FORECAST OF FDI INFLOW IN INDIA

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***Abstract*: Foreign direct investment (FDI) is an important source of private external finance for developing and developed economies due to its contribution in the productivity gains through new projects. Certain pecuniary benefits of FDI have encouraged persistent efforts by the emerging economies in harnessing more FDI inflows to encourage investment in the major sectors of the economy such as manufacturing, infrastructure, financial sector, etc. The literature suggests that past and present information can be used to generate reliable forecasts of FDI, therefore present study seeks the generation of forecasts of FDI.Data of FDI in terms of Indian Rupees covering the period from 1991-2016 on yearly basis was taken from the official website of World bank indicators.The objective of this study is to forecast the volume of FDI for twenty years (2017 – 2037) beyond the end of sample period (1991-2016). DES Holt's model and Box-Jenkins methodology of building ARIMA model are employed under the study.**

A comparison between the two models has been done on the basis of forecast accuracy errors. On the basis of forecast accuracy errors results ARIMA has outperformed than the DES Holt's models. So finally, ARIMA model is employed to generate the forecast of FDI inflows in India.Forecast of FDI in India for the years will also give a clear picture of this investment in the future in a scientific manner, which helps them in making appropriate decisions for the development of economic policies that will help them attract FDI.

***Keywords*: DES holts' method, forecast, ARIMA, forecast accuracy errors**

I. INTRODUCTION

Future is highly uncertain but most people view the future as consisting of a large number of alternatives. Like, it is projected that India GDP may slow down from 8.6% in 2015 to 7.0% in 2017 because of disruptions by demonetization and GST, the World Bank has forecast and warned that subdued private investment due to internal bottlenecks could put downside pressures on the country potential growth(The Hindu,11 Oct., 2017). But, if GST is implemented successfully it will attract more FDI across sectors due to tax transparency and ease of doing business (Economic Times, 13 Sept., 2016). Thus, forecasting involves the best way of examining the different alternatives, identifying the most probable ones and thus reducing the uncertainty to the least. Forecasting is the best designed tool to help decision making and planning in the present (Walonick, 1993).

Therefore, forecasting of FDI in India for the years will also give a clear picture of this investment in the future in a scientific manner, which helps them in making appropriate decisions for the development of economic policies that will help them attract FDI.

Believing this, the study endeavors to generate the forecasts of FDI inflows to India on the basis of study of past behavior assuming that it may help the policy makers in the country to monitor the FDI inflows the way they think most appropriate.

II. OBJECTIVES OF THE STUDY

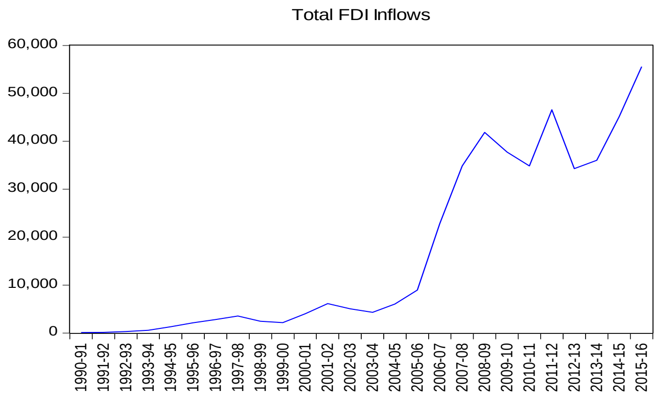
- To forecast the volume of FDI for twenty years (2017 – 2037) beyond the end of sample period (1991-2016).
- To use the best fitted model to generate the forecast of FDI inflows in India.

III. RESEARCH METHODOLOGY

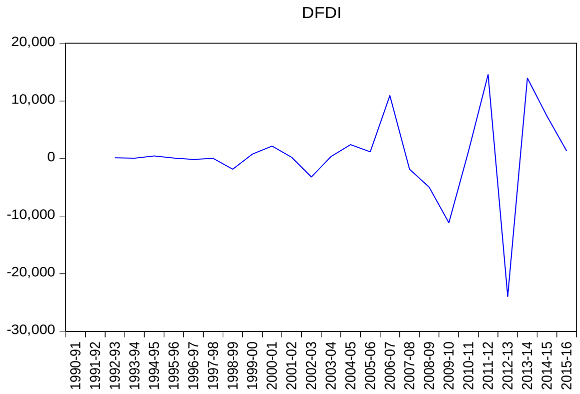
The study models FDI inward series in rupees using a univariate model,Double exponential Smoothing Holt's (DES Holt's) Method and the Auto-Regressive Integrated Moving Average (ARIMA) model proposed by Box, Jenkins and Reinsel (1994). As economic variables are always influenced by its past events and lags in behaviour is said to be prevalent, therefore, it is rarely assumed that such variables are independent across time. Thus, before proceeding with the estimation, it becomes important to test that whether the FDI variable is independent of time or not.

