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Modeling and Forecasting of Foreign Direct Investment (FDI) Inflow in BRICS countries using ARIMA

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Introduction

Foreign Direct Investment has been playing a fundamentalrole in developing countries in attracting necessary investment. Foreign direct investment (FDI) is the direct investment equity flows into the host economy. According to Organisation for Economic Co-Operation and Development (OECD), "FDI is defined as the establishment of a lasting interest in andasignificant degree of influence over the operations of an enterprise in one economy by an investor in another economy. Ownership of 10% or more of the voting power in an enterprise in one economy by an investor in another economy is evidence of such a relationship". FDIcovers the investment of all cross-border transactions and positions between the bodies in a foreign direct investment relationship.According to OECD, "There are three main components to FDI statistics: 1) financial flows, which capture debt and equity investments between related parties in a specific period; 2) income, which represents the return on equity and debt investment to the direct investor in a specific period; and 3) positions, which are the value of the accumulated direct investment at a specific point in time".

About BRICS

Brazil, Russia, India, China and South Africa (BRICS) are the five leading emerging economies in the world. According to BRICS Summit, (2017), "Together, they account for 26.46% of world land area, 42.58% of world population, 13.24% of World Bank voting power and 14.91% of IMF quota shares." According to IMF, "BRICS countries generated 22.53% of the world GDP in 2015 and had contributed more than 50% of world's economic growth during the last ten years".

Economist Jim O'Neill of Goldman Sachs used the acronym BRIC first in 2001 in their Global Economics Paper, "The World Needs Better Economic BRICs."The official grouping of BRIC startedafter the meeting of the Leaders of Russia, India, and China in Petersburg in 2006. The first BRIC Meetingwas held in Yekaterinburg, Russia on 16th June 2009. During the BRIC Foreign Ministers' meeting held in New York in September 2010, it was resolved to include South Africa in the Association thus expanding BRIC into BRICS. The third BRICS meeting was attended by South Africa in Sanya, China, in April 2011 (BRICS Summit, 2016).

FDI plays a vital role in capital formation especially in filling the gap between the savings and investments. FDI has been essential in getting the advanced technology into the host countries especially the developing countries. FDI inflow in developing countries like Brazil, Russia, India, China and South Africa (BRICS) has been significant during recent past. In BRICS countries, three countries hold the position among top ten countries in FDI inflow. China ranks the 3rd after US and Hong Kong; Brazil is in the 7th spot, India ranks the 10th (World Investment Report, 2016).

China emerged as the second-largest investor of FDI in the World. BRICS association has received 11 percent of the world FDI inflow.India is almost stagnant at US$ 44 billion in receiving FDI inflows(World Investment Report, 2017).

Based on the income criteria countries in the world have been categorised into High Income, Low Income, Lower Middle Income and Upper Middle Income by World Bank. According to this classification in BRICS countries, Brazil, Russia, China and South Africa fall into Upper Middle-Incomecategoryand India into a Lowermiddle-income group.

I) Literature review

ARIMA technique has been used extensively inessential studies previously done for forecasting FDI inflow. In the previous studies, different models havebeen used for forecasting. Among all the models, ARIMA has been preferred as one of the best technique to forecast the future values.

ARIMA model was used to describe the autocorrelation and volatility of FDI in China, based on time series data for the period 1955-1997. The results showed that China FDI exhibited an ascendant trend(Shi Hongyan et al., 2012). Box-Jenkins ARIMA model had been used to forecast the net FDI inflow in India based on the time series data for the period 1992-2014 and projected values from 2015 onwards up to

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2024 (Biswas, 2015). ARIMA hadbeen modelled for forecasting FDI inflow in Jordan. Based on the secondary data from 1976 to 2003, the ARIMA model results revealed an increasing trend in FDI over the forecasting period 2004-2015 (Bashier & Talal, 2007). For forecasting FDI into Zambia during the time 1970-2014 Simple Exponential smoothing (SES), Holt-Winters exponential smoothing (HWES) and ARIMA model were used. The analysis revealed that ARIMA model was preferred as the best fit over the other two methods because of its minimum error property as compared to the other two methods (Chilyabanyama et al., 2017). By using the ARIMA model, it hadbeen shownthatFDI inflow into Brazil exhibited theMoving Average pattern.Theil's Coefficient was adopted to analyse the forecast accuracy (Agr. et al., 2014). ARIMA technique had been used to forecast the Foreign Direct Investment for SAARC countries between 2013 and 2037, based on secondary data for the period 1970 to 2012. Results showedthat both mean and variance varied with the changing trend for forecasting period. The residual diagnostic checks were carried out with the help of Box-Ljung test(Perera, 2015).

