The First Three Decades of Foreign Direct Investment (FDI) in India: Temporal Variation, Sectoral Trends, and Time-Series Analysis

DOI: https://zenodo.org/records/11230169

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Abstract

This article presents a synoptic view of India's FDI journey up to the financial year (FY) 2020 since the liberalization of the Indian economy in 1991. A semi-log model suggested that India's FDI grew at about 20% per year over the last three decades. Meanwhile, sectoral investment patterns exhibited a clear shift from the automobile to the services sector. With a cumulative inward FDI of $697 billion, India's FDI journey has been promising thus far, yet it lags well behind China and Singapore. An Auto-Regressive Integrated Moving Average (ARIMA) was applied for time-series model development (training, testing, and forecasting) using 29 years of FDI data. The non-stationary behavior of original FDI-time data was circumvented by using their logarithmic functions. Supported by a small prediction mean square error (0.0016), the predicted values for the next two financial years (2020-21 and 2021-22) at $87.9 billion and $94.8 billion, respectively, are considered to be reliable within the 95% confidence limit.

Keywords*:* Foreign direct investment; Time-series analysis; Sectoral investments; Indian Economy; Economic liberalization; Forecasting.

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1 Introduction

In a globalized world, capital inflows are one of the most crucial elements to mobilize developing countries (e.g., India) and underdeveloped economies. Until about the eighties, the inflows were predominantly in the form of foreign commercial bank loans (Demirhan and Masca, 2008); however, debt crises of the banks in the 1980s reduced capital lending drastically, leading countries to look for alternative options. Amongst these, foreign capital in the form of Foreign Direct Investment (FDI) was one of the successful modes that many countries adopted, and the distance and the trade barriers became constraints of lesser importance. Additional benefits of FDI compared to commercial bank loans include transfers of technology and managerial skills to make the industrial production process more efficient.

Economic liberalization from the restricted regimes led to a significant inflow of Foreign Direct Investment (FDI) into India since 1991. In almost these three decades, until FY 2019-20, India received a cumulative FDI of ~697 billion US dollars ($), and the FDI increased from a meagre value of ~$0.13 billion/year (during FY 1991-92) to a value of ~$73 billion/year (during FY 2019-20). Studies have shown that FDI inflows had a positive impact on the economic growth of India (Ahmed, 2013 and references therein), and it is partly reflected in the country's GDP (US $), which increased from ~0.3 trillion (in 1990; data.worldbank.org) to a value of ~2.7 trillion (in 2018; data.worldbank.org). Though India has witnessed several reversals in the political regimes at the Central Government, by and large, each continued with economic reforms. FDI policies were reviewed from time to time, and changes were made (mostly) pertaining to fixing FDI’s sectoral cap and its entry route, keeping in view the global competitiveness in attracting FDI.

Despite gross optimism about FDI inflows into India and its impacts on economic growth (Ahmed, 2013), scepticism was also presented in earlier studies; e.g., the quantum of FDI was thought to be too low to enforce big impact on growth (Brat et al., 2004; Kamalakanthan and Laurenceson, 2005); need for a change of character of FDI to cause better growth (Balasubramanyam and Mahambare, 2003); necessity for more openness in the policies to be an attractive FDI destination (Bajpai and Sachs, 2000). These papers represented India's FDI journey of the first one-and-half decades, and critical analysis of the FDI data in the latter one-and-half decades is limited. This study is an attempt in that direction to bridge the gap that exists. The purpose of this article is to present a synoptic view of

India’s journey into FDI during (1991-2020), with the following specific objectives: (i) analyse the temporal variation of FDI inflows into India by fitting common empirical equations; (ii) determine trends of sector-wise inflows of FDI into India in context with policies affecting them and (iii) finally, the major objective targeted in this study is the time-series modelling of reasonably long-time data. Perhaps this is the first study to attempt a time-series analysis of India's three-decade-old FDI data. An Auto-Regressive Integrated Moving Average (ARIMA) time-series model is suitably used for analyzing and modeling data followed by short to medium-term forecasting.