3.1 Test of Stationarity

The first step in studying time series data is to know if the time series is stationary and if it also presents a seasonality pattern or not. A time series is said to be stationary if its statistical properties do not vary with time (Guo-Hong Zhang, 2005). Generally, there are three important methods to check stationarity; visual inspection; correlograms and unit root test(De Mello,1999). Henceforth, the graphical representation of FDI series before and after differencing is presented in the Chart 1.1 and Chart 1.2 respectively.



Chart



1.1 FDI Chart 1.2 First Difference of FDI

The graphical analyses of FDI in Chart 1.1 allow identifying trend patterns in the series over the time period. It can also easily be inferred from the above Chart 1.1 that the time series is not stationary at its levels but it appears to be stationary both in its mean and variance after its first differencing as represented in Chart 1.2. Therefore, graphical representation of FDI against time shows that it has an increasing trend over time and has a random walk time series with a non-zero mean and a non-constant variance.Identifying these patterns will help first in extrapolating them in the future and to perform more accurate forecast (Box et al., 1970). After accounting for the presence of trend in FDI, stationary tests allow verifying further whether a series is stationary or not (Phillips &Perron, 1988).

The results of ADF and PP tests for stationarity of FDI series are presented in the Table 1.1 and 1.2 respectively.

Table 1.1
ADF Test

Variable- FDI				
		t- Stat	Critical Value at 5 %	Particulars
At Level	Intercept	0.31	-3.52	Non-Stationary Series
	Trend & Intercept	-1.66	-4.08	Non-Stationary Series
	None	1.32	-2.59	Non-Stationary Series
With 1st Difference	Intercept	-5.60	-3.51	Stationary Series
	Trend & Intercept	-5.84	-4.08	Stationary Series
	None	-5.43	-2.59	Stationary Series

Table 1.2
PP Test

Variable-FDI				
		t- Stat	Critical Value at 5 %	Particulars
At Level	Intercept	.379	2.98	Non-Stationary
	Trend & Intercept	1.77	3.60	Non-Stationary Series
	None	1.48	1.95	Non-Stationary Series
With 1st Difference	Intercept	3.93	2.99	Stationary Series
	Trend & Intercept	4.13	3.61	Stationary Series
	None	3.53	1.95	Stationary Series

Table 1.1 reports the results of ADF unit root test for the FDI series. It is observed that the absolute value of ADF test statistics is less (in absolute terms) than the critical values at levels. Thus, series is non-stationary in their levels and become stationary when they are first differenced as the computed ADF test - statistics is greater than the critical values at different significant levels. Unit-root test results accept the null hypothesis at 5% level of significance indicating that the series is stationary in its first difference.

Table 1.2 reports the results of the PP unit root test for the FDI series. The PP test produces results similar to those of ADF test. The level of significance of the PP statistics is 5% for the FDI series. These results again confirm the earlier results ofthe ADF test indicating that the FDI in India behave asrandom walks providing support for the weak-form of the efficient market hypothesis. Therefore, FDI series is integrated of order one, I(1).

The results obtained after carrying out the two tests, ADF and PP are similar.Furthermore, they present the same limitations, using too few lags would not include all the autocorrelations, while usinga large number of lags leads to an increase in standard errors of the coefficients(Gujarati, 2004).

3.2 Double Exponential Smoothing Holt's Method (Des Holt's)

The time series plot of FDI inflows for India plotted inChart 1.1 displays a trend with no seasonal pattern and the growth rate has been changing over time. Because of these features that exist in the series plotted in Chart 1.1,DES Holt's Method is adopted under the study to forecast future values of FDI in India. This method uses a linear combination of the previous values of a series for generating and modelling future values (Gardner,1985).In DES Holt's method, the smoothed trend component calculated separately using different parameters, namely α and β (Kumar & Singh, 2008). In this technique the value of the trend can be smoothed by using different weights. However, these two parameters need to be optimized so the search for the best combination of parameters is more complicated than using only one parameter(Pankratz, 1983). In addition, the components of season in this technique are not taken into account.