II) Methodology

Various international organisations have measured FDI in different ways. According to World Bank, "The Data on FDI flows are presented on net bases (capital transactions' credit less debits between direct investors and their foreign affiliates). Net decreases in assets or net increase in liabilities are recorded as credits, while net increases in assets or net decreases in liabilities are recorded as debits. Hence, FDI flows with a negative sign indicate that at least one of the components of FDI is negative and not offset by positive amounts of the remaining components. These are instances of reverse investment or disinvestment". According to OECD, "Data on FDI net-inflows and outflows are based on the sixth edition of the Balance of Payments Manual (2009) stated by the International Monetary Fund (IMF)".Thisreference makes the FDI statistics includedin the balance of payments (BOP). FDI flows have also been measured as FDI inflows to GDP ratio.In this paper, the data used is measured as net Foreign Direct Investment inflow (BoP) in current US$.

The present study is based on secondary Time Series data collected on FDI inflow from various sources like World Bank and International Financial Statistics Year Books of the International Monetary Fund. The period of study depended on the annual time series data available for various BRICS countries. The data available for BRICS countries are as follows Brazil (1975-2016), Russia (1992-2016), India (1975-2016), China (1982-2016) and South Africa (1970-2016).

This paper attempts to model the BRICS inward FDI series in US Dollars (US$) using Auto-Regressive Integrated Moving Average (ARIMA) model proposed by Box-Jenkins and Reinsel (1994). The objective of analysing FDI data in BRICS is to predict or forecast the future values of variable inflow FDI using ARIMA. ARIMA process is a combination of Auto-Regressive (AR) and Moving Average (MA) process.

The AR is the process wherecurrent value of the variable $X_t$is expressed as a function of past values of the variable and an error term(Bashier & Talal, 2007)

$X_t = f(X_{t-1}, X_{t-2}, \ldots\ldots\ldots, X_{t-p})$

Or

$X_t = \theta_1 X_{t-1} + \theta_2 X_{t-2}, \ldots\ldots\ldots\ldots, \theta_k X_{t-p} + \mu_t$

Where $X_t$is the variableforecasted, p denotes the number of lagged values of the variable used, θ_p denotes the autoregressive parameter of order p and μ is the error term.

In MA process the current value of the variable $X_t$is a function of the past values of the error term and a constant. TheMA of order (q) can rewriteas

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

Or

$X_t = \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t2} + \ldots\ldots\ldots\ldots, \phi_q \varepsilon_{t-q} + u_t$

Where q is the number of lagged value of the error term, $\phi_t$is the moving average parameter of order q, and u_t is the white noise

To form an ARIMA model, the AR and MA specifications are combined into one equation, as follows

$X_t = \theta_1 X_{t-1} + \theta_2 X_{t-2}, \ldots\ldots\ldots\ldots, \theta_k X_{t-p} + \mu_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t2} + \ldots\ldots\ldots\ldots, \phi_q \varepsilon_{t-q} + u_t$

Where θ and ϕ are the coefficients of the AR and MA respectively.

The Box-Jenkins (BJ) method includes three-stage cycle which is iterative in nature. Model identification is the first step of BJ process.This stage involves the identification of the order of autoregressive, integration and moving average (p,d,q) of the ARIMA model with the help of Correlogram and partial Correlogram plots. Integration implies the orderof a series at which a series is stationary. Therefore, the first step begins with testing the stationarity of the series. A series is said to be stationary if its statistical parameters like mean and variance are time invariant.For visual inspection, Correlogram analysis will show the data as non-stationary if the series is having a slowly decaying autocorrelation function (ACF) and partial autocorrelation function (PACF).

Many statistical tests have been used by the researchers to check the unit root (stationarity) of the time series data. The most popular tests Augmented Dickey-Fuller (ADF) test and,Philips-Perrontest. Philips-Perron test does not require to select the level of serial correlation as in ADF. For this paper, EViews-9 has been used to analyse and forecast the data.

After identification of the values for p,d,qof ARIMA model in the first step, the second step is model Estimation using appropriate econometric technique and checking the adequacy of the fitted model.Hence, this step requires employing series of statistical testing to ensure the accuracy of selected ARIMA model so that the model is the best fit.One important test is to test for the white noise (residuals should normallybe distributed and random)of the residuals with the help of autocorrelation plot. The autocorrelation plot also contains Ljung-Box (LB) test which checks for the "overall" randomness of residuals based on some lags, instead of testing randomness at individual lags. For this reason, it is often termed as "portmanteau" test (Lartey Samuel et al., 2016). The last step is to forecast the values for the variable under consideration. To check the accuracy of the forecast, various measures likemean Error (ME), Mean Absolute Error (MAE), mean square error (MSE), mean percentage error (MPE), mean absolute percentage error (MAPE) and Theil's U-statistic are employed (Bashier & Talal, 2007).