2 Methodology

2.1 Data Sources

Two major data resources are used in the study. The first resource is the openly accessible website of the Directorate of Industrial Promotion Policy (DIPP; *https://dipp.gov.in/*), Ministry of Finance, Government of India (DIPP-data). We have used the DIPP for the data on temporal variation of FDI; investments made by different foreign countries in India, and investments made in various sectors. The second one is the Centre for Monitoring the Indian Economy (referred to as CMIE-data) through access to their (subscription) database (*https://www.cmie.com/*). CMIE data has been used for the gross FDI and the sectoral investments. It must be mentioned that CMIE is regarded as one of the best reliable data agencies that publishes data on parameters related to the Indian economy. We accessed the CMIE data during 2018, and due to the non-accessibility of CMIE data after that, FDI inflows for the FYs 2018-19 and 2019-20 were taken from the DIPP website, which is declared as provisional data.

Questions have sometimes been raised about the quality of secondary data on the Indian economy (Nagaraj 2003), which have been a part of several studies in the past. For example, Nagaraj (2003) *that cautioned, “Therefore, the assessment of foreign investment reported in this study remains preliminary*.” The caution may also apply to many other studies published at around that time. In the context of India's FDI data during the earlier years, refinements in FDI data of the various components were often made to align with the best practices adopted by other countries of the World and other financial institutions.

One of the inherent advantages of the present dataset is that it congregated FDI data at a much later time (i.e., 2018) than the earlier studies (say, before 2008), thus allowing the scope of the refinements to be made by then. Hence, the data collected in recent times is expected to be of better quality. To ensure the coherence of FDI data used in the present study, e.g., expressed in different currencies or obtained from sources, we have performed two cross-validation exercises. Wherever data is reported in USD INR, we have ensured that the value reported in USD is nearly identical to that of the equivalent INR (or vice versa) using the corresponding conversion ratio. To do this, an *apparent exchange rate/value* is calculated using the ratio of numerical values of the FDI reported in USD and INR and then compared with that of the (historical) annual average exchange rate. The exercise was done for the time frame of 2000-2017; we obtained a linear regression fit (equation type: $Y= mX$; $r^2=0.98$; slope $=1.0058$; $p<0.01$), which confirms uniformity in the data reported in these two currencies.

The second cross-validation exercise was done for data resources accessed (e.g., CMIE versus DIPP). We observed perfect agreement between the FDI datasets (FY 1991-92 to 2017-18) with an excellent correlation (equation type: $Y= mX$; $r^2>0.99$; slope $=1.0025$; $p<0.01$) obtained for the linear fit. In the first nine years (FY 1991-92 to 1999-2000), there exist some disagreements in CMIE and DIPP data; the CMIE data being lesser than the corresponding DIPP value by up to ~23% (e.g., FY 1991-92) whereas the corresponding average for these nine years is ~10%. Post FY 1999-2000, there is excellent agreement between the datasets. These exercises, by and large, confirm the consistency between the data resources of secondary data accessed in the present study, especially during the last two decades.

2.2 Time-series Analysis

Monitoring the movement of the data and extrapolating their future evolution according to the past available information is an objective of time-series, and it has enormous applications. This study uses FDI data for the last 29 years (FY 1991-92 to 2019-20; the last two years are provisional data published by DIPP) for ARIMA time-series and building forecasting models. The model is tested following standard guidelines for time-series modeling and forecasting, trained with 80%, and tested with 20% off available data. The model is then used to forecast the FDI data for the next two years (FY 2020-21 and FY 2021-22). MATLAB® is used for model development, training, testing, and forecasting. The MATLAB® results are reported in this paper through the genre of outcomes of statistical tests, parameters, and graphical illustrations.

3 Discussions

3.1 FDI Inflows and their Temporal Variation

During the study period of twenty-seven financial years (FY), annual FDI increased by a factor of ~475, from ~$130 million (1991-92) to ~$ 62 billion (2017-18). The first ten FYs (1991-92 to 2000-01) witnessed cumulative FDI of ~$ 19.5 billion, which compares to ~ $ 203 billion during the second ten-year period (2001-02 to 2010-11) and ~$ 340 billion for the first seven years (2011-12 to 2017-18) of the third ten-year period. In terms of the average investment (per year), the corresponding values are $ 1.95, 20.3, and 48.5 billion per year for these time frames. During the first ten years, there is a sluggish FDI investment growth rate compared to the second ten-year period. If the provisional data of FYs 2018-19 and 2019-20 are considered, the cumulative amount would increase to ~$ 475 billion during the third ten-year period and the corresponding average to ~$ 52.8 billion per year.