Thus, the DES model indicates that the parameters $\alpha = 0.31$and $\beta = 0.41$, giving us the following equations:

$$\overline{X}_t = .31X_t + 0.69(\overline{X}_{t-1} + b_{t-1})$$
$$b_t = 0.41(\overline{X}_t - \overline{X}_{t-1}) + 0.59b_{t-1}$$

Initial values and optimum smoothing parameters for level and growth components has been computed with the help of SPSS software. Only those values of α and β were selected which corresponded to the lowest figure of accuracy measure used. The best value for the smoothing constant is the one that results in the smallest sum of the squared errors(Makridakis, Wheelwright, & Hyndman, 1998)

Before generating forecasts, it is imperative to check the adequacy of the forecasting technique used (Judi2007).Present study confirms the appropriateness of DES Holt's model to generate forecasts by making use of two identificationtechniques namely autocorrelation function and LjungBox Test (Dickey&Fuller, 1979).

Computed values of auto correlation coefficient,$r_k(e)$ and the lag k were displayed graphically to depict autocorrelation function (ACF) also known as correlogram in Chart 1.3 Residual ACF, which lies within the 95% interval taken as insignificant and insignificance of ACF, implies adequacy of DES Holt's to generate forecasts.

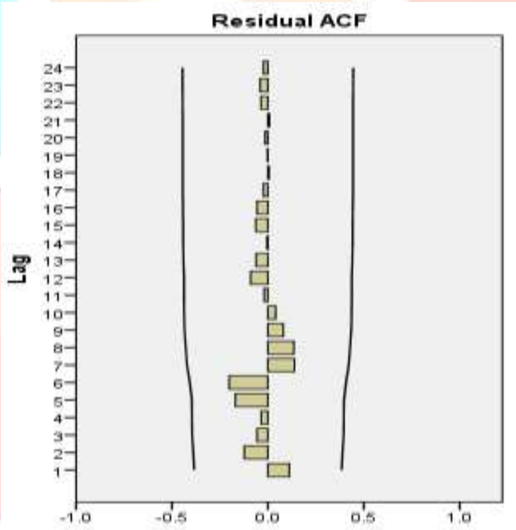


Chart 1.3 Correlogram of Residuals

Ljung-Box test which can be used to test multiple autocorrelation coefficients and instead of testing randomness at each distinct lag, tests the overall randomness based on a number of lags. The results of Ljung-Box Q statistics computed from the model's residuals are presented in the Table 1.3

Table 1.3
Ljung Box Q Statistics

Statistics	DF	Sig.
6.477	16	.982

The value of Q- statistics for FDI found to be insignificant at 5 percent level of significance. Thus,the non-significance of Q-statistics ensures the adequacy of DES model used to generate the forecasts. Thus, DES using level and trend components can be used to generate forecast.

The forecast equation for h period ahead from time t is as follows:

$$\hat{X}_{t+h} = \overline{X}_t + hb_t$$

Forecast accuracy errors of DES Holt's model have been represented in the Table 1.8 for comparison between the accuracy errors by DES Holt's and ARIMA. The model which will be having low forecast accuracy errors will be used for the forecast of FDI for the period 2017-2037 under the study(DeLurgio 1998).

3.3 Autoregressive Integrated Moving Average Model (ARIMA)

Stochastic models attributed to Box-Jenkins known as the ARIMA have been found to be more efficient and reliable even for short term forecasting. Further, stochastic models are distribution-free as no assumptions are required about the data. Univariate Box-Jenkins (Box and Jenkins 1968, 1994) approach is based on identifying the pattern followed by past values of a single variable and then extrapolating the pattern in the past for near future as well. One of the advantages of Box-Jenkins over other forecasting models is that this modelling approach is not based on economic theory and is capable of capturing slightest variation in the data (Hyndman&Khandakar 2008)

The proposed ARIMA modelling procedure has four steps: 1) identification 2) estimation 3) diagnostic check and 4) forecast. The procedure starts with model identification, where the original series has to be filtered so as to identify its generating process and make it stationary. The correlograms of the ACF and PACF were used to determine whether the data generating process is auto-regressive (AR) or moving-average (MA) and to ascertain the order of integration (I) and their respective orders.

