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Forecasting Foreign Direct Investment Inflow in Jordan: Univariate ARIMA Model

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Abstract: The present study is an attempt to build a Univariate time series model to forecast the FDI inflows into Jordan over the coming period 2004-2025. The study employs Box-Jenkins methodology of building ARIMA (Autoregressive Integrated Moving Average) model to achieve the goals of the study. An annual sample time series data for the FDI in Jordan was utilized over the period 1976-2003. The data were collected from the Central Bank of Jordan publications. The accuracy of the selected models was tested by performing different diagnostic tests to ensure the accuracy of the obtained results. Results of the study show that ARIMA model provides a better model for forecasting FDI in Jordan. The empirical results of ARIMA model have shown that FDI is following an increasing trend over the forecasted period (2004-2025). The empirical results indicate the expected positive impact of FDI inflows on different macroeconomic variables in Jordan economy.

Key words: FDI, ARIMA, forecasting, univariate analysis, box-jenkins methodology

INTRODUCTION

FDI is known as that "Investment made by multinational business enterprises in foreign countries to control assets and manage production activities in those countries"[1]. The issue of Foreign Direct Investment, hereafter, (FDI), has created an extensive debate among scholars and policy-makers over the consequences of Multinational Corporation on the economies of the host-countries. The issue been investigated thoroughly, particularly, in terms of its impact on the economic activities in the host countries on the macroeconomic level and microeconomic level[2-6]. Moreover, inward foreign direct investment has created a great fear among host countries that stems from being a source of foreign influence (politically and economically) and competition with domestic establishments[7]. Nevertheless, inward FDI has been viewed as source of new technology and employment opportunities[8].

Jordan has been pursuing a set of economic development strategies to promote national economic development. The driving force behind these strategies is to reduce the most challenging problems facing Jordan economy; employment and poverty. Financing economic development projects is one of the most obstacles facing Jordan's ambitions. For this reason along with other reasons, Jordan committed itself to attract foreign financial resources to promote economic development projects. The commitment is in the form of a new package of investment laws to facilitate the flow of foreign financial resources into Jordan since 1992 by implementing a significant number of laws and incentives to create a desirable business environment[9].

There have been enormous forecasting models ranging from most sophisticated models to simple models. Box-Jenkins models provide a simple means for choosing the effective forecasting models[10]. Box-Jenkins model is in two types. Type one is called Univariate models, which is considered the simplest model that uses only current values and past values of the variable under consideration. Type two is called Transfer Function Models. This type of models uses other variables to describe the behavior of the variable of interest. The wide use of B-J models can be explained by many reasons. First is the rapid use of such models. The second reason is that these models are cheaper to maintain. The third reason is that they are very simple.

Our objective is to forecast the volume of FDI twenty two (22) years beyond the end of the sample period. Forecasting FDI inflow to Jordan is very important to economic policy-makers. The importance of the present study arises from the fact that FDI flows play a key role in developing countries through affecting macroeconomic variables mentioning economic growth, employment and exports. Therefore, forecasting the volume of Fdi inflows in Jordan over the future period 2004-2025 provides policy-makers with a clear vision of the volume of future inflows. This will help them planning their economic strategy accordingly. As far to the knowledge of the authors, this study could be the first to forecast the FDI inflows in Jordan using ARIMA methodology.

The foreign direct investment flow in Jordan: FDI includes both Arabic and Non-Arabic capital inflow invested in projects owned by non-Jordanians. The

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yearly FDI inflow to Jordan from 1976-2003 varies over the period with peaks followed by valleys, or cycles appearing in the series.

The behavior of FDI inflows can be better understood by looking at their annual growth rates. One can conclude that the negative growth rates indicate a decline in the FDI volume in current period compared to the previous period and that can be seen in years 1976, 1979, 1982, 1985, 1988, 1989, 1991, 1993 and 1994. This behavior can be explained by the instability that the region witnessed during the study period.