In order to understand critically the FDI variation as a function of time (t=0 for FY 1990-91), we tried to fit the data into five empirical forms such as linear, exponential, power, 2nd order polynomial, and logarithmic, using two similar approaches. In the first, the (FDI versus time) data of the entire time frame was considered, empirical equations were fitted to the data, and it was qualitatively assessed how closely the estimated trend matched the real-time FDI data. The coefficient of determination (r^2) ranges from 0.88-0.94 for all but the logarithmic form (r^2=0.57), indicating the goodness of these fits. For example, if one considers the exponential form (FDI=489×$e^{0.196\times t}$; r^2=0.90; Figure 1a), the estimated and the actual data match very closely until about the 15th year, and then, the model, in turn, under and over-estimates the FDI values, each for 6-7 years. The slope of this exponential curve (or a simplified form: ln(FDI) = 6.2 + 0.196×t) predicts a per cent FDI growth rate of ~20% per year. Another commonly used curve, the 2nd order polynomial form, which fits the FDI-time data, is FDI= $93.7\times t^2 - 176.6\times t - 933$ (r^2=0.94; Figure 1b). There seems to be an excellent agreement to the actual data in the initial and the final years of the time frame; however, in the middle, it overestimates the actual values. The first-order derivative of the polynomial form, the slope of the curve is time-dependent, and for t > 2 years, the slope (growth rate) becomes positive. In contrast, the limitation of the linear form is that the slope ($\frac{\partial FDI}{\partial t}$) does not change with time (i.e., a constant); therefore, the linear model is not able to explain any fluctuations in FDI-time space

(Figure 1c). In the case of power law (FDI=67×$t^{2.08}$; r^2=0.93; Figure 1d), which almost resembles the parabolic law, the slope is also time dependant. The estimated curve closely matches the actual data in the initial years and some data points later with the power law.

In the second approach, the FDI-time data of the first twenty years was used to fit into each empirical model, and then the estimation/prediction was applied to the next seven years of data. The second exercise is a simple way of forecasting without performing rigorous time-series analysis and forecasting. The ratio, R, of the empirically estimated to the actual FDI, was used to measure the correctness of the forecasting (Table 1). Among the different empirical equations, the exponential and the polynomial types overestimate all (n=7) FDI values, with respective averages (R ± σ) of 1.43±0.41 and 1.45±0.21. For the exponential fit, R varies between 0.71─2.05, which means the maximum underestimation and maximum overestimation made by the exponential model are ~30% and ~200%, respectively.

Similarly, the corresponding overestimation varies from 3% to 70% for the polynomial fit. The closest agreement between estimated and actual FDI is observed for the linear fit, with an average R-value of 0.85±0.14, ranging from 0.69-1.00. This suggests that, on average, the linear model underestimates FDI values by ~15%, whereas the corresponding underestimated average (considering all years) values for the power and logarithmic fits are ~35% and ~27%.

The FYs 2018-19 and 2019-20 data have not been taken into empirical analyses above, as those were provisional data. The above-estimated values of R, following the second approach, the above-estimated values of R would change (marginally) if one considers these two years of provisional data. For comparative analyses, these have been incorporated in Table 1.

Temporal variation of FDI can be fitted into several empirical forms; however, the theoretical support for and comparative advantage of any of the forms over another is unknown. High values of r^2, though, suggest a strong dependence in any correlation exercise; the above discussion shows that forecasting future FDI investments with empirical equations can, at best, be used for obtaining information about temporal variation. An economic basis should support the statistical relevance of the empirical relations with a high r^2 value, and forecasting should only be made using rigorous time-series models.

