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DETERMINING FDI INFLOWS IN INDIA: USING BOX-JENKINS ARIMA APPROACH

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Abstract

Using time series data for FDI inflow in India from 1991 to 2021, the study seeks to model and predict the FDI inflows in India. The Autoregressive integrated moving average (ARIMA) model created by Box and Jenkins (1976) was utilised to develop the model. Identification of the UBJ included determining the appropriate AR (autoregressive) and MA (moving-average) polynomial orders, i.e., p and q values. The rankings were used to determine the stationary series' autocorrelation and partial autocorrelation functions. It was determined that FDI data were not static and that a single-order difference was sufficient to create the required stationary series. The study identified a low BIC value and then proposed the ARIMA model (0,1,2) as an appropriate FDI predictor in India. The expected FDI inflows for 2022–23 through 2029-2030 were within the confidence interval. The percentage variation between predicted and observed numbers assures that our forecast prices are near actual prices.

Keywords: *FDI Inflows, ARIMA Model, Forecasting FDI Inflows*

1. INTRODUCTION

Foreign Direct Investment (FDI) has been a substantial non-debt financial resource for India's economic development and a crucial driver of economic growth. Foreign firms invest in India to take advantage of the country's unique investment benefits, such as tax reductions and lower wages. This assists India in developing technological know-how and creating jobs, among other benefits. These investors have flocked to India because of the country's welcoming business environment, rising global competitiveness, and growing economic importance.

In recent years, India has emerged as an appealing location for FDI, owing to various factors promoting FDI. The Global Competitive Index ranked India 68th; the economy has improved tremendously during the pandemic. India has also been rated the 48th most innovative country in the top 50. Reduced FDI requirements in PSUs, oil refineries, telecommunications, and defence are among the recent actions taken by the government. Reduced FDI requirements in PSUs, oil refineries, telecommunications, and defense are among the recent actions taken by the government. FDI inflows into India hit record levels in 2020-21. Total FDI inflows totalled US$ 81,973 million, representing a 10% increase over the previous fiscal year. According to the World Investment Report 2022, India placed eighth among primary FDI beneficiaries in the world in 2020, up from ninth in 2019. In FY22, the largest recipients of FDI were information and technology, telecommunications, and automobiles. Multinational corporations (MNCs) have pursued strategic collaborations with top domestic business groups, fuelling an 83% growth in cross-border M&A to US$ 27 billion, thanks to substantial technological and health transactions.

Forecasting outcomes is crucial for policymakers. Using time series data for FDI inflow in India from 1991 to 2021, the study seeks to model and predict the FDI inflows in India. The Autoregressive integrated moving average (ARIMA) model created by Box and Jenkins (1976) was utilised to develop the model.

2. OBJECTIVES OF THE STUDY

1. To make projections for the total amount of FDI for the nine years (2022–2030) that extend beyond the end of the sample period (1991-2021).
2. To generate the prediction of FDI inflows in India using the model that best fits the data.

3. LITERATURE REVIEW

Using the ARIMA, coefficient, linear, and compound models, Ramachandran and Rajalakshmi (2011) analysed the foreign investment flows from 1991 to 2011 in the automobile sector, focusing on the passenger automobiles, using the coefficient model. Policy recommendations were made to address the challenges India faces in attracting FDI in the automobile sector by examining the trajectory and composition of FDI flows and the impact of FDI on economic growth. Using macroeconomic factors, Singhania and Gupta (2011) investigated the determinants of foreign direct investment in India. It was determined that the ARIMA model best explains the fluctuation in India's FDI inflows. It was observed that GDP, inflation rate, and scientific research are significant variables and that FDI Policy changes between 1995 and 1997 substantially affected FDI inflows into India. By employing an autoregressive regressive integrated moving average forecasting technique, Anitha (2012) looked at the FDI inflow into India after liberalisation and predicted its trajectory over the next five years, from 2010-11 to 2014-15. Different elements that affect FDI flow were analysed, the reasons for low FDI influx were determined, and recommendations were made to boost FDI in India. Khan (2012) examined the effects of FDI on India's GDP growth rate and FDI inflows in various sectors. He also investigated the distribution of FDI inflows by industry to identify the sector that has grabbed the lion's share. FDI was found to have a considerable impact on India's GDP, exports, and GDCF. Foreign direct investment (FDI) flows mainly to the service, telecommunications, real estate, construction, and IT hardware and software industries. Using GDP data and the