The investigation of the FDI inflows movements reveals that its size was relatively small over the period 1971-1992, but it increased rapidly over the rest of the study period. The relative small size of FDI can be explained by the fact that during the period 1971-1992 the region experienced a history of political instability. Foreign investors considered it as a risky venture to invest in Jordan. However, after signing the Jordan-Israeli peace agreement in year 1994, joining the European partnership, joining the WTO, establishing the free trade zones and passing new laws for encouraging and attracting FDI, the volume of the foreign capital flow increased rapidly.

The FDI inflow increased from JD (0.1) million in 1971 to JD (1774.5) billions in year 2003 with average equals to JD (277.2) million and (1010.47%) average growth rate. . In order to focus on the development of FDI inflow over the study period, a three sub-periods reflecting the changing economic situation were designed. First, the sub-period (1976-1983) where on the average, the FDI was JD (6.62) million and average growth rate equals to (108.9%). The second sub-period that covers the (1984-1989) period achieved a higher average equals to JD (18.5) million. The third sub-period covers (1990-2003) period. The statistical data have shown that the nineties witnessed a considerable increase in the volume of FDI inflow with average equals to JD (89.6) million and average growth rate equals to (2625.3%). The take-off in the FDI inflow into Jordan can be thought as a result of the implementation of a set of economic policies in order to attract the foreign capital

MATERIALS AND METHODS

The objective of analyzing economic and financial data was to predict or forecast the future values of economic variables. Box-Jenkins[11] introduced a methodology is to fit data using ARIMA model. ARIMA approach combines two different parts into one equation; they are the Autoregressive process and Moving average process.

The autoregressive process (AR) is one where the current value of the variable (Yt) is a function of its past values plus an error term; as in:

$$Y_t = f(Y_{t-1}, Y_{t-2}, \ldots\ldots\ldots\ldots\ldots\ldots, Y_{t-p})$$

Or

$$Y_t = u + \theta_1 Y_{t-1} + \theta_2 Y_{t-2}, \ldots\ldots\ldots\ldots\ldots\ldots, \theta_p Y_{t\text{-}p}$$

where Y_t is the variable is being forecasted, p is the number of the past values used and u is the error term and normally distributed. The AR process can be written in lag operator form as:

$$\theta(L)Y_t = \beta + \mu_t$$

Where, $\theta(L) = \left(1 - \theta_1 L - \theta_2 L^2 + \ldots\ldots\ldots\ldots\ldots + \theta_p L^p)\right)$

A moving average process assumes the current value of the variable Y_t as a function of the past values of the error term plus a constant. A moving average of order (q), MA (q) is expressed as:

$$Y_t = f(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\ldots\ldots\ldots\ldots\ldots, \varepsilon_{t-q})$$

Or

$$Y_t = u + \mu_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2}, \ldots\ldots\ldots\ldots\ldots\ldots, \phi q Y_{t-q}$$

The MA process can be written in lag operator form as:

$$Y_t = u + \phi(L)u_t$$

Where, $\theta(L) = \left(1 - \phi_1 L - \phi_2 L^2 + \ldots\ldots\ldots\ldots\ldots + \phi q L^q)\right)$

To create an ARIMA model, one begins by combining the two specifications into one equation with no independent variable, as follows:

$$Y_t = u + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots\ldots\ldots\ldots$$

$$+\theta_p Y_{t-p} + \mu_t + \varphi_1 \varepsilon_{t-1} + \varphi_2 \varepsilon_{t-2}, \ldots\ldots\ldots, \varphi q Y_{t-q}$$

Where θ and ϕ are the coefficients of the RIMA respectively. In lag operator form the ARIMA model can be as follows:

$$\theta(L)Y_t = u + \phi(L)u_t$$

The proposed BJ methodology involves iterative three-stage cycles. The first step requires model identification. This stage the researcher should determine the order of autoregressive, integration and moving average (p,d,q) of the ARIMA model with aid of Correlogram and partial Correlogram. Having identified the values of ARIMA model, the second step is Diagnostic Checking. This stage involves a series of statistical testing to ensure the accuracy of ARIMA model selection, that the chosen ARIMA model fits the data well, for it is possible model that another model might fit the data better. One simple test to ensure the chosen model is to test the residuals estimated from this model whether or not they are white noise. If the residuals turned out to be white noise, then one accepts the particular fit; otherwise, one should restart over the selection process. The third step is the Estimation of the parameters of the selected autoregressive and moving average forms include in the model. The final step in the procedure is Forecasting. This step involves forecasting future value of the variable based on the ARIMA model. To complete the work, the accuracy of forecasting should be investigated. A number of statistical measures are available for this purpose. They are mean error (ME), mean absolute error (MAE), mean square error (MSE), mean percentage error (MPE), mean absolute percentage (MAPE) and Theil's U-statistic to compare the accuracy of various models.