3.2 Time-series Analysis and Forecasting

As mentioned before, the data for the last 29 years (FY 1991-92 to 2019-20) are considered in time-series modeling. The entire dataset is divided into training and testing subsets, with the training dataset containing the first 23 years (FY 1991-92 to 2014-15 constituting 80% of total data) and the testing dataset containing the last 5 years (FY 2015-16 to 2019-20 comprising 20% of comprehensive data). This follows the 80-20 rule for dividing the entire data among training and testing data. The time series for training data is plotted in Figure 2.1a. Visual inspection suggests that the time series is not stationary, the variance fluctuates, and there is a time-varying (up and down) trend. In addition, no proper seasonality is observed. Such time-series data are challenging to model, so it is required to perform objective tests for stationarity. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit-root and trend stationarity tests are used for the purpose (Frain, 2010; see supplementary file). The MATLAB® results (using MATLAB Econometrics Toolbox Documentation. 2020; *https://in.mathworks.com /help/econ/*) reported here also support the visual inspection. The logarithm of time-series data is taken to somewhat stabilize the variance (Figure 2b). Also, the difference of the resulting time series (Figure 2c) is taken (one sample less than the original series), and the stationarity test is conducted again on resulted time series. The differenced time-series data passes the stationarity test and suggests an Auto-Regressive Integrated Moving Average (ARIMA) model with parameter $d = 1$ to circumvent the non-stationarity in the original time series.

The next step is to obtain the Auto Correlation Function (ACF) and Partial Auto-Correlation Function (PACF) of the logarithm of the original time series to decide the parameters p and q of the ARIMA time-series model. The results in Figure 2.2a suggest ACF decays slowly, and the minimum value of q must be taken as 4, while the PACF (Figure 2.2b) suggests that the value of $p = 3$ seems to be sufficient. Therefore, the time-series model for the given training data is ARIMA (3, 1, 4). The coefficients and other model parameters can be estimated by fitting the model to the time-series data. The Akaike Information Criteria (AIC) value of the fitted model can be computed, and it is found to be very low (in fact, negative here), which indicates a good model fitting to the given training data (See supplementary file).

Subsequently, the check on goodness-of-fit is carried out for the final fitted model. This can help identify areas of inadequacy in the model and also can suggest ways to improve it. A residual diagnostic plot is a useful way to assess the violation of model assumptions. Residuals are checked for normality and residual autocorrelation. If the residual of ACF and PACF provide a significant result, there is a need to improve the model fit by adding AR or MA terms. The predictive performance checks require dividing the total available data into two parts: training and validation sets. The model is fitted only on the training data, and then the fitted model is used to forecast over the validation period using testing data. By comparing model forecasts against the true, holdout observations, one can assess the model's predictive performance. Prediction means square error (PMSE) can be calculated as a numerical summary of the predictive performance. The testing data is stored in a separate file and loaded in MATLAB® separately. Figure 2.3a shows the results of the residual diagnosis. The quantile-quantile plot (QQ-plot) and kernel density estimate show no obvious violations of the normality assumption. ACF and PACF plots of residuals in Figure 2.3b confirm that the residuals are uncorrelated.

Figure 2.4 illustrates the forecasting capability of the fitted model within a 95% confidence interval. The forecasting is done here for seven years, out of which five years (FY 2015-16 to FY 2019-20) are tested with available data, and the next two years (FY2020-21 and FY 2021-22) are future predicted values. Finally, the PMSE calculated with a five-year testing dataset is 0.0016; however, the prediction error is very small for testing data. The predicted values for the next two FYs, 2020-21 and 2021-22, at $87.9 billion and $94.8 billion (reliable with 95% confidence), were found to be ~7% and ~11% than their respective reported data.

3.2 Sector-wise FDI

Analyses of sectoral trends in FDI investments are essential for at least three reasons: First, the same amount of investment in different sectors may (but not necessarily) have different growth rates (Nunnenkamp & Chakraborty, 2008) and other impacts on the economy as a whole; second, it can affect differently to the socio-economic upliftment of the various strata of the population as employment in different sectors require human resources with other skills; and last, and most important, whether it creates a crowding-out effect, suppressing or even eliminating domestic competitors.