3.3.1 Identification Stage

The stationary check of time series data has been performed in the section 3.1,which has revealed that the FDI series is non-stationary. The non-stationary time series data were made stationary by first order differencing and best fit ARIMA models were developed using the data from 1991 to 2016 and used to forecast the FDI inflow from 2017-2037. ARIMA models are identified by finding the initial values for the orders of non-seasonal parameters “p”and “q”. They are obtained by looking for significant spikes in autocorrelation and partial autocorrelation functions.Therefore, determining the lag order for each modelis crucial partbecause determining the appropriate lag will have a great implication on forecasting exercise. This task can be accomplished based on the inspection of the correlograms of autocorrelation and partial autocorrelation of each series (Pankratz, 1983). Based on correlogram, the procedure consists to determine whether the series can be modelled as AR(p), MA(q) or a combination of these terms to correct the correlation. The ACF helps in choosing the appropriate values for ordering of moving average terms (MA) and PACF for those autoregressive terms (AR).In others words when the correlation and partial autocorrelation are white noise there is no need to search out for another ARIMA model (Nagar, 2001).

At the identification stage, one or more models were tentatively chosen which seem to provide statistically adequate representations of the available data. Then, precise estimates of parameters of the model were obtained by least squares.

The correlogram of FDI series are represented below in the Chart 8.4 and Chart 8.5 with no differencing and first differencing respectively.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.845	0.845	20.808	0.000
		2	0.715	0.000	36.301	0.000
		3	0.626	0.076	48.699	0.000
		4	0.540	-0.025	58.354	0.000
		5	0.391	-0.260	63.654	0.000
		6	0.300	0.087	66.922	0.000
		7	0.203	-0.124	68.500	0.000
		8	0.063	-0.217	68.660	0.000
		9	-0.073	-0.081	68.888	0.000
		10	-0.174	-0.110	70.267	0.000
		11	-0.220	0.136	72.626	0.000
		12	-0.254	0.053	75.990	0.000

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.384	-0.384	3.9947	0.046
		2	-0.135	-0.331	4.5099	0.105
		3	0.117	-0.103	4.9185	0.178
		4	-0.058	-0.114	5.0247	0.285
		5	0.029	-0.026	5.0532	0.409
		6	-0.214	-0.309	6.6362	0.356
		7	0.130	-0.158	7.2547	0.403
		8	-0.004	-0.188	7.2553	0.509
		9	-0.022	-0.124	7.2754	0.608
		10	0.078	-0.059	7.5483	0.673
		11	0.006	0.002	7.5499	0.753
		12	-0.045	-0.106	7.6536	0.812

Chart 1.4 ACF and PACF of FDI

Chart 1.5 ACF and PACF of 1stDifference of FDI

ACF and PACFasshown in Chart 1.4 are at level. It illustrates that there is a significant spike at ACF and PACF at lag 1, and after the first lag, the ACFs and PACFs are slowly declined. Thus, it can be concluded again that the time series is non - stationary. Whereas the Chart 1.5 represents the ACF and PACF of the difference series in the estimation period and it is observed that it has asignificant spike at lag 1. Since the ACF and PACF have spikes at lag 1, so the differences can be used for ARIMA model. It can also be concluded from ACF and PACF (Chart 1.5) that the order of p and q can at most be 2.

3.3.2 Estimating ARIMA Models

Since the time series become stationary after the first difference, it is possible to estimate the following models as presented in the Table1.4 and choose the most appropriate model for forecasting. The number of non-zero coefficients in ACF determines order of MA terms and the number of non-zero coefficients in PACF plots determines order of AR terms.

The ACF and PACF plots for d = 1 in Chart 1.5 indicate that the first differenced FDI series are stationary hence require further examination to establish the most suitable ARIMA. ACF and PACF both are significant at first lag; therefore, tentative model for ARIMA is ascertained with at most two lag terms of AR and MA.

The appropriate p, d and q values of the model and their statistical significance can be judged by t-distribution. Bayesian information criterion (BIC) is adopted for model identification as it is a criterion for model selection among a finite set of models and is suitable when the sample size is less than 150 (Stevens, 2009). The minimum value of BIC may be regarded as best fitted model. Standard computer package like STATA and SPSS etc. are available to find the estimate of relevant parameters using iterative procedures.