III) Results and Discussions

A) Stationary test results

The application of Box-Jenkins methodologyrequires that the series be stationarybeforestarting the process of model building. Therefore, the process begins with testing the series for the countries Brazil, Russia, India, China and South Africa. Non-stationarity can be checked graphically with the help of ACF and PACF functions. For all the BRICS countries it is observed thatthere is a slow decaying pattern of ACF and PACF function. The Augmented Dickey-Fuller (ADF) and Philip-Perron (PP) tests show that that data series of all five nations Brazil, Russia, India, China and South Africa are stationary at the 1st difference and non-stationary at level (Table: I).

B) Model selection

After the series becomes stationary by taking the first difference, the next step is to identify the order of AR and MA parts of the ARIMA model. ACF and PACF help us in selecting AR and MA process. There are several methods used in the selection of the best model from a set of infinite alternatives. In this paper, the procedure forselecting the most suitable model depends on choosing the model with the minimum AIC and SBC criteria.According toLartey Samuel et al., (2016), "The Akaike information criterion (AIC) is a measure of the relative quality of a statistical Model, for a specified set of data. As such, AIC provides a means for model selection. AIC deals with the trade-off between the goodness of fit of the model and the complexity of the model. Bayesian information criterion (BIC) is a criterion for model selection among a finite set of models."The best models with minimum AIC and SBC selected for Brazil, Russia, India, China and South Africa countries are as (3,1,2); AR(2) MA(2); (3,1,3); AR(1) MA(3)and AR(1,2,3,5) MA(6,7) respectively (Table: II to VI). After identifying the fitted model, there is a need to do further checks to ensure that the model selected is accurately the best fit.

C) Diagnostic checking

This step involves applying various diagnostic checking for the estimated ARIMA models in step 2 to see whether models are technically adequate for forecasting. For this, we employed Ljung-Box test for verification of White Noise pattern of residuals. The ACF and PACF of residuals for ARIMA models fitted to Brazil, Russia, India, China and South Africa are presented in Figure 1 to 5 respectively. It is observed from the figures that the ACF and PACF for all the BRICS countries lie within the limit of 95% confidence interval, i.e., none of ACF and PACF issignificantexhibiting any pattern. Further, it is observed that all the p-values in the Ljung box lie outside the 95% confidence interval, which is indicating that residuals are independent.The estimated model is consideredinadequate if the p-value associated with the Q statistic is small (p-value $<\alpha$). In the present case, in all the Figures for all the countries, considering Q-stat of residuals of variable FDI, the p-value is higher than 5%. Therefore we conclude that the residuals are random by accepting the null hypothesis. Thus the ARIMA models for Brazil (3,1,2), for

Russia AR(2) MA(2), for India (3,1,3), for China AR(1) MA(3) and South Africa AR(1,2,3,5) MA(6,7) indicate that the models fit data well.

Finally, since all the assumptions under the residual test hold true, it can be concluded that the selected models are best-fitted models to forecast annual FDI inflow into the countries Brazil, Russia, India, China and South Africa respectively for the period 2017 to 2026.

Plots of observed values and fitted values are shown in Figures 6 to 10 of countries Brazil, Russia, India, China and South Africa respectively. The Figure represents the closeness of the fitted values to its actual values.It could be seenfrom these figures that in all cases of five BRICS countries, the fitted line lies close to the actualline. It shows that the model is capturing the pattern present in the actual data.

D) Forecasting

The selected ARIMA models for BRICS countries are as follows

1) For Brazil, the ARIMA model (3,1,2) can be written as

$X_t = 2.06E+09 – 1.3453\ X_{t-1} – 1.2557\ X_{t-2} – 0.4726\ X_{t-3} + 1.2392\varepsilon_{t-1} + 0.8748\ \varepsilon_{t-2} + \varepsilon_t$…. (1)

2) For Russia the ARIMA model AR(2) MA(2) can be written as

$X_t = 1.92E+09 + 0.4469\ X_{t-2} – 1.\varepsilon_{t-2} + \varepsilon_t$ ………….. (2)

3) For India the ARIMA model (3,1,3) can be written as

$X_t = 1.0E+09 + 0.745\ X_{t-1} + 0.4523\ X_{t-2} – 0.7251\ X_{t-3} – 0.6623\ \varepsilon_{t-1} - 0.7758\ \varepsilon_{t-2} + 0.8849\ \varepsilon_{t-3} + \varepsilon_t$… (3)

