model performance they measure. The measures that have been used in this study are:

(1) Akaike Information Criterion (AIC): Balances model fit and complexity by penalizing models with more parameters.

$$AIC = \ln(б^2) + \frac{2K}{T} \ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Where:
σ^2: is the estimated variance of the residuals, **K** is the number of parameters, and **T** is the number of observations.

(2) **Bayesian Information Criterion (BIC)**: Similar to AIC but with a harsher penalty for complexity, useful for model comparison.

$$\text{BIC} = \ln(\sigma^2) + \frac{K \ln(T)}{T} \ldots\ldots\ldots\ldots\ldots\ldots (14)$$

2. Applications

A. Data Description

The dataset encompasses the economic indicators of Iraq, specifically Gross Domestic Product (GDP in millions), Interest Rate (IR), and Foreign Direct Investment (FDI in millions), spanning the years 2005 to 2023. During this period, Iraq's GDP reflects a trajectory influenced by various factors, including post-conflict recovery and fluctuating oil prices, contributing to significant growth rates, particularly in the early years following 2005. Interest rates have varied and have been influenced by monetary policy and economic conditions, affecting both domestic investment and consumer behavior. Meanwhile, FDI has shown fluctuations, responding to political stability, economic reforms, and regional dynamics, with a notable increase in investment inflows in certain years as the country sought to diversify its economy beyond oil. This dataset provides critical insights into the evolving economic landscape of Iraq, capturing the interplay between these three key indicators over nearly two decades.

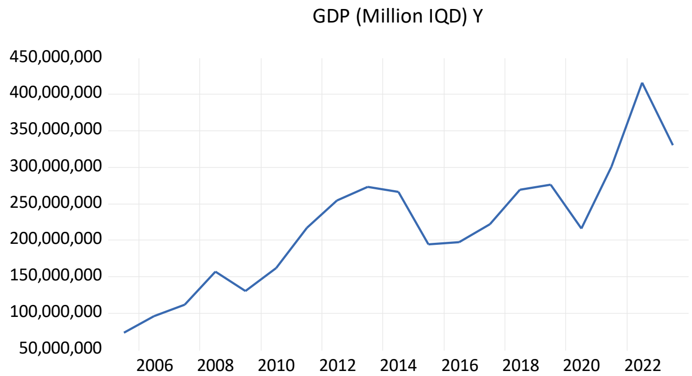

Figure (1): represents the GDP of Iraq through the years (2005 to 2023).

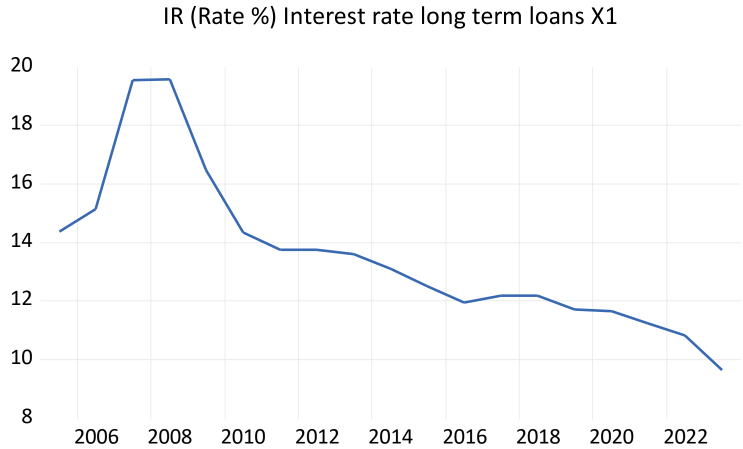

Figure (2): represents the IR of Iraq through the years (2005 to 2023).