To employ Box-Jenkins process to forecast a time series, the stationarity of the series must be maintained. Therefore, the first step in the process begins with testing for stationarity of the series. A time series is said to a stationary if both the mean and the variance are constant over time and the autocorrelation at two different time periods. The stationarity test examines the properties of the time series variable, in order to have a reliable regression tests to make sure that our model could not be subjected to "Spurious Regression". The problem of spurious regression arises because time series data usually exhibit non-stationary tendencies and as a result, they could have non-constant mean, variance and autocorrelation as time passes. This could lead to non-consistent regression results with misleading coefficients of determination (R^2) and other statistical test.

In practical term, to make the series stationary requires performing three processes: removing the trend, having a constant variance and finally, removing the seasonality. First differencing the data for many economic series data removes the trend and make the variance constant. The visual representation, Correlogram analysis where non-stationary series is having a slowly decaying ACF and PACF, Philips-Perron test and the unit-root tests of the data provide the tool for determining whether the series is stationary or not.

A plot of the series against time gives an idea about the characteristics of the series. If the time plot of the series shows that the data scattered horizontally around a constant mean, then the series is stationary at it levels. On the other hand if the time plot is not horizontal, the series is non-stationary. Equivalently, the graphical representation of the autocorrelation functions (ACF & PACF) can be employed to determine the stationarity of the series. If the ACF and PACF drop to or near zero quickly, this indicates that the series is stationary. If the ACF and PACF don no drop to zero quickly, then the non-stationarity is applied to the series.

The most popular test to establish stationarity properties of the time series is the Augmented Dickey-Fuller "ADF"[12,13]. The order of integration (d) identified the differencing times to make the series stationary and the series contains (d) unit roots and the series is said to be integrated of order (d). If d=0, the series is said to be integrated of degree zero and stationary at level.

The augmented Dickey-Fuller test is based on the estimate of the following regression:
ADF(p); without deterministic trend where (p) is the number of Augmentation terms included in ADF test $\left(\Delta Y_{t-1}, \qquad ,\Delta Y_{t-p}\right)$

$$\Delta X_t = \alpha_0 + \alpha_2 X_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta X_{t-1} + \varepsilon_t$$

2-ADF (p) with deterministic trend

$$\Delta X_t = \alpha_0 + \alpha_2 X_{t-1} + \sum_{i=1}^{p} \alpha_i \Delta X_{t-1} + \beta t + \varepsilon_t$$

P= is the number of lags which should be large enough to ensure the error terms are white noise process and small enough to save degrees of freedom. The number of lags can be determined and will be chosen based on the AIC and SBC selection. The error term is normally distributed. If the t-ratio of the estimated coefficient is greater than the critical t-value, the null hypothesis of unit root (nonstationary variable) is rejected indicating the variable is stationary at level and integrated of degree zero denoted by I(0). On the hand if the series found to nonstationary at levels, a transformation of the variable by differencing is need until we achieve stationarity that is non-autocorrelated residuals.

RESULTS

The FDI data for Jordan over the period (1976-2003) consists of 28 annual observations are used to build a suitable ARIMA (p, d, q) model to forecast the FDI series over the period (2004-2025) (Table 1).