Based on the first difference order to be (1), different forms of ARIMA models can be suggested as the following: ARIMA (1,1,0), ARIMA (0,1,1),ARIMA (1,1,1), ARIMA (2,1,2), ARIMA (0,1,2), ARIMA (1,1,2), ARIMA (2,1,0) and ARIMA (2,1,1). The procedure of choosing the most suitable model relies on choosing the model with the minimum SIC, MSE and RMSE criteria. The initial estimates of the parameters of various ARIMA models are presented in the Table 1.4

Table 1.4
Initial estimates of the Parameters of various ARIMA Models

Model	Parameters				
	C	AR1	AR2	MA1	MA2
ARIMA(1,1,0)	-434904.1	0.067			
ARIMA(1,1,1)	-434766.1	-0.820		-0.943	
ARIMA(1,1,2)	-434868.7	0.457		0.639	0.359
ARIMA(2,1,2)	-434869.6	0.376	0.051	0.558	0.44
ARIMA(2,1,1)	-434808.7	0.844	-0.291	0.994	
ARIMA(2,1,0)	-411611.2	0.071	-0.165		
ARIMA(0,1,1)	-443024.1			-0.95	
ARIMA (0,1,2)	-462790.5			0.313	0.685

Geuntand Ibrahim (1975)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 1.4 shows the value of different parameters p and q in the ARIMA model. Model with the lowest BIC value is considered to be the best fit of the model. Hence, ARIMA (1, 1, 1) is considered the best model for forecasting FDI inflow in India as it has the lowest BIC value.

3.3.3 Measuring Forecast Accuracy

A fundamental concern in forecasting is the measure of forecasting error for a given data set and a given forecasting method. Accuracy can be defined as "goodness of fit" or how well the forecasting model is able to reproduce data that is already known (Makridakis&Wheelwright, 1989).Raman (1995)shows that in order to calculate forecasting accuracy, the estimated results are evaluated by four different statistical methods- Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Mean Square Error(MSE). The mathematical calculation of the forecast accuracy errors is presented in the Table 1.5

Table1.5
Forecast Accuracy Errors

Criteria	Formula	Criteria	Formula
MAE	$\frac{i}{n}\sum_{i=1}^{n} 100\,\lvert\varepsilon_i\rvert$	MAPE	$\frac{i}{n}\sum_{i=1}^{n}\left\lvert\frac{\varepsilon_i}{x_i}\right\rvert * 100$
RMSE	$\sqrt{\frac{i}{n}\sum_{i=1}^{n}\varepsilon^2{}_i}$	MSE	$\frac{\sum_{i=1}^{n}(X_t-\hat{X}_t)2}{n}$

Therefore, the above criteria can be used in the comparison between the different models on the basis of least value.

Table 1.6
Results of Accuracy test for the suggested ARIMA models

Estimate	Variable- FDI					
Model	R Square	MSE	RMSE	MAPE	MAE	BIC
(1,1,0)	0.913	33161819	5758.63	41.40	3439.44	17.703
(0,1,1)	0.913	33089438	5752.34	42.98	3390.46	17.792
(1,1,1) *	0.917	28028024*	5294.15	45.63	2993.64	17.701*
(2,1,2)	0.931	30404549	5514.03	47.82	3120.12	18.003
(0,1,2)	0.927	29438579	5425.73	62.13	3411.96	17.711

(1,1,2)	0.932	28787088	5365.36	47.59	3094.32	17.819
(2,1,0)	0.916	33734490	5808.14	37.52	3217.49	17.849
(2,1,1)	0.933	33407152	5779.89	38.62	3266.65	17.839

Table 1.6 shows the details of various ARIMA models along with the error measures. The accuracy of forecasts for both ex-ante and ex-post were tested using the tests such as Mean Square Error (MSE) and Mean Absolute Percentage Error (MAPE) (Markidakis and Hibbon 1979). Results demonstrate that an ARIMA model with lowest error measures specifically the BIC and MSE is considered the best model for forecasting. In this case an ARIMA (1, 1, 1) is considered as best fit model because it has the lowest value of the BIC, MSE and RMSE statistics. Therefore, ARIMA (1, 1, 1) is the best model to be used for the forecast.

3.3.4 **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. Goodness of fit for time series models involves testing if the model residuals form a white noise process (Mackinnon,1996). It is through diagnostic checks that a model can be declared statistically adequate and thereafter can be used to forecast(Sidhu&Neerja 2009). If the diagnostic tests fail a new process (cycle) of identification, estimation and diagnosis is done until the best fit model is found.

The plots of ACF, normal Q-Q and histogram of residuals show that the residual are a white noise process. Thus, diagnostic check for an ARIMA (1,1,1) model in Table 1.6 indicates that the model is good (best fit).