4) For China the ARIMA model AR(1) MA(3) can be written as

$X_t = 1.50E+09 + 0.1704\ X_{t-1} + 0.6461\ \varepsilon_{t-3} + \varepsilon_t$ ……. (4)

5) For South Africa the ARIMA model AR(1,2,3,5) MA(6,7) can be written as

$X_t = 1.03E+09 – 0.4267\ X_{t-1} – 0.6536\ X_{t-2} – 0.5066\ X_{t-3} - 0.3263\ X_{t-5} + 0.2126\ \varepsilon_{t-6} - 0.3659\ \varepsilon_{t-7} + \varepsilon_t$ … (5)

The above fitted ARIMA models for BRICS countries are used to forecast the FDI values for the period 2017 onwards to 2026. Theforecasted values aregiven in Table VII.There are four expressions on the table. The first one represents the forecastedvalues of Foreign Direct Investment (FDI) from 2017 to 2026. The second expression shows the standard error of the predicted FDI. The last two represent the upper and lower limits of the (approximate) 95% forecast interval

The forecast accuracy has been checked with the help RMSE, MAE, MAPE and accuracy parameters Thiel Inequality coefficient (Table: VIII). In the table, it is observed that Thiel's coefficient is close to zero in most of the models. Thus, we can conclude that the forecast values are reasonably accurate.

IV) Conclusion

This paper attemptedto develop time series models that could be used to forecast annual Foreign Direct Investment (FDI) inflow to Brazil, Russia, India, China and South Africa (BRICS) for the period 2017 to 2026. FDI is an essential component of capital financing and capital formation for developing countries like BRICS. In recent years, the FDI has shown an increasing trend for all BRICS countries. The results showeda rising pattern of FDI over the forecast period. The results have shown that for BRICS countries the FDI may increase from 83.06 billion US$ in 2017 to 101.59 billion US$ in 2026 with a growth rate of 2.03 % for Brazil. 47.02 billion US$ in 2017 to 64.30 billion US$ in 2026 with a growth rate of 3.18 % for Russia. For India, it may increase from 39.73 billion US$ in 2017 to 48.74 billion US$ in 2026 with a growth rate of 2.06 %. China may get FDI inflow of50.52billion US$ in 2017 to 64.01billion US$ in 2026 with a growth rate of 2.39 %. For South Africa,the FDI inflow may increase from 4.76 billion US$ in 2017 to 5.68 billion US$ in 2026 with a growth rate of 1.79 %.Among all the countries, Brazil gets the highest FDI inflow whereas South Africa receives lowest FDI inflow even in a forecasted period in BRICS. The forecast values for FDI inflow are of significant importance to policymakers as these figures will help them to get new insights regarding proper investment promotion strategies in BRICS countries. These countries are in need of infrastructure and skilled labour to achieve the required target of their economic growth. This requires enormous investments,andthese forecast values will enable the policy makers to frame policies in thesedirectionstomeet the requirements of such inflow about infrastructure and skilled labour.

Tables and figures

Table-I: Augmented Dickey-Fuller (ADF) and Philips-Perron (PP) test of Stationary for BRICS countries.

Countries	Test used	t-Statistic (at level)	Test critical values 5% level	Prob.* (at level)	t-Statistic (1st diff.)	Test critical values 5% level	Prob.* (1st diff.)
Brazil	ADF[1]	3.284036	-2.957110	1.0000	-3.375785	-2.94584	0.0186
	PP[2]	-0.460461	-2.935001	0.8886	-7.683669	-2.93694	0.0000
Russia	ADF	-1.804543	-2.991878	0.3694	-5.011258	-2.998064	0.0006
	PP	-1.695988	-2.991878	0.4205	-5.153071	-2.998064	0.0004
India	ADF	4.758359	-2.957110	1.0000	-6.739031	-2.936942	0.0000
	PP	0.147324	-2.935001	0.9656	-6.738323	-2.936942	0.0000
China	ADF	0.885192	-2.951125	0.7807	-2.714742	-2.981038	0.0851
	PP	-0.916787	-2.951125	0.7706	-5.375297	-2.954021	0.0001
South Africa	ADF	-0.850350	-2.931404	0.7942	-7.978400	-2.931404	0.0000
	PP	-3.227057	-2.926622	0.0247	-15.72720	-2.928142	0.0000

*MacKinnon (1996) one-sided p-values. Source: EViews 9

1) ADF= Augmented Dickey-Fuller test statistic

2) PP= Phillips-Perron test statistic.