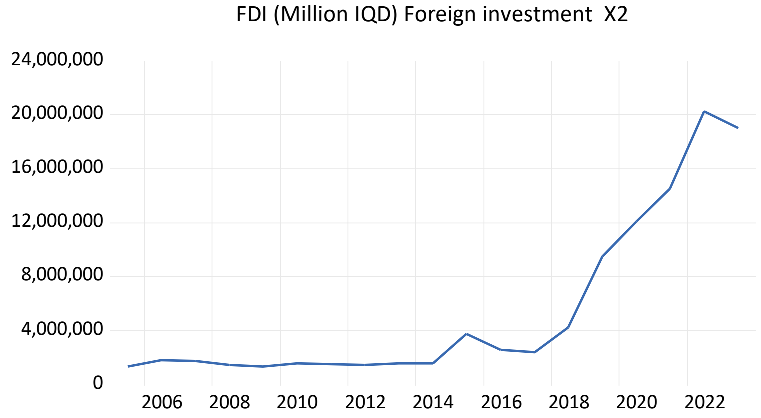

Figure (3): represents the FDI of Iraq through the years (2005 to 2023).

B. Estimating ARDL Model

Estimating an Autoregressive Distributed Lag (ARDL) model involves several key steps aimed at analyzing the relationship between GDP as the dependent variable, and IR and FDI as independent variables over time. First, we check for the stationarity of the time series data using tests such as the Augmented Dickey-Fuller test to ensure that the series can be modeled appropriately. Once the data is confirmed to be stationary, the ARDL model is specified, incorporating both current and lagged values of the dependent variable as well as current and lagged values of the independent variables. The coefficients of the model are then estimated using Ordinary Least Squares (OLS), allowing for the analysis of both short-term and long-term dynamics among the variables. Importantly, model selection criteria like AIC, BIC, and the F-statistic are employed to determine the optimal lag length and assess the overall significance of the model.

Table (1): Represents the stationary test of the variables

Augmented Dickey-Fuller test statistic			
	Variables	**t-Statistic**	**P-value**
At level	GDP	-1.25733	0.6219
	IR	1.196015	0.9966
	FDI	-2.97747	0.0586
First Diff.	GDP (-1)	-5.00605	0.0013
	IR (-1)	-3.45852	0.0494
	FDI (-1)	-11.322	0.000

The stationary test results presented in Table (3-1) utilize the Augmented Dickey-Fuller (ADF) test to assess the stationarity of the variables GDP, IR (interest rate), and FDI (foreign direct investment). At the level form, the t-statistics for GDP (-1.25733) and IR (1.196015) indicate non-stationarity, as their corresponding p-values (0.6219 and 0.9966) are well above the conventional threshold of 0.05. Conversely, FDI shows a t-statistic of -2.97747 with a p-value of 0.0586, which suggests it is marginally non-stationary but close to stationarity. However, upon taking the first difference, all three variables demonstrate significant stationarity: GDP (-5.00605, p-value = 0.0013), IR (-3.45852, p-value = 0.0494), and FDI (-11.322, p-value = 0.000). These results indicate that while the original variables may be non-stationary, differencing them successfully achieves stationarity, because the three variables are stationary at first difference then the main assumption of using the ARDL model is achieved.

Table (2): shows the selection of the best model among all possible models

Model Selection Criteria Table						
Model	LogL	AIC*	BIC	HQ	Adj. R-sq	Specification
1	-315.431	38.168	38.609	38.212	0.721	ARDL(2, 2, 2)
2	-318.064	38.360	38.753	38.399	0.662	ARDL(2, 2, 1)
3	-318.343	38.276	38.619	38.310	0.685	ARDL(2, 2, 0)
4	-316.268	38.149	38.541	38.188	0.726	ARDL(2, 1, 2)
5	-319.437	38.404	38.747	38.438	0.642	ARDL(2, 1, 1)
6	-319.910	38.342	38.636	38.372	0.656	ARDL(2, 1, 0)
7	-316.804	38.095	38.438	38.129	0.737	ARDL(2, 0, 2)
8	-319.700	38.318	38.612	38.347	0.664	ARDL(2, 0, 1)
9	-320.226	38.262	38.507	38.286	0.673	ARDL(2, 0, 0)
10	-316.325	38.156	38.548	38.195	0.724	ARDL(1, 2, 2)
11	-320.500	38.529	38.873	38.564	0.594	ARDL(1, 2, 1)
12	-321.052	38.477	38.771	38.506	0.607	ARDL(1, 2, 0)
13	-316.623	38.073	38.416	38.107	0.743	ARDL(1, 1, 2)
14	-320.819	38.449	38.743	38.479	0.617	ARDL(1, 1, 1)
15	-321.451	38.406	38.651	38.430	0.622	ARDL(1, 1, 0)
16	**-317.068**	**38.008**	**38.302**	**38.037**	**0.754**	**ARDL(1, 0, 2)**
17	-320.931	38.345	38.590	38.369	0.644	ARDL(1, 0, 1)
18	-321.597	38.306	38.502	38.325	0.645	ARDL(1, 0, 0)