At present, DIPP enlists more than 60 sectors in which FDI is made, which indicates that there is diversification of the investments, thus allowing each of these sectors to survive or thrive. From April 2000 to December

2019, the cumulative contribution of the top 10 industries, which accounts for two-thirds of total FDI (DIPP FDI statistics published for Oct 2019-Dec 2019) inflows, implied a somewhat skewed investment pattern. An exhaustive comparative discussion considering all 60-odd sectors is beyond the scope of this article, and sector-wise cumulative inflows in only the top 10 sectors have been considered for analysis. Sector-wise data are available for the time-frame FY 2002-03 to 2018-19 from CMIE, which is the only reason to choose the above timeframe. During this time frame, the service sector has attracted the highest cumulative FDI ($74627 M) followed by computer software and hardware ($36095 M), telecommunication ($31850 M), automobile Industry ($20491 M), construction and infrastructure activities ($19271 M), and trading ($19064 M). Non-fertilizer chemicals, power, drug and pharmaceuticals, and construction development are the other sectors in the top ten. It must also be mentioned that some inconsistencies exist for sectoral investment data, e.g., in the form of data gaps between financial years and the non-availability of data before a certain FY. Sometimes, redefining/splitting of sectors has been done; for example, household construction was defined as a sector (before FY 2010-11) split into two sectors construction (infrastructure) activities and construction development. Thus, no data is available for the construction development sector before FY 2010-11. An important trend observed post 2006-07 is the consistent dominance of the service sector in attracting FDI. The cumulative investment (from 2002 to 2019) in the service sector is more than twice the investment made in the second and third-ranked sectors, e.g., the telecommunications sector and the software and hardware sector.

Inconsistency in data, in the form of gaps, limits the use of cumulative investment as a robust criterion to compare the performance of each sector. For example, the trading sector has only ~~6~~ six years of data. Yet, its incremental investment ($ 19064 M) is very similar to that of investment in the automobile sector ($ 20491 M) that it had accrued over 15 years. One way to have a reasonable comparison is to consider the average investment (cumulative/ total number of years of investment) as an index. Based on averages (per FY), the sectoral trend is service sectors ($4390 M) > trading (($3177 M) > computer software and hardware ($2406 M) > construction activities ($1927 M) > telecommunication ($1874 M) > automobile ($1366 M).

FY-wise sectoral data are likely unavailable before FY 2002-03 as we could not find these from the CMIE data source (accessed in June/July 2018). The only data listed in the DIPP FDI statistic (Dec 2005) is the cumulative data from August 1991 to December 2005. It is observed that the top three sectors during (1991-2005) were electrical equipment ($ 4886 M), transportation industry ($ 3143 M), and services sectors ($ 2971M). Compared to the investment data from April 2006 to March 2019, the service sector has witnessed tremendous investments ($ 73000 M) compared to a much lower value of $ 20226 M for the automobile sector. Two distinct observations are made; firstly, there is a clear shift in the investment pattern from the automobile sector to the services sector, and secondly, the cumulative investments made in the services sector in the latter half is more by a factor of ~25 compared to the former half (of the three decades).

Intuitively, one of the reasons for higher investment in the financial service sector is that it creates a sizable profit-generating advantage and provides the scope for foreign investors to repatriate profits. The service sector constitutes financial and non-financial sub-sectors. Economic sectors include insurance and banking, whereas the non-financial sector is comprised of business, outsourcing, R&D, courier, technical testing and analysis, and others. In the earlier regimes of FDI, the maximum cap of the sectors under the service sector was fixed at 49% to 51%, which was further relaxed to 74% during FDI policy change, and subsequently, 100% FDI was allowed in most sectors. The inclusion of several sectors into the service sectors and the easing of FDI norms has allowed this sector to grow more than 200 % per year during the last five years.

4 Conclusions

India opened its door to the World market in 1991, what is known as the famous economic liberalization in the (economic) history of India. We present a synoptic view of India’s journey into FDI during (almost) the last three decades (1991-2019) on two aspects: temporal variation of FDI in context to different empirical models, trends, and patterns in the sectoral FDI investments.