Table-II: ARIMA model (3, 1, 2) for inward FDI of Brazil

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.06E+09	2.41E+09	0.853958	0.3991
AR(1)	-1.345332	0.383729	-3.505948	0.0013*
AR(2)	-1.255767	0.480255	-2.614791	0.0132*
AR(3)	-0.472649	0.331755	-1.424693	0.1634
MA(1)	1.239207	0.437454	2.832773	0.0077*
MA(2)	0.874878	0.691242	1.265661	0.2142
R-squared	0.349075	Mean dependent var		1.89E+09
Adjusted R-squared	0.234206	S.D. dependent var		1.29E+10
S.E. of regression	1.13E+10	Akaike info criterion		49.35003
Sum squared resid	4.35E+21	Schwarz criterion		49.64259
Log likelihood	-1004.676	Hannan-Quinn criter.		49.45656
F-statistic	3.038893	Durbin-Watson stat		1.889679
Prob (F-statistic)	0.017294			

**- significant at 1% confidence interval* Source: EViews 9

Table-III: ARIMA model for inward FDI of Russia

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.92E+09	1.36E+09	1.407312	0.1747
AR(2)	0.446996	0.327930	1.363083	0.1880

MA(2)	-1.000000	1496.653	-0.000668	0.9995
R-squared	0.299710	Mean dependent var		1.33E+09
Adjusted R-squared	0.194666	S.D. dependent var		1.67E+10
S.E. of regression	1.49E+10	Akaike info criterion		49.98734
Sum squared resid	4.47E+21	Schwarz criterion		50.18368
Log likelihood	-595.8480	Hannan-Quinn criter.		50.03943
F-statistic	2.853197	Durbin-Watson stat		2.297704
Prob(F-statistic)	0.063082			

Source: EViews 9

Table-IV: ARIMA model for inward FDI of India

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.00E+09	2.45E+09	0.409403	0.6849
AR(1)	0.745119	1.459886	0.510396	0.6132
AR(2)	0.452327	1.122924	0.402812	0.6897
AR(3)	-0.725112	0.701498	-1.033662	0.3088
MA(1)	-0.662353	20.57941	-0.032185	0.9745
MA(2)	-0.775826	33.89821	-0.022887	0.9819
MA(3)	0.884925	17.89971	0.049438	0.9609
R-squared	0.149625	Mean dependent var		1.08E+09
Adjusted R-squared	-0.030758	S.D. dependent var		5.01E+09
S.E. of regression	5.09E+09	Akaike info criterion		47.76100
Sum squared resid	8.54E+20	Schwarz criterion		48.09536
Log likelihood	-971.1006	Hannan-Quinn criter.		47.88276
F-statistic	0.829486	Durbin-Watson stat		2.256977
Prob(F-statistic)	0.570449			

Source: EViews 9

Table-V: ARIMA model for inward FDI of China

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.50E+09	1.21E+10	0.124008	0.9021
AR(1)	0.170408	0.192273	0.886280	0.3825
MA(3)	0.646149	0.143443	4.504584	0.0001*
R-squared	0.218075	Mean dependent var		5.00E+09
Adjusted R-squared	0.139882	S.D. dependent var		2.95E+10
S.E. of regression	2.74E+10	Akaike info criterion		51.06124
Sum squared resid	2.25E+22	Schwarz criterion		51.24081
Log likelihood	-864.0411	Hannan-Quinn criter.		51.12248
F-statistic	2.788950	Durbin-Watson stat		1.808151
Prob(F-statistic)	0.057592			

**- significant at 1% confidence interval* Source: EViews 9

Table-VI: ARIMA model for inward FDI of South Africa

Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
C	1.03E+08	1.19E+08	0.867347	0.3912
AR(1)	-0.426738	0.177272	-2.407250	0.0210**
AR(2)	-0.653693	0.158075	-4.135321	0.0002*
AR(3)	-0.506615	0.134529	-3.765855	0.0006*
AR(5)	-0.326384	0.205534	-1.587982	0.1206
MA(6)	0.212623	0.234812	0.905505	0.3709
MA(7)	-0.365991	0.211417	-1.731133	0.0915***
R-squared	0.533071	Mean dependent var		41664883
Adjusted R-squared	0.447058	S.D. dependent var		2.46E+09
S.E. of regression	1.83E+09	**Akaike info criterion**		45.71224
Sum squared resid	1.27E+20	**Schwarz criterion**		46.03026