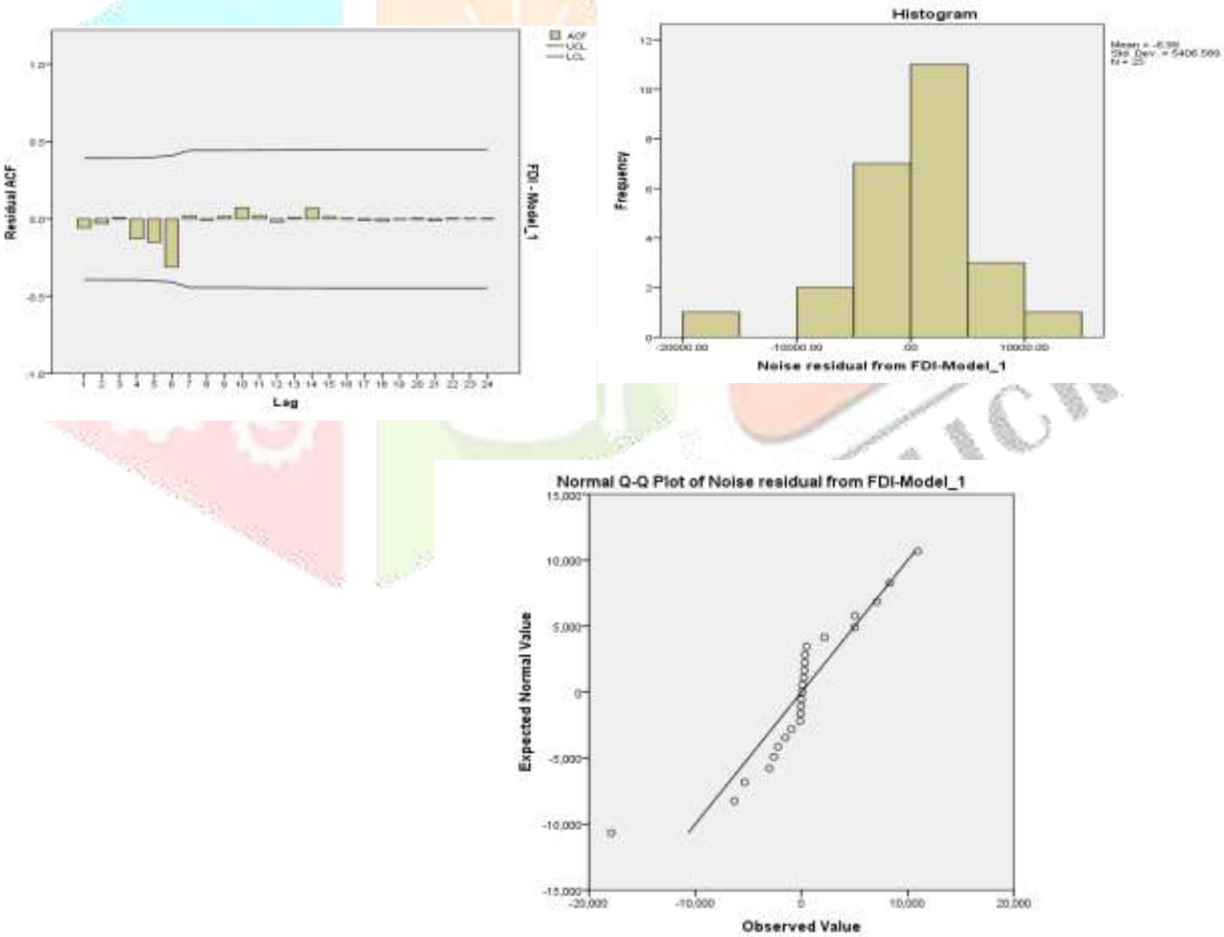


Chart 1.6 Plots of ACF, Histogram and Normal Q-Q of residuals

The careful investigation from the Q-Q plot of standard residuals in the fitted modelinfers that standard errors are roughly constant in its mean and variance overtime. This is confirmed by the histograms of the residuals as well. The histograms (of the errors' distribution) in Chart 1.6 infer that the errors are (almost) normally distributed and mean of the distribution seems to be zero. The Q-Q plot also seems to confirm the normality in errors. To investigate further whether there are any correlations between successive forecast errors ACF of the forecast errors has been plotted.It is clearly evident from the ACF plot in Chart 1.6 that none of the autocorrelation coefficients between lag 1 and 24 are breaching the significant limits i.e. all the ACF values are well within the significant bounds.The residual test required that residuals are random with zero mean, constant variance and uncorrelated. Test for randomness of residuals are presented in Table1.6. Hence, the results are supportive of the randomness of residuals of model (1, 1, 1) at 95% significance level.