India started with a nominal FDI per annum of $ 0.1 billion (FY 1990-91), which increased to about $ 62 billion in 2017-18), and $ 62 billion and $ 73 billion in the next two years, while the cumulative investment until FY 2019-2020 is about $ 700 billion. On a cumulative basis, the second 10-year period increased by a factor of ~10 relative to the first, and the third by a factor of ~2 compared to the second. Log-linear fitting of FDI-time data shows that FDI grew on an average at about 20% per year relative to the previous year (r^2=0.92; p<0.01). During the time frame for which individual sectoral investment data is accessed (2002-03 to 2018-19), the services sector received an FDI ($ 74627 M), which is more than the total of the second and third-ranked sectors in computer software and hardware and telecommunications. A clear shift in investment patterns from the manufacturing sector to the services sector was observed from the first half to the second half of India's FDI regime, i.e., on either side of 2005.

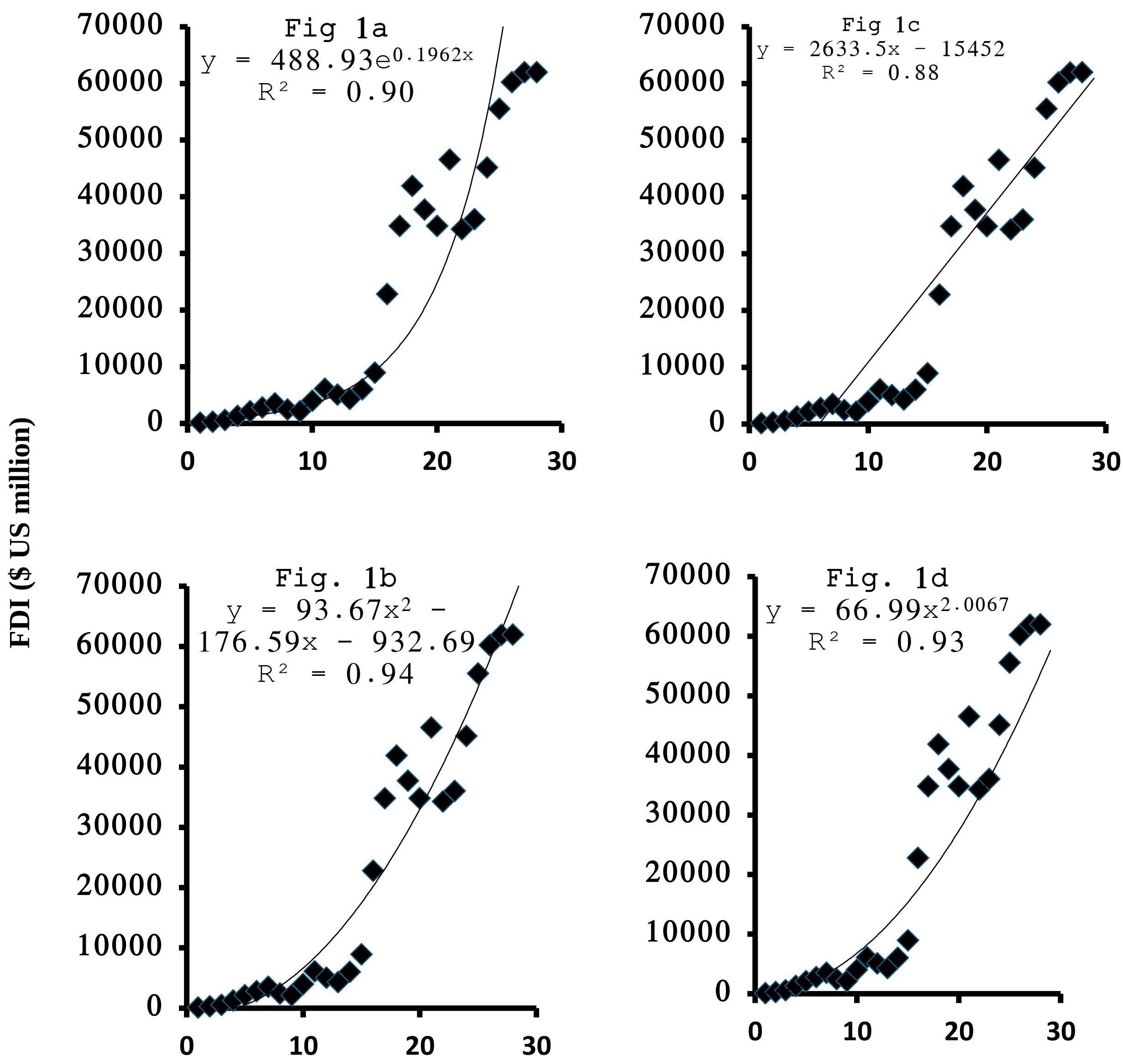
Time-series analysis of the FDI data was made using the ARIMA model. Though the data produces a non-stationary time-series structure, it was circumvented using logarithmic functions for the time-series modeling. The model is further trained and tested with 80% and 20%, respectively, of available data. The forecasting is done here for seven years, of which five years (FY 2015-16 to FY 2019-20) are tested with available data, and the next two years (FY2020-21 and FY 2021-22) are future predicted values. Finally, the prediction square error (PMSE) calculated with a five-year testing dataset is only 0.0016, indicative of a small prediction error. The predicted values for the next two years (FY 2020-21 at $87.9 billion and 2021-22 at $94.8 billion) were found to be higher by about ~7% and ~10% than their actual (reported) values. This may hint towards a decline in FDI due to the global pandemic.