Table 1: FDI volume over the period (1976-2003) in Million JDs

Year	1	2	3	4	5
1980-1976	6.90	9.10	18.60	8.20	11.70
1985-1981	46.90	33.00	13.70	29.90	9.60
1990-1986	10.50	13.50	9.60	1.00	45.80
1995-1991	0.20	47.10	40.50	21.40	37.60
2000-1996	79.20	176.00	217.60	230.60	1562.28
2003-2001	1614.30	1693.60	1774.50	-	-

Stationarity test results: The application of Box-Jenkins methodology in building an ARIMA model requires that the series is stationary. Therefore, the process starts with testing the series for stationarity using the plot diagram, Correlogram and also performing Unit-root test (ADF).

The graphical representation of the series against time indicates that the underlying series exhibit an increasing trend over time and has a random walk time series with a non-zero mean and a non-constant variance. Hence, the plotted graph provides a clear cut that the underlying series is non-stationary in its level. But the first difference of the series was stationary (Fig. 1 and 2).

The advance analytical technique for testing the stationarity of the time series data uses the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test. The unit-root test results reject the null hypothesis at 5% level of significance indicating that the series is non-stationary in its level (Table 2).

Table 3 presents the unit root test for the first difference of the series. Therefore, one can reject the hypothesis at a 5 percent level of significance that the series is stationary at its first difference form. The FDI series is integrated of order one, I(1).

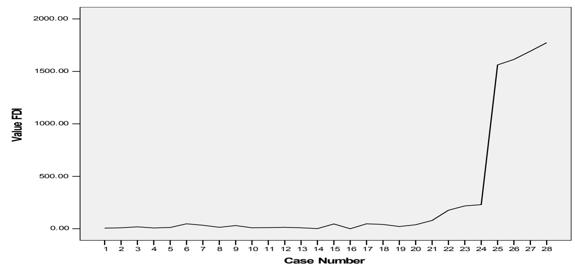

Fig 1: Graph for the FDI series against time (level form)

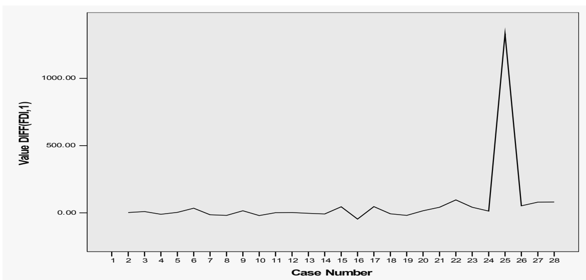

Fig 2: Graph for the FDI series against time (difference form)

The Correlogram analysis of the level form shows that FDI is not stationary at its level form (see fig). The PCF lies outside the 95% confidence interval: differs from zero. The PACF decays gradually. It is clear that ACF had significant spikes at lag 1 and lag 4.

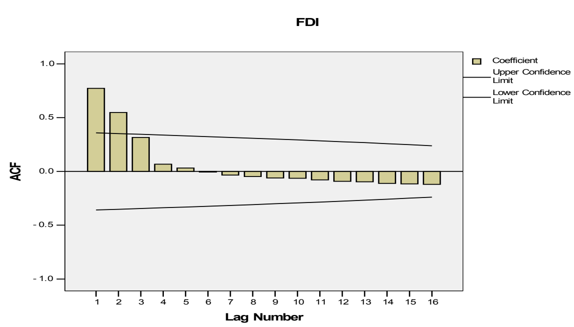

Fig. 3: The PACF lies outside the 95% confidence interval: differs from zero. The PACF decays

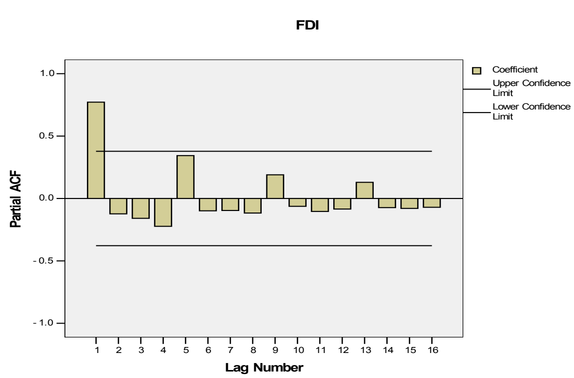

Fig. 4: The ACF & FACF for FDI series

Table 2: The unit-root test for FDI series in its level form

Unit Root Test	Computed Value	Critical Value at 5% Level
Augment Dickey-Fuller (ADF)	0.410396	-2.9665
Phillips-Perron (PP)	0.549348	-2.9665