ARIMA (1, 2) model, Maity and Chatterji (2012) projected India's GDP growth rates. According to the findings, the autoregressive and moving average terms are only meaningful for a single period. Additionally, both the absolute numbers and the growth rates of the predicted GDP point to an upward trend in the future. Sharmila Devi and Ali (2013) used the ordinary least square method to analyse the macroeconomic variables that may affect FDI inflows. Export, the Index of Industrial Production, and Inflation are statistically significant at the 5% level among the chosen variables. Using Regression Analysis and Box Jenkins methodology to build autoregressive integrated moving averages, Biswas (2015) constructed a time series model to predict FDI inflows in India using annual time series data from 1992 to 2014. The ARIMA model's results indicated that FDI would increase throughout the foreseeable future (2015-2034). Using the ARIMA Model (111), which was found to best match the data, Singh (2015) predicted FDI in India from 2014 to 2020.
According to the model, India might receive up to US $ 74,935.27 million in FDI in 2020, with an average of US $ 51982.39 million for the anticipated year. The compounded annual growth rate of FDI inflows between 2014 and 2020 is expected to be 14.31%.

4. RESEARCH METHODOLOGY

Data were gathered from several RBI Bulletin issues for the 31-year Foreign Direct Investment (FDI) period from 1991 to 2021. Data from 1991 to 2017 were used to create the model, and data from the next four years were used to judge the model's validity. The Autoregressive Integrated Moving Average (ARIMA) of the FDI projection in India underwent a statistical study to better the pertinent relationship.
While past events and behavioural lags continually shape economic variables that are claimed to be expected, it is rarely assumed that such variables are independent over time. Consequently, before starting with the estimation, it is necessary to determine whether the FDI variable is time independent or not.
4.1 Test of Stationarity: The first stage in evaluating time series data is determining whether or not the time series is stationary and whether or not it exhibits a seasonality pattern. If the statistical features of a time series do not change over time, it is said to be stationary (Guo-Hong Zhang, 2005). Stationarity can be checked using three methods: visual inspection, correlograms, and the unit root test (De Mello,1999).
Charts 1.1 and 1.2, which show the FDI series prior to and following differencing, respectively, provide a graphical representation of the data.

CHART 1.1 TOTAL FDI INFLOWS

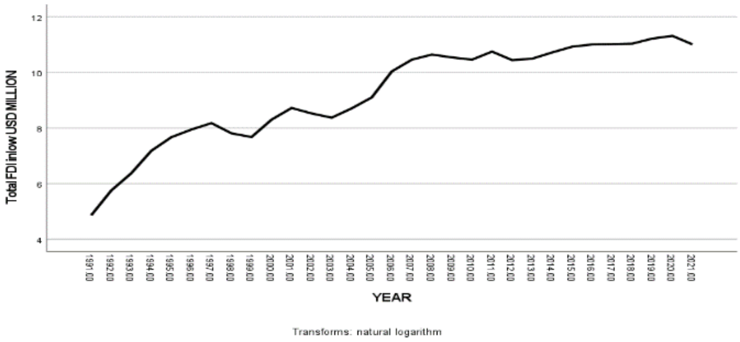

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CHART 1.2 DFDI (First Difference of FDI)