Acknowledgments

We would like to thank the library section of The Maharaja Sayajirao University of Baroda (MSU, Baroda) for providing access to their CMIE data (in 2018).

Table 1. Five empirical equations were fitted to the first 20 years (FY 1991-92 to 2010-11) of India’s FDI-time data. Based on the best-fit lines/curves, the FDI values were estimated for the next 7 years (FY 2011-12 to FY 2017-18), and compared to the actual FDI data. R, the ratio of the estimated to actual FDI values, was calculated for each year. The average and the range of R are reported in the table. The numbers in parentheses represent the corresponding estimated values of R, if the next 9 years were (FY 2011-12 to FY 2019-20) considered. Note that FDI data for the FYs 2018-19 and 2019-20 were provisional data.

Equation type	Empirical equation	r^2	$R_{average}$	R_{range}
Linear	FDI= 2009.1t - 9983.2	0.69	0.81±0.14 (0.79±0.13)	0.69-1.00 (0.66-1.00)
Exponential	FDI= $292.59e^{0.2559t}$	0.90	1.43±0.41 (1.70±0.65)	0.71-2.05 (0.71-2.72)
2nd order polynomial	FDI=$205.49t^2$ - 2306.2t + 5839.5	0.88	1.45±0.21 (1.48±0.20)	1.03-1.71 (1.03-1.71)
Power	FDI=$84.644t^{1.8553}$	0.89	0.65±0.10 (0.65±0.09)	0.52-0.79 (0.52-0.79)
Logarithmic	FDI=11487ln(t) - 13203	0.42	0.73±0.20 (0.70±0.19)	0.47-1.00 (0.47-1.00)


FDI ($ US million)
Fig 1a
y = 488.93e0.1962x
R² = 0.90
Fig 1c
y = 2633.5x - 15452
R² = 0.88
Fig. 1b
y = 93.67x² - 176.59x - 932.69
R² = 0.94
Fig. 1d
y = 66.99x2.0067
R² = 0.93
70000
60000
50000
40000
30000
20000
10000
0
0
10
20
30