Log likelihood	-1043.381	Hannan-Quinn criter.	45.83137
F-statistic	6.197543	Durbin-Watson stat	2.048777
Prob(F-statistic)	0.000071		

**- significant at 1% confidence interval* Source: EViews 9
***- significant at 5% confidence interval*
****- significant at 10% confidence interval*

Table-VII: Forecasting of FDI for BRICS countries for the period 2017-2026

C	year	Predicted FDI (US Bn. $)	Standard Error	Upper limit (95% C.I)	Lower limit (95% C.I)
Brazil	2017	83.06	11E+10	30E+10	-14E+10
	2018	85.11	11E+10	31E+10	-14E+10
	2019	87.17	11E+10	32E+10	-14E+10
	2020	89.23	12 E+10	32E+10	-15E+10
	2021	91.29	12 E+10	33E+10	-15E+10
	2022	93.35	12 E+10	34E+10	-15E+10
	2023	95.41	12 E+10	34E+10	-15E+10
	2024	97.47	13 E+10	35E+10	-16E+10
	2025	99.52	13 E+10	36E+10	-15E+10
	2026	101.59	13E+10	37E+10	-15E+10
Russia	2017	47.02	4E+10	13E+10	-34E+9
	2018	48.94	4 E+10	13E+10	-34E+9
	2019	50.86	4 E+10	14E+10	-34E+9
	2020	52.78	4 E+10	14E+10	-35E+9
	2021	54.70	5 E+10	15E+10	-35E+9
	2022	56.62	5 E+10	15E+10	-36E+9
	2023	58.54	5 E+10	15+E10	-36E+9
	2024	60.46	5 E+10	16E+10	-36E+9
	2025	62.38	5 E+10	16E+10	-37E+9
	2026	64.30	5 E+10	17E+10	-37E+9
India	2017	39.73	10 E+10	24E+10	-16E+10
	2018	40.73	10 E+10	25E+10	-17E+10
	2019	41.71	10 E+10	25E+10	-17E+10
	2020	42.70	10 E+10	26E+10	-18E+10
	2021	43.70	11 E+10	27E+10	-18E+10
	2022	44.70	11 E+10	27E+10	-18E+10
	2023	45.70	12 E+10	28E+10	-18E+10
	2024	46.71	12 E+10	28E+10	-19E+10
	2025	47.72	12 E+10	29E+10	-19E+10
	2026	48.74	12 E+10	29E+10	-20E+10
China	2017	50.52	50 E+10	11E+11	-96E+10
	2018	52.02	52 E+10	11 E+11	-98E+10
	2019	53.52	53 E+10	11 E+11	-10E+11
	2020	55.02	54 E+10	11 E+11	-10E+11
	2021	56.52	55 E+10	12 E+11	-11E+11
	2022	58.02	57 E+10	12 E+11	-11E+11
	2023	59.52	59 E+10	12 E+11	-11E+11
	2024	61.02	59 E+10	12 E+11	-11E+11
	2025	62.51	60 E+10	13 E+11	-11E+11
	2026	64.01	62 E+10	13E+11	-12E+11
S.Af	2017	4.80	6 E+9	18E+9	-85E+8
	2018	4.90	7 E+9	18 E+9	-86E+8
	2019	5.00	7 E+9	19 E+9	-87E+8

r	2020	5.10	7 E+9	19 E+9	-89E+8
i	2021	5.20	7 E+9	19 E+9	-90E+8
c	2022	5.30	7 E+9	20 E+9	-91E+8
a	2023	5.40	7 E+9	20 E+9	-92E+8
	2024	5.50	7 E+9	20 E+9	-94E+8
	2025	5.60	8 E+9	21 E+9	-95E+8
	2026	5.70	8 E+9	21 E+9	-96E+8