From the above table to select the best model from the provided criteria, we focus on minimizing the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQ), while maximizing the Log-Likelihood (LogL) and Adjusted R-squared (Adj. R-sq). Among the models, **Model 16** (ARDL (1, 0, 2)) stands out with the lowest **AIC** value of **38.008**, indicating a strong fit relative to its complexity. It also boasts a high **Adjusted R-squared** of **0.754**, suggesting that it explains a significant portion of the variance in the data. Additionally, it balances model simplicity with effectiveness, making it a compelling choice. Thus, Model 16 is recommended as the best candidate based on these criteria.

Table (3): demonstrate the estimated parameters of ARDL (1,0,2) model

Selected Model: ARDL (1, 0, 2)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
GDP(-1)	0.362	0.231	1.566	0.146
IR	-7347152	5894187	-1.247	0.239
FDI	8.992	4.980	1.805	0.098
FDI(-1)	-22.891	8.577	-2.669	0.022
FDI(-2)	23.342	9.279	2.516	0.029
C	224000000	119000000	1.878	0.087
R-squared		0.830719		
Adjusted R-squared		0.753773		
Adjusted R-squared		0.753773		
F-statistic		10.79614		
Prob(F-statistic)		0.000597		
AIC		38.00802		

In the selected ARDL (1, 0, 2) model, the estimated parameters provide insights into the relationships between the variables and their effects on the dependent variable. The coefficient for GDP(-1) is 0.362, indicating a positive impact on the dependent variable, though it is not statistically significant (p-value = 0.146). The interest rate (IR) has a large negative coefficient of -7,347,152, but this effect is also not statistically significant (p-value = 0.239). Foreign direct investment (FDI) has a positive coefficient of 8.992 with a p-value of 0.098, suggesting a potential positive impact on the dependent variable, but it remains marginally significant. Notably, the lagged terms of FDI show significant effects: FDI(-1) has a negative coefficient of -22.891 (p-value = 0.022), while FDI(-2) has a positive coefficient of 23.342 (p-value = 0.029), indicating a dynamic relationship over time. The constant term (C) is 224,000,000 with a p-value of 0.087, it is statistically not significant. The model demonstrates a strong fit, with an R-squared value of 0.831 and an **Adjusted R-squared** of **0.754**, indicating that approximately **75%** of the variance in the dependent variable is explained by the model. The F-statistic of 10.79614 and its significance (p-value = 0.000597) suggest that the overall model is statistically significant.

Table (4): explains the econometrics ’problems

Multicollinearity Test		Autocorrelation Test	Heteroskedasticity Test	
Variable	**VIF**	**Durbin-Watson stat**	**F-statistic**	**Prob. F(5,11)**
GDP (-1)	5.7364			
IR	2.993085			
FDI	8.91246	2.176819	1.762626	0.2012
FDI (-1)	9.47192			
FDI (-2)	4.28344			

Summing the up table which shows the diagnostic tests of econometric ’problems, the VIF values are all less than 10 implying that the postulated model does not suffer from multicollinearity problem, furthermore, the Durbin-Watson test value is 2.176 which lies between (dl < D-W < 4-dl) implies that the serial autocorrelation problem does not exist, where dl = 0.481 “from D-W table”, the p-value of the last test is greater than 0.05 that means the model does not suffer from heteroskedasticity problem, after passing the three tests then we can use the estimated model.