Table 3: The unit-root test for FDI series in its difference form

Unit Root Test	Computed Value	Critical Value at 5% Level
Augment Dickey-Fuller (ADF)	-4.945413	-2.9798
Phillips-Perron (PP)	-4.952465	-2.9798

Table 4: Values of AIC and SBC criteria for ARIMA models

Model	AIC	SBC
(0.1.1)*	378.993	381.584
(1.1.0)	378.992	381.584
(0.1.2)	381.064	384.952
(2.1.0)	381.066	384.953
(1.1.1)	381.062	384.949

Table 5: Comparison of different models (Randomness tests of residuals)

Model	(0.1.1)*	(1.1.0)
1-Runs above and below median		
Median	-56.4644	-56.5015
Number of runs above and below median	10	10
Expected number of run	14.0	14.0
Large sample test statistic z	1.40112	1.40112
P-value	0.161177	0.161177
2-Runs up and down		
Number of runs up and down	17	17
Expected number of run	17.6667	17.6667
Large sample test statistic z	0.0787621	0.0787621
p-value	0.937216	0.937216
3-Box - Pierce Test		
Test based on first 9 autocorrelation		
Large sample test statistic z	0.327332	0.327396
p-value	0.999974	0.999974

Table 6: Comparison of ARCH-LM test

Model	F-statistic	Probability
(0.1.1)*	0.044362	0.834959
(1.1.0)	0.046210	0.831690

Table 7: The estimation results of ARMA (0,1,1)

Variable	Coefficient	St.Error	Probability
C	65.48076	49.74643	0.2000
MA(1)	-0.007800	0.200008	0.9692
R^2=0.000076		C=378.993	
Adjusted-R^2=-0.040		C=381.584	
D-W=1.998		Statistic=0.0016,	
Prob.(F- Statistic)=0.0968220			

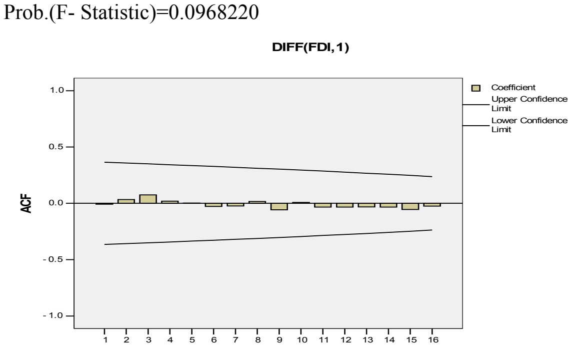

Fig. 5: ACF of the first difference of the FDI

Table 8: Results of Accuracy test for the suggested ARIMA models

Model	RMSE	MEA	MAPE	ME	MPE	Theil's
(0.1.1)*	260.45	98.2558	2604.37	-0.01450	-2596.93	0.457447
(1.1.0)	260.45	98.2473	3604.76	-0.14389	-2597.32	0.449100

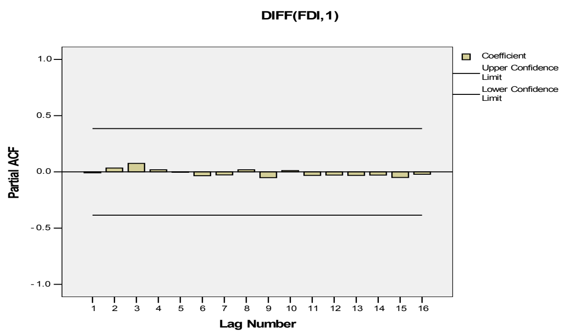

Fig. 6: PACF in the difference form of FDI

After series become stationary by taking the first differencing, the first step is to identify the order of both the AR and MA parts of the ARIMA model. However, it is possible to determine order (2) as the upper limits of their orders. Based on the first difference order to be (1), different forms of ARIMA models can be suggested as the following: ARIMA (2.1.0), ARIMA(0.1.2), ARIMA(1.1.0) and ARIMA(1.1.0). The procedure of choosing the most suitable model relies on choosing the model with the minimum AIC and SBC criteria. It can be seen that ARIMA (1.1.0) is the best model (Table 4).