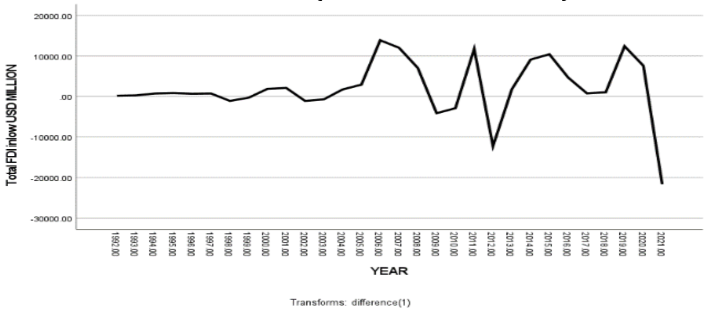


Chart 1.1's graphical analysis of FDI enables the identification of time-varying trend patterns in the series. It is also clear from Chart 1.1 that the time series is not stationary at its levels, but it looks to be stationary in both mean and variance after its initial differencing, as shown in Chart 1.2. As a result, graphing FDI against time reveals an increasing trend over time and a random walk time series with a non-zero mean and a non-constant variance. Recognising will aid in extrapolating them in the future and doing more accurate forecasting (Box et al., 1970). After monitoring for a trend in FDI, stationary tests confirm whether or not a series is stationary (Phillips & Perron, 1988). The outcomes of the ADF test to determine the stationarity of the FDI series are detailed in Tables 1.1 and 1.2, respectively.

Table: 1.1 Test Statistics of Unit root Test at Level

	ADF test statistics
probability	0.882513
t-Statistics	-4.547003
Test critical value:	
1%	-3.669920
5%	-2.964071
10%	-2.621171

Table: 1.2 Test Statistics of Unit root Test at First Order of Differencing

	ADF test statistics
probability	0.300713
t-Statistics	-1.968145
Test critical value:	
1%	-3.809209
5%	-3.021645
10%	-2.650713

Table 1.1 displays the ADF unit root test results for the FDI series. At levels, the ADF test statistics are lower than the critical values. As a result, series are non-stationary at their levels and become stationary when they are first differenced because the calculated ADF test - statistics are larger than the critical values at various significant levels. At the 5% significance level, the unit-root test findings accept the null hypothesis, showing that the series is stable in its first difference.

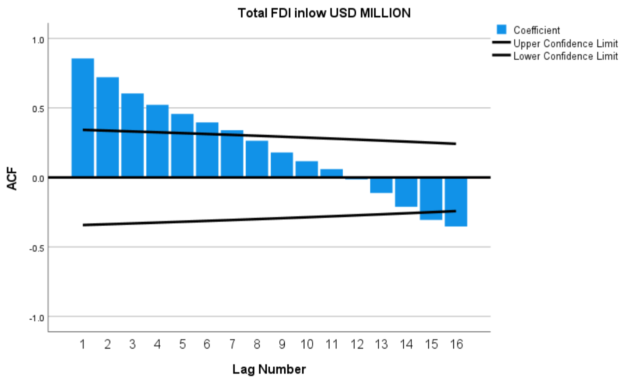
4.2 Autoregressive Integrated Moving Average Model (ARIMA)

Even for short-term forecasting, stochastic models related to Box-Jenkins, known as the ARIMA, have been more efficient and trustworthy. Moreover, stochastic models are distribution-free since no data-related assumptions are necessary. The univariate Box-Jenkins (Box and Jenkins, 1968, 1994) method is based on recognising the pattern followed by past values of a single variable and then projecting the past into the near future. One of the benefits of Box-Jenkins over other forecasting models is that this approach is not based on economic theory and can catch the most negligible data variations (Hyndman & Khandakar 2008). Four steps comprise the proposed ARIMA modelling procedure: 1) identification, 2) estimation, 3) diagnostic examination and 4) prediction. The approach begins with model identification, during which the original series must be filtered to identify its generating process and stabilise it. The correlograms of the ACF and PACF were utilised to discover whether the data-generating process is auto-regressive (AR) or moving-average (MA), as well as the order of integration (I) and their respective order.

4.2.1 Identification Stage

Section 4.1 performed a stationary check on time series data, which found that the FDI series is non-stationary. First-order differencing and the best fit were used to make the non-stationary time series data stationary. ARIMA models were constructed and used to anticipate FDI inflows from 2022 to 2037 using data from 1991 to 2021. The initial values for the orders of the non-seasonal parameters "p" and "q" are used to identify ARIMA models. They are discovered by scanning autocorrelation and partial autocorrelation functions for unusual spikes. As a result, establishing the lag order for each model is critical since determining the optimal lag significantly impacts the forecasting process. This work can be completed by inspecting each series's autocorrelation and partial autocorrelation correlograms (Pankratz, 1983). The approach comprises determining if the series can be described as AR(p), MA(q), or a mixture of these terms based on the correlogram to correct the correlation. The ACF assists in determining the correct values for moving average terms (MA) ordering and the PACF for those autoregressive terms (AR). During the identification stage, one or more models that appear to provide statistically sound representations of the relevant data were tentatively chosen. The model's parameters were then precisely estimated using least squares. To put it another way, if the correlation and partial autocorrelation are white noise, there is no need to look for another ARIMA model (Nagar, 2001). Charts 1.3 and 1.4 display the correlograms of the FDI series with first and no differencing, respectively.