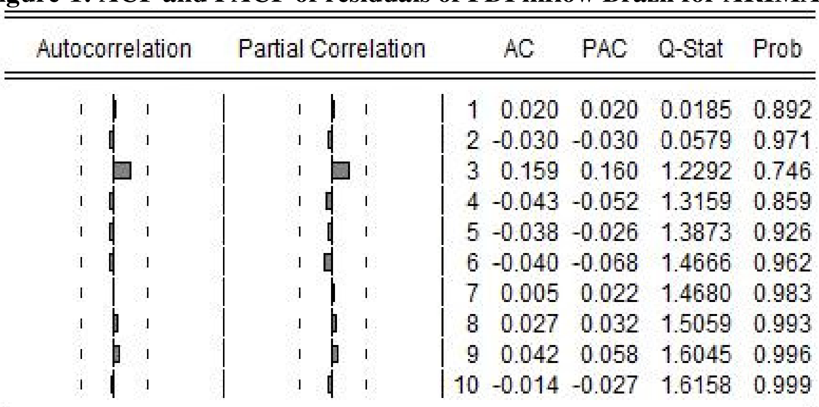
Source: EViews 9

Table-VIII: Model accuracy parameters

Country	ARIMA model	RMSE	MAE	MAPE	Thiel Inequality
B	(3,1,2)	2.44E+10	2.15E+10	706.1287	0.274
R	AR(2) MA(2)	1.82E+10	1.45E+10	148.7220	0.2935
I	(3,1,3)	1.26E+10	1.10E+10	6093.970	0.304
C	AR(1) MA(3)	1.05E+11	6.75E+10	77.87	0.65
S	AR(1,2,3,5) MA(6,7)	2.24E+09	1.92E+09	2854.68	0.356

Source: EViews 9

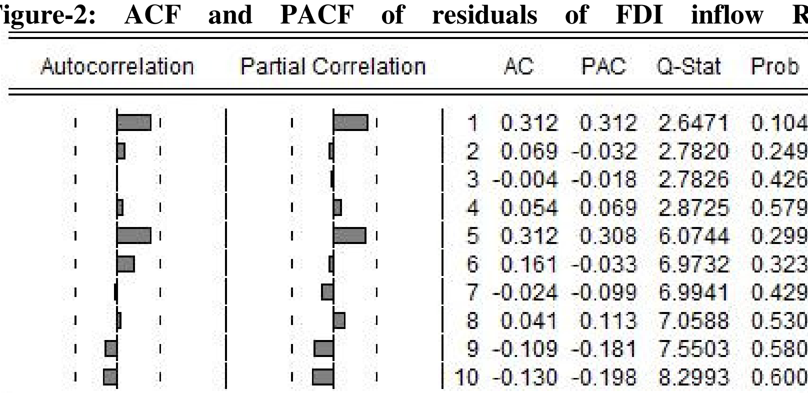
Figure-1: ACF and PACF of residuals of FDI inflow Brazil for ARIMA (3, 1, 2)



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.020	0.020	0.0185	0.892
		2	-0.030	-0.030	0.0579	0.971
		3	0.159	0.160	1.2292	0.746
		4	-0.043	-0.052	1.3159	0.859
		5	-0.038	-0.026	1.3873	0.926
		6	-0.040	-0.068	1.4666	0.962
		7	0.005	0.022	1.4680	0.983
		8	0.027	0.032	1.5059	0.993
		9	0.042	0.058	1.6045	0.996
		10	-0.014	-0.027	1.6158	0.999

Source: EViews 9

Figure-2: ACF and PACF of residuals of FDI inflow Russia for AR(2) MA (2)



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.312	0.312	2.6471	0.104
		2	0.069	-0.032	2.7820	0.249
		3	-0.004	-0.018	2.7826	0.426
		4	0.054	0.069	2.8725	0.579
		5	0.312	0.308	6.0744	0.299
		6	0.161	-0.033	6.9732	0.323
		7	-0.024	-0.099	6.9941	0.429
		8	0.041	0.113	7.0588	0.530
		9	-0.109	-0.181	7.5503	0.580
		10	-0.130	-0.198	8.2993	0.600

Source: EViews 9

Figure-3: ACF and PACF of residuals of FDI inflow India for ARIMA (3,1,3)

Lag	AC	PAC	Q-Stat	Prob
1	0.139	0.139	0.8505	0.356
2	0.231	0.216	3.2670	0.195
3	0.126	0.076	4.0052	0.261
4	0.180	0.118	5.5488	0.235
5	-0.032	-0.111	5.6004	0.347
6	0.031	-0.027	5.6496	0.464
7	-0.017	-0.019	5.6641	0.579
8	-0.059	-0.069	5.8470	0.664
9	-0.012	0.034	5.8551	0.754
10	-0.026	-0.003	5.8927	0.824

Source: EViews 9

Figure-4: ACF and PACF of residuals of FDI inflow China for AR(1) MA(3)

Lag	AC	PAC	Q-Stat	Prob
1	0.189	0.189	1.3304	0.249
2	0.017	-0.020	1.3410	0.511
3	-0.016	-0.016	1.3510	0.717
4	0.132	0.144	2.0632	0.724
5	0.058	0.005	2.2029	0.820
6	0.230	0.230	4.5191	0.607
7	0.044	-0.038	4.6063	0.708
8	-0.028	-0.046	4.6435	0.795
9	-0.008	0.018	4.6464	0.864
10	-0.034	-0.111	4.7066	0.910