Table (5): represents the Bound Test

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDP (-1)	-0.638112	0.231119	-2.760964	0.0185
IR	-7347152	5894187	0	0
FDI	8.991533	4.980242	1.805441	0.0984
FDI (-1)	9.442143	3.508238	2.69142	0.021
FDI (-2)	-23.34161	9.278674	-2.515619	0.0287

Table (3-5) presents the results of the Bound Test, which helps differentiate between long-term and short-term relationships among the variables in the model. The coefficient for GDP(-1) is -0.638, indicating a significant long-term relationship with the dependent variable, suggesting that increases in GDP(-1) are associated with decreases in the dependent variable in the long run term. For foreign direct investment (FDI), the coefficient of 8.992 (t-statistic = 1.805, p-value = 0.0984) shows a positive short-term effect because its p-value is less than 0.05. In contrast, the lagged FDI(-1) and FDI(-2) terms exhibit significant long-term dynamics: FDI(-1) has a positive coefficient of 9.442, indicating that the previous period's FDI positively affects the GDP. However, FDI(-2) presents a negative coefficient of -23.342, which means increasing one unit in FDI(-2) leads to a decrease of 23.342 units in GDP in the long run term.

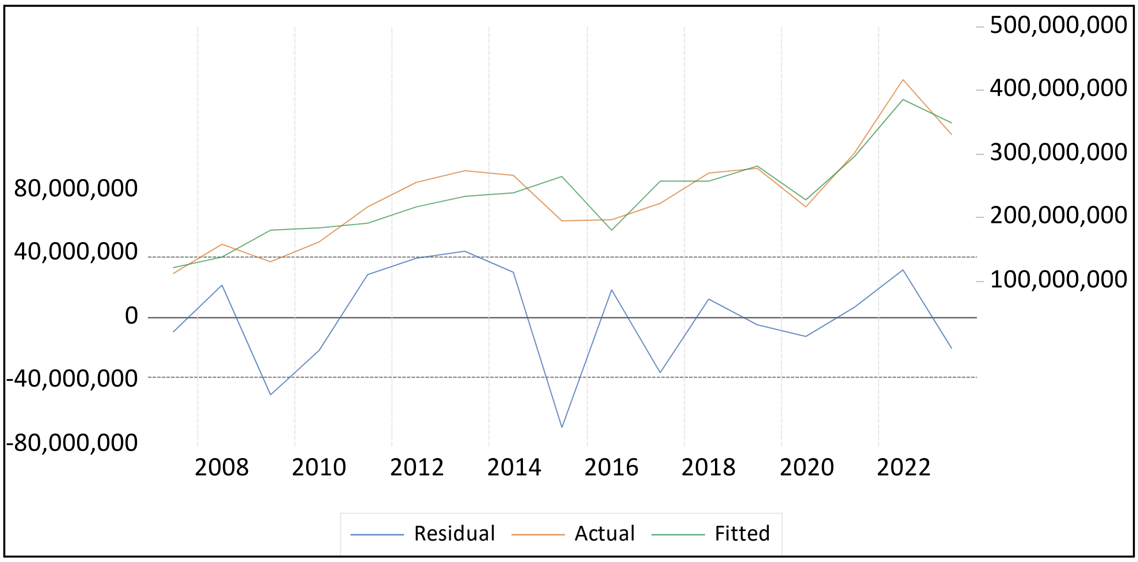

Figure (4): represents the fitted model.

3. Conclusions

A. Economic Dynamics: The analysis of Iraq's economic indicators from 2005 to 2023 reveals a complex interplay between GDP, Interest Rates, and Foreign Direct Investment (FDI). The significant GDP growth, especially post-2005, highlights the effects of political stability and oil price fluctuations, while FDI trends demonstrate the country's efforts to diversify its economy.

B. Modeling Approach: Utilizing the ARDL model allowed for a nuanced understanding of the variables' short-term and long-term relationships. The selected ARDL(1, 0, 2) model effectively captures these dynamics, with an Adjusted R-squared of 0.754 indicating that the model explains a substantial portion of the variance in GDP.

C. **Significant Relationships:** The model's results indicate that while the immediate impacts of interest rates on GDP are not statistically significant, FDI exhibits a potential positive short-term effect on GDP. Notably, the lagged effects of FDI demonstrate complex relationships, suggesting that past investments can both positively and negatively influence current economic performance.

D. **Robustness of Results:** Diagnostic tests confirm the robustness of the ARDL model, showing no issues with multicollinearity, autocorrelation, or heteroskedasticity. This supports the reliability of the model's estimates, providing a solid foundation for policymakers to consider FDI and interest rate strategies aimed at fostering economic growth in Iraq.

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