Chart: 1.3 The Levels' Correlogram



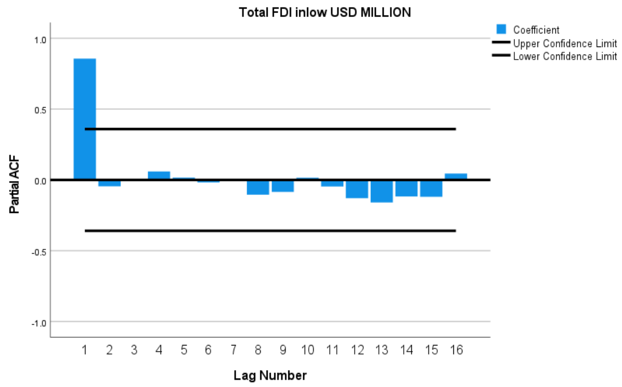


Table: 1.3 ACF and PACF of FDI

Total FDI INFLOW USD MILLION							
Lag	Autocorrelation	Std. Error	Partial Autocorrelation	Std. Error	Box-Ljung Statistic		
					Value	df	Sig. b
1	0.856	0.171	0.856	0.18	25.001	1	<.001
2	0.721	0.168	-0.045	0.18	43.343	2	<.001
3	0.604	0.165	-0.008	0.18	56.693	3	<.001
4	0.522	0.162	0.06	0.18	67.033	4	<.001
5	0.457	0.159	0.017	0.18	75.258	5	<.001
6	0.396	0.156	-0.018	0.18	81.663	6	<.001
7	0.34	0.153	-0.002	0.18	86.598	7	<.001
8	0.264	0.15	-0.104	0.18	89.706	8	<.001
9	0.18	0.147	-0.084	0.18	91.204	9	<.001
10	0.117	0.143	0.016	0.18	91.866	10	<.001
11	0.06	0.14	-0.046	0.18	92.049	11	<.001
12	-0.014	0.136	-0.129	0.18	92.059	12	<.001
13	-0.112	0.133	-0.159	0.18	92.768	13	<.001
14	-0.211	0.129	-0.117	0.18	95.453	14	<.001

15	-0.306	0.125	-0.119	0.18	101.44	15	<.001
16	-0.353	0.121	0.045	0.18	109.923	16	<.001

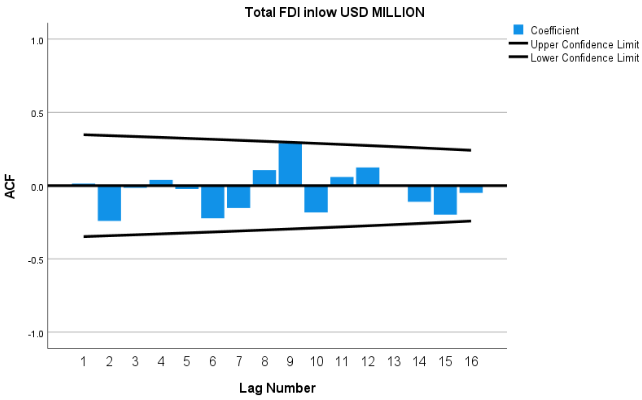
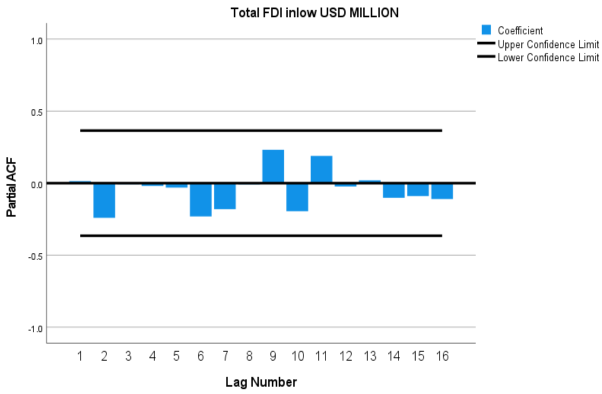