The ARCH-LM test statistic is computed from an auxiliary test regression to test the null hypothesis that there is no ARCH up to order q in the residuals.

Table 1.6
ARCH LM Test

Model	F Statistics	Probability
(1,1,1)	0.044362	0.834959

Results presented in the Table 1.6 demonstrate the absence of autocorrelation among residuals, thus null hypothesis cannot be rejected at 1%. In absence of residuals autocorrelation, prediction is moreaccurate, because error in given forecast period is independent from the previous ones.

3.3.4 Estimation Results

The diagnostic check results as reported inTable 1.6 and graphical representation in Chart 1.6 it isevident that AR and MA model with lag1 more accurately forecast FDI inflow to India. On the basis of this results, ARIMA (1, 1, 1) model has been selected. The estimation results of ARIMA(1,1,1) model are represented in the table given below:

Table1.7
Estimation Results of ARIMA Model (1, 1,1)

Variable	Co-efficient	St.Error	Probability
C	-434766.098	348030.707	.225
AR(1)	-0.8	1.106	.0477
MA(1)	-0.943	1.269	.0466

R^2.917

Adjusted R^2.117

D-W 1.988

Probability(F Statistics)0.0968220

According to the estimation results, the coefficient of AR (1) and MA(1) is significant at level 5% significance. The low coefficient of determination R^2 is not important due to differencing the variable FDI. The Durbin-Watson (DW) indicates no serial correlation. The ARIMA (1,1,1) model can be rewritten in the lag operator form as follows which can be used for forecast.

$$FDI= -434766.098 - 0.8_{t-1} - 0.943_{\varepsilon-1}$$

But before proceeding with the forecast, the two models of forecast- DES Holt's and ARIMA method are compared so that best fit model can be selected for forecast. Comparison of models is done in the next section.

IV. COMPARISON OF MODELS

The forecast equation has been estimated using both the model-DES Holt's and ARIMA; however, forecast for the period under study will be generated from the best fitted model. Therefore, a comparison between the two models has been done on the basis of forecast accuracy errors (Nanda, 1988).Initially, the results of actual and forecasted FDI for the period 1991-2016 using DES Holt's and ARIMA are plotted in the Chart 1.7 and Chart 1.8 given below.

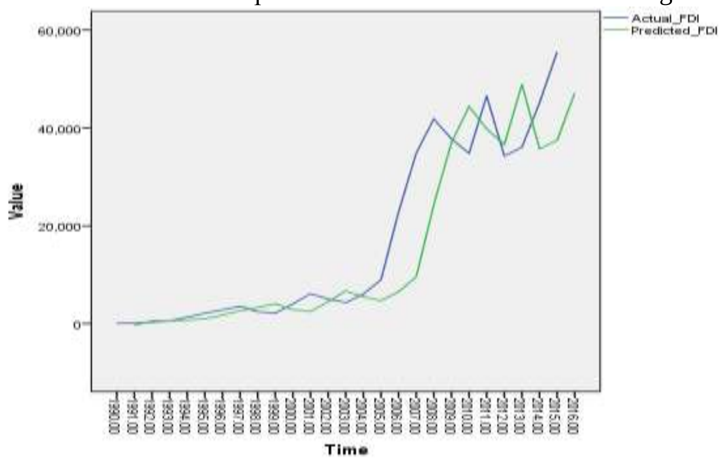


Chart 1.7 Forecast by DES Model

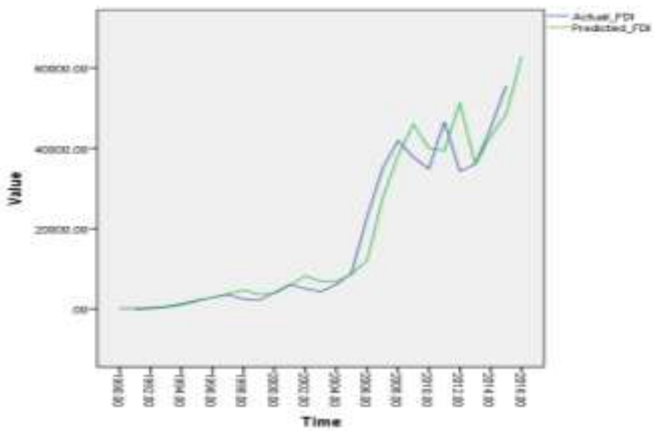


Chart 1.8 Forecast by ARIMA

Chart 1.7 and Chart 1.8 plots the predicted FDI inflow in India using DES Holt's and ARIMA with the actual FDI for the period from 1991-2016 respectively. Chart 1.7 clearly depict that DESHolt's method deviates much from the actual FDI inflow as compared to ARIMA. Further to understand between DES Holt's method and ARIMA, various forecast accuracy measures are computed and compared. In order to fit the best model that shows the characteristics of actual series, Schwarz's Bayesian Information criterion has been applied for model selection (Vandaele1983). Table 1.8 shows the test results of the model accuracy.