Diagnostic checking: Once the ARIMA model is identified, the test of the suitability of the selected ARIMA model, the analysis of residuals of each model is carried out. Table 3 showed that we have two models that are very close in their AIC and SBC values. Therefore, further tests are necessary to determine the model. The residual test required that residuals are random with zero mean, constant variance and uncorrelated. Test for randomness of residuals are presented in Table 5.

The randomness tests have the identical results. Hence, the results are supportive of the randomness of residuals of both models at 95% significance level. Another feature of residuals is variance constant and not correlated. The ARCH –LM test for residuals is used. The ARCH-LM test reveals that ARIMA(0.1.1) better fits and describes the behavior of underlying series (Table 6).

Estimation results: As the diagnostic checking tests showed in Table 4 and 5), it is clear that MA model with lag1 more accurately forecasts FDI inflow to Jordan. Therefore, the above model is selected. Table 7 presents the estimation results of ARIMA(0,1,1) model.

According to the estimation results, the coefficient of MA(1) is significant at level 5% significance level.

Table 9: Forecasting results of FDI over the period 2004-2025 ARIMA(0,1,1)

Year	Forecast	Lower Limit (95% Limit)	Upper Limit (95% Limit)
2004	1839.86	1303.45	2376.26
2005	1905.33	1149.66	2661.01
2006	1970.81	1046.50	2895.12
2007	2036.29	969.673	3102.90
2008	2101.76	909.716	3293.81
2009	2167.24	861.756	3472.73
2010	2232.72	822.894	3642.54
2011	2298.19	791.239	3805.15
2012	2363.67	765.476	3961.87
2013	2429.15	744.648	4113.65
2014	2494.62	728.032	4261.22
2015	2560.10	715.064	4405.14
2016	2625.58	705.298	4545.86
2017	2691.06	698.372	4683.74
2018	2756.53	693.985	4819.08
2019	2822.01	691.888	4952.13
2020	2887.49	691.871	4083.10
2021	2952.96	693.751	5212.17
2022	3018.44	697.373	5339.51
2023	3083.92	702.601	5465.23
2024	3149.39	709.316	5589.47
2025	3214.87	717.414	5712.32

The low coefficient of determination R2 is not important due to differencing the variable FDI[14]. The Durban-Watson (DW) indicates no Serial correlation. The ARIMA (0,1,1) model can be rewritten in the lag operator form as follows:

$FDI=65.480.008e_{t-1}$

or

$$\varphi(L)FDI = \mu + \varphi(L)\mu_t$$

Forecasting: Gunts and Ibaham[15] stated that the selected model is not necessary is the one that provides best forecasting. Therefore, further accuracy tests should be done to ensure the selection of the model. Table 8 shows the test results of the model accuracy. As the above table shows, all accuracy tests favored ARIMA (0,1,1) based on the minimum values of RAMA and MAPE, while ME and MPE values are close to zero. On the other hand, ARIMA (1,1,0) only Theil's test is close to zero.

Table 9 presents the forecasting results of FDI over the period 2004-2025. The inflows of FDI mean equals to JD 2527 millions with average annual growth rate equals to 2.7%.

CONCLUSION

The present study presented and described the development of Fdi inflows into Jordan over the period 1976-2003. Moreover, the study mainly intended to forecast the expected future FDI inflows for the coming period 2004-2025. A set of Box-Jenkins time series forecasts has been suggested to forecast the future FDI inflows into Jordan. The accuracy evaluation of the proposed ARIMA models is very important in model selection and evaluating the performance of FDI inflows into Jordan. The forecasting results revealed an increasing pattern of FDI over the forecasted period. In light of the forecasted results, policy-makers should gain insight into more appropriate investment promotion strategy and meat the needs of such inflow in terms of infrastructure and skilled labor.

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