Chart: 1.4 The Correlogram (at 1st Differences)



Lag	Autocorrelation	Std. Error	Partial Autocorrelation	Std. Error	Box-Ljung Statistic		
					Value	df	Sig. b
1	0.014	0.174	0.014	0.183	0.006	1	0.936
2	-0.241	0.171	-0.241	0.183	1.994	2	0.369
3	-0.015	0.168	-0.008	0.183	2.002	3	0.572
4	0.04	0.165	-0.019	0.183	2.06	4	0.725
5	-0.023	0.161	-0.031	0.183	2.081	5	0.838
6	-0.223	0.158	-0.231	0.183	4.066	6	0.668
7	-0.153	0.155	-0.181	0.183	5.04	7	0.655
8	0.106	0.151	-0.009	0.183	5.533	8	0.699
9	0.288	0.148	0.231	0.183	9.326	9	0.408
10	-0.183	0.144	-0.195	0.183	10.935	10	0.363
11	0.059	0.141	0.189	0.183	11.114	11	0.434
12	0.124	0.137	-0.024	0.183	11.938	12	0.451
13	0.002	0.133	0.02	0.183	11.938	13	0.533
14	-0.11	0.129	-0.102	0.183	12.664	14	0.553
15	-0.198	0.125	-0.09	0.183	15.162	15	0.44
16	-0.05	0.121	-0.11	0.183	15.331	16	0.501

Table: 1.4 ACF and PACF of 1st difference of FDI

As seen in Chart 1.3, ACF and PACF are equal. It demonstrates a considerable increase in ACF and PACF at lag 1, followed by a gradual reduction following the first lag. Hence, it may be determined that the time series is non-stationary. While Chart 1.4 depicts the ACF and PACF of the difference series during the estimation period, a significant spike is noted at lag 1. Since the ACF and PACF have peaks at lag 1, the differences can be utilised for the ARIMA model. ACF and PACF (Chart 1.4) also suggest that the order of p and q can be no greater than 2.

4.2.2 Estimating ARIMA Models

Because the time series become stationary after the first difference, it is possible to estimate the forecasting models shown in Table 1.5 and select the best applicable model. ACF coefficients control the order of MA terms, while PACF coefficients determine the order of AR terms. Chart 1.4's ACF and PACF plots for d = 1 reveal that the first differenced FDI series are stable, necessitating additional analysis to determine the most appropriate ARIMA. ACF and PACF are both significant at the first lag; consequently, the ARIMA model is defined with a maximum of two lag components for AR and MA. Using the t-distribution, the model's relevant p, d, and q values and their statistical significance can be determined. Bayesian information criterion (BIC) is utilised for model identification since it is a criterion for model selection from a finite set of models and is appropriate when the sample size is less than 150. (Stevens, 2009). The best-fitting model might be the BIC minimum value. Automated procedures can be used to estimate critical parameters using standard computer programs like STATA and SPSS.

Under the assumption that the first difference order is (1), the following ARIMA models can be proposed: ARIMA (1,1,0), ARIMA (1,1,1), ARIMA (1,1,2), ARIMA (2,1,2), ARIMA (2,1,1), ARIMA (2,1,0), ARIMA (0,1,1), and ARIMA (0,1,2). The optimal model technique involves selecting the model with the lowest SIC, MSE, and RMSE values. Table 1.5 presents the initial estimates of the parameters of several ARIMA models.

Table: 1.5 Initial estimations of various ARIMA Model parameters

Model	Parameters				
	C	AR1	AR2	MA1	MA2
ARIMA (1,1,0)	-85126.526	0.002			
ARIMA (1,1,1)	-85150.597	-0.777		-1.000	
ARIMA (1,1,2)	-95097.174	0.382		0.435	0.564
ARIMA (2,1,2)	-97847.873	-0.094	0.417	0.02	0.979
ARIMA (2,1,1)	-160931.378	0.054	-0.407	0.029	
ARIMA (2,1,0)	-159607.558	0.028	-0.407		
ARIMA (0,1,1)	-85124.755			-0.002	
ARIMA (0,1,2)	-286831.269			0.240	0.758

Geuntand Ibrahim (1975) noted that the best forecasting model is not necessarily the one chosen. Hence, further accuracy tests should be conducted to confirm that the best model is selected. The model with the lowest BIC value is deemed the most suitable. As it has the lowest BIC value, ARIMA (0, 1, 2) is considered the best model for forecasting FDI inflow in India. Table 1.5 displays the values of the ARIMA model parameters p and q.