Table 1.8
Comparison of Forecast Accuracy Results – HWES and ARIMA

Model	DES Holt's	ARIMA (1,1,1)
MSE	33132687.21	28028024.22
RMSE	5756.10	5294.15
MAPE	135.63	45.63
MAE	3949.24	2993.64
BIC	49.36	45.63

On observing the forecast accuracy measures between the two models as presented in Table 1.8it can be concluded that ARIMA (1,1, 1) model performed better than the DES Holt's method on FDI data for India due to the minimal error. As the above Table1.8 shows, all accuracy tests favored ARIMA (1,1,1) based on the minimum values of MSE, RMSE, MAPE and MAE. As per the BIC model selection also, ARIMA (1, 1, 1) has the lowest value as compared to DES Holt's method as presented in the Table 1.8. Hence, ARIMA model best predicts the FDI inflow in India. Therefore, the test of the suitability of the selected model is done in the next step.

V. FORECAST

Mainly an ARIMA model is used to produce the best average forecasts for a single time series(Reimers 1992). The accuracy of forecasts for both ex-ante and ex-post were tested using the tests such as RMSE, MSE, MAE, MAPE (Markidakis&Hibbon 1979). ARIMA models are developed basically to forecast the corresponding variable. To judge the forecasting ability of the fitted ARIMA model important measure of the sample period forecasts accuracy was computed. The MAPE for FDI is 45.63 in ARIMA model. This measure indicates that the forecasting inaccuracy is low. The forecasts for FDI during 2017 to 2037 showing increasing trend are given in Table1.9

In the study ARIMA (1, 1, 1) were developed models for FDI. From the forecast available by using the developed model it can be seen that forecasted FDI to increase in the next four years. The validity of the forecasted value can be checked when the data for the lead periods become available. The model can be used by researchers for forecasting FDI inflow in India. However, data need to be updated from time to time with incorporation of current values.

Table1.9 presents the forecasting results of FDI over the period 2017-2037.

Table1.9
Forecasting Results

Years	Forecast	LCL	UCL
2017	66438.74	48227.8	84649.6
2018	73391.02	51391.3	95390.8
2019	78033.22	52259.2	103807
2020	84916.22	56244.5	113588
2021	90399.33	58811.3	121987
2022	97395.14	63349.6	131441
2023	103573.52	67077.9	140069
2024	110798.53	72126.9	149470
2025	117579.01	76756.7	158401
2026	125107.88	82311.9	167904
2027	132430.78	87695.2	177166
2028	140311.25	93757.6	186865
2029	148138.36	99803.6	196473
2030	156400.87	106373	206429
2031	164707.85	113023	216393
2032	173372.01	120097	226647
2033	182143.17	127312	236974
2034	191221.47	134886	247556

2035	200446.81	142640	258253
2036	209947.26	150711	269184
2037	219620.37	158984	280257

In this study, the ARIMA(1,1, 1) was the best model selected for making predictions for upto 20 years for FDI inflow in India using time series data. ARIMA was used for the reasons of its capabilities to make predictions using a time series data with any kind of pattern and with autocorrelations between the successive values in the time series. The study also statistically tested and validated that the successive residuals (forecast errors) in the fitted ARIMA time series were not correlated, and the residuals seem to be normally distributed with mean zero and constant variance. Hence, we can conclude that the selectedARIMA(1, 1,1) seem to provide an adequate predictive model for FDI inflow in India.

VI. CONCLUSION

The forecast of FDI over the coming twenty years has been done using a best fit model and it has been found that thetotal value of FDI expected for the next twenty years (2017-2037) is Rs. 1672895.18 million and average FDI expected for the next twenty-five years is Rs. 66915.81 million for India. There is an expected smooth increase of FDI inflows in to India in the long term. Therefore, an accurate forecasting can be valuable for policy making.

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