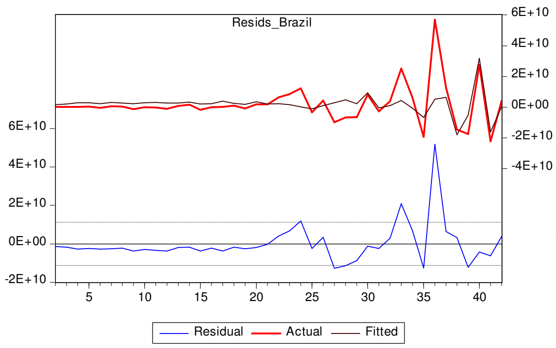
Source: EViews 9

Figure-5: ACF and PACF of residuals of FDI South Africa for AR(1,2,3,5) MA(6,7)

Lag	AC	PAC	Q-Stat	Prob
1	0.222	0.222	2.4269	0.119
2	-0.017	-0.070	2.4419	0.295
3	0.136	0.164	3.3860	0.336
4	0.053	-0.021	3.5328	0.473
5	0.016	0.028	3.5472	0.616
6	0.128	0.108	4.4468	0.616
7	0.296	0.260	9.4100	0.225
8	-0.044	-0.184	9.5226	0.300
9	0.003	0.081	9.5230	0.390
10	0.133	0.028	10.611	0.389

Source: EViews 9

Figure-6: Actual and fitted values of Brazil **Figure: 7: Actual and fitted values of Russia**



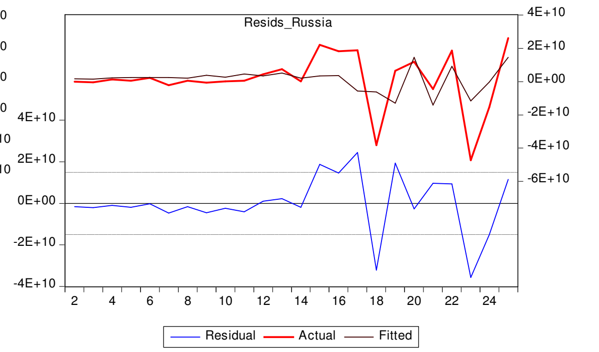


Figure-8: Actual and fitted values of India

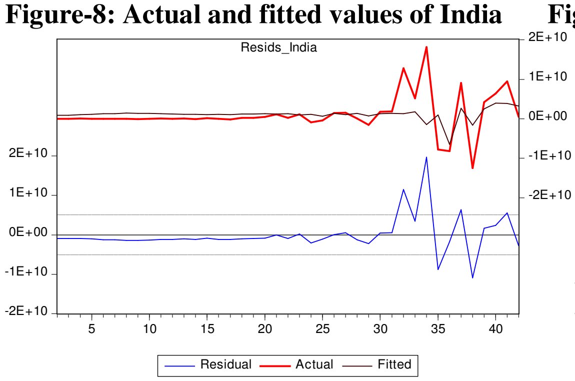


Figure-9: Actual and fitted values of China

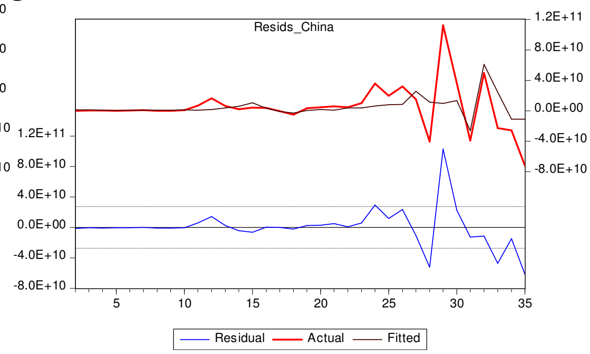
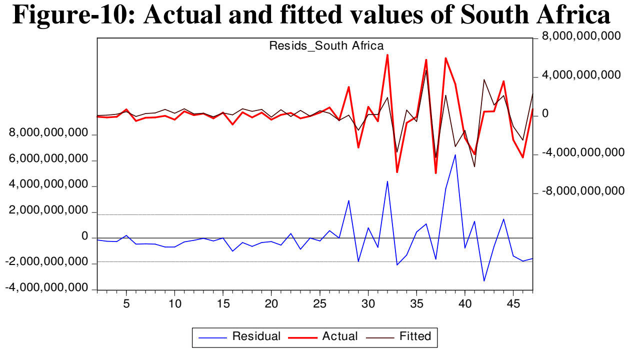


Figure-10: Actual and fitted values of South Africa



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