4.2.3 Testing the Reliability of Predictions

It is essential to measure inaccuracy for a particular data set and forecasting strategy. Accuracy can be described as the "fitness of the model" or the ability of the forecasting model to recreate known facts (Makridakis & Wheelwright, 1989). Raman (1995) demonstrates that to evaluate the accuracy of a forecast, four statistical approaches are used: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Mean Square Error (MSE).

Table: 1.6 Accuracy test results for the suggested ARIMA models

Estimate model	VARIABLE FDI (Model Fit Statistics)					
	R square	MSE	RMSE	MAPE	MAE	BIC
(1,1,0)	0.924	33700370.125	7441.53	44.798	4640.805	18.17
(1,1,1)	0.932	33659772.502	7209.126	41.413	4374.849	18.22
(1,1,2)	0.94	33667081.063	6908.498	72.037	4776.683	18.248
(2,1,2)	0.942	33516073.707	6905.529	73.196	4770.292	18.36
(2,1,1)	0.933	33663400.996	7278.493	40.412	4262.039	18.352
(2,1,0)	0.933	33681392.803	7137.365	40.449	4267.886	18.2
(0,1,1)	0.924	33675950.981	7441.521	44.465	4639.319	18.17
(0,1,2)	0.942	32020567.875	6607.518	37.888	4356.703	18.045

Table 1.6 displays the error measurements and specifics of several ARIMA models. Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) tests were used to evaluate the accuracy of ex-ante and ex-post projections (Markidakis and Hibbon 1979). Findings show that the optimal model for predicting is an ARIMA model with the lowest error measures, notably the BIC and MSE. Because it has the lowest values for the BIC, MSE, and RMSE statistics, an ARIMA (0, 1, 2) is regarded as the best-fit model. As a result, the optimal model to utilise for the forecast is ARIMA (0, 1, 2).

4.2.4 Diagnostic checking

The diagnostic checking and estimation results of the ARIMA (0,1,2) model are shown in the following tables.

Table: 1.7 Autocorrelations of residuals for diagnostic purposes: Model of FDI (0,1,2)

Model	Model Fit Statistics							Ljung-Box Q (18)		
	Stationary R-squared	R-square	MSE	RMSE	MAPE	MAE	Normalised BIC	Statistics	DF	Sig.

		d								
Mod el (0,1, 2)	0.243	0.942	33667081. 063	6607.5 18	37.8 88	4356.7 03	18.045	12.61 7	1 6	0. 7

Table: 1.8 Parameter estimates of ARIMA model (0,1,2)

	Estimate	SE	t	Sig.
Constant	-286831.269	165621.829	-1.732	0.095
Difference	1	-	-	-
MA1	0.24	13.707	0.018	0.986
MA2	0.758	10.472	0.072	0.943

5. FORECAST

Generally, an ARIMA model is utilised to get the most accurate average forecasts for a single time series (Reimers 1992). Ex-ante and ex-post accuracy of predictions were evaluated using tests such as RMSE, MSE, MAE, and MAPE (Markidakis & Hibbon 1979). The primary purpose of ARIMA models is to forecast the relevant variable. To evaluate the predictive capabilities of the fitted ARIMA model, a crucial metric of the sample period forecasts' precision was derived. In the ARIMA model, the MAPE for FDI is 37.888. This metric suggests that the forecasting error is minimal. The predictions for FDI from 2022 to 2030 indicate a growing trend (Table 1.8). ARIMA (0, 1, 2) models for FDI were built in the study. Using the developed model, the available forecast indicates that FDI is expected to rise during the following years. When data for lead periods become available, the accuracy of the anticipated value can be verified. The model can be used by researchers to predict FDI flows into India. However, data must be updated on a regular basis to reflect current values. The outcomes of FDI forecasts for the years 2022 to 2030 are presented in Table 1.8.

Table: 1.8 Forecasting Results

YEAR	FORECAST	LCL	UCL
2022	67053.32	53570.8	80535.85
2023	86043.35	68872.91	103213.78
2024	91173.81	74003.35	108344.27
2025	96448.52	79278.91	113618.12
2026	101867.48	84699.46	119035.49
2027	107430.69	90264.87	124596.51
2028	113138.15	95975.03	130301.28
2029	118989.86	101829.85	136149.88
2030	124985.82	107829.26	142142.39

In this study, the ARIMA (0,1,2) model was found to be the best one for predicting FDI influx in India for up to nine years using time series data. ARIMA was chosen because it can use time series data with any pattern to make predictions and because it can use autocorrelations between values that come after it. In addition, the fitted ARIMA time series' successive residuals, or prediction errors, were examined and statistically confirmed to be uncorrelated. The residuals appear to have a normal distribution with a constant variance and a mean of zero. As a result, the ARIMA (0, 1, 2) model that was chosen is a good predictor of FDI flow into India. The percentage difference between the forecasted and actual values is within acceptable ranges, as shown in Table 1.9, so the projected values of FDI for the years 2018–19 to 2021–22 are close to the actual values. To calculate percent deviation (RD%), use the formula: Forecasted yield divided by actual yield/actual yield divided by 100.

Table: 1.9 Per cent deviation between Actual & fitted values India's FDI from 2018-2019 to 2021-2022. (Value in Million USD)

Year	FDI Actual (Y)	FDI Forecast (F)	Relative Deviations
2018-2019	62001	64761.55	4.452428187
2019-2020	74391	65293.22	-12.22967832
2020-2021	81973	79076.22	-3.533822112
2021-2022	76502	79394.22	3.7805809

Chart: 1.5 Forecasting Result using ARIMA Model (0,1,2)

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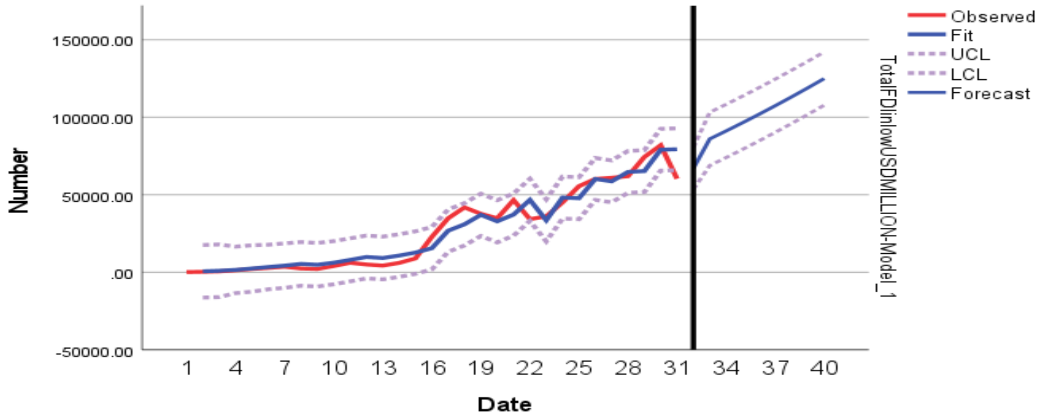

6. CONCLUSION

This study determines that the ARIMA (0, 1, 2) model is the optimal, best, and most suitable model for modelling and forecasting net FDI inflows in India. A best-fit model was used to predict FDI over the next nine years, and it was found that the total amount of FDI expected for the next nine years (2022-2030) is 907131 USD million. The average amount of FDI expected for the next nine years is 453563 USD million for India. In the long term, FDI will keep coming into India steadily. In India, there is a need for robust policies that require appropriate and adequate implementation. There is a need for purpose-driven policies with clearly defined objectives and goals and foreign direct investment attraction strategies that are solely realistic. A plausible prediction can therefore assist policymakers in making sound decisions. Forecasted values of the inward flow of FDI, a limitation of the study is that only the inward flow of FDI is considered an economic variable, and the projection of the inward flow of FDI is made using only the time series data of FDI inflow, while other variables are neglected.

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