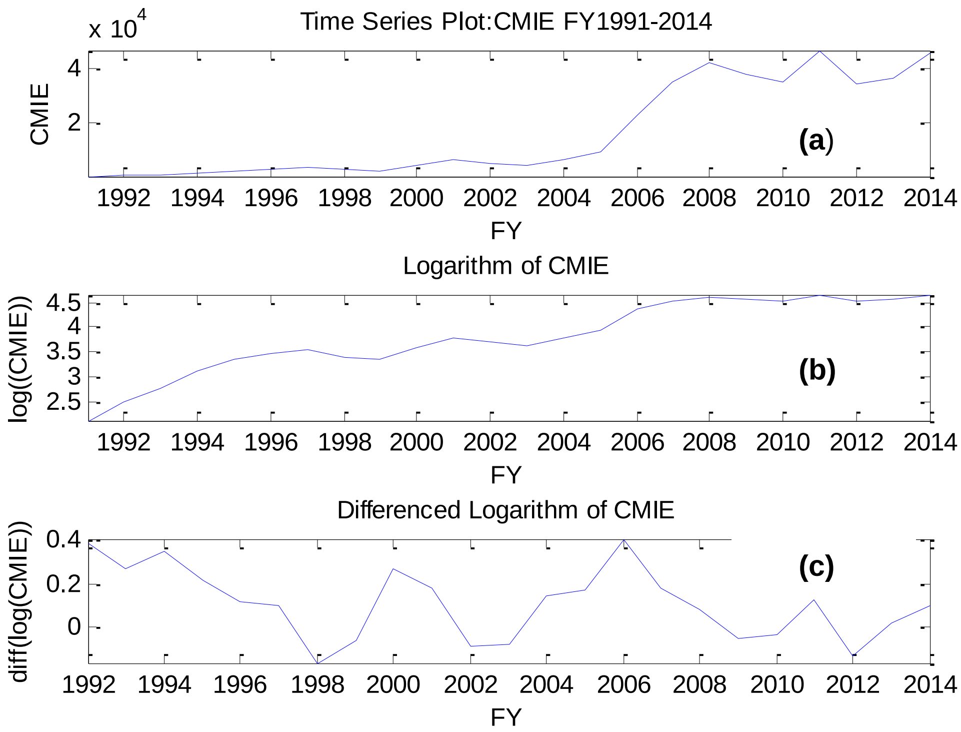


Figure 2.1: Plot of FDI data from FY 1991-92 to FY 2014-15 in different Forms.

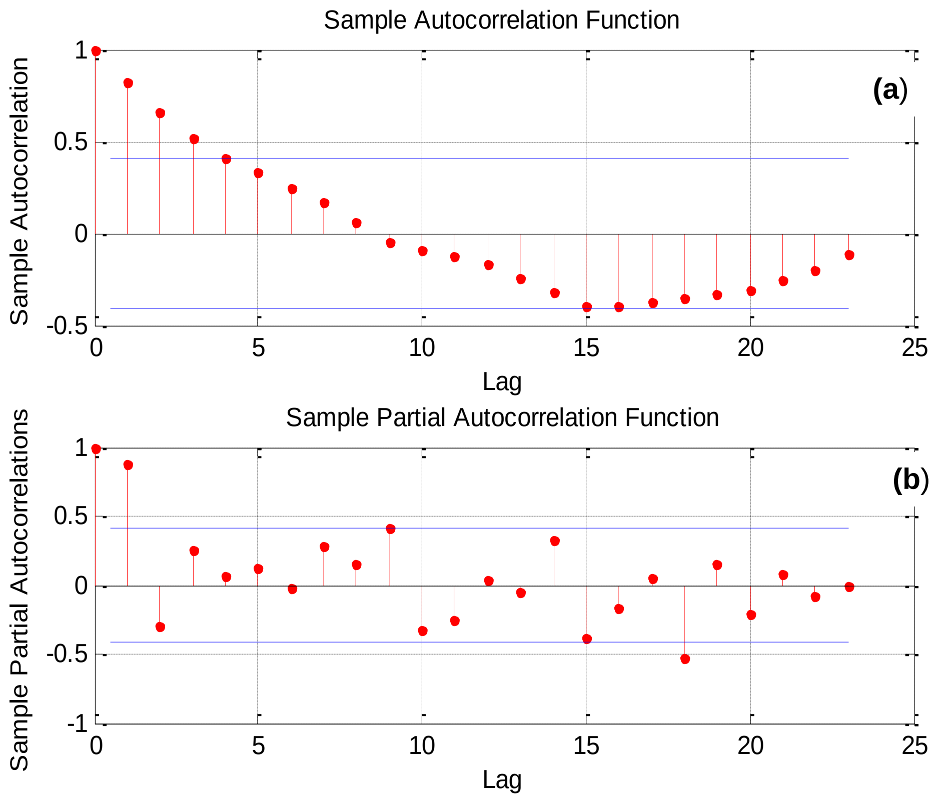


Figure 2.2: Plot of ACF and PACF of time-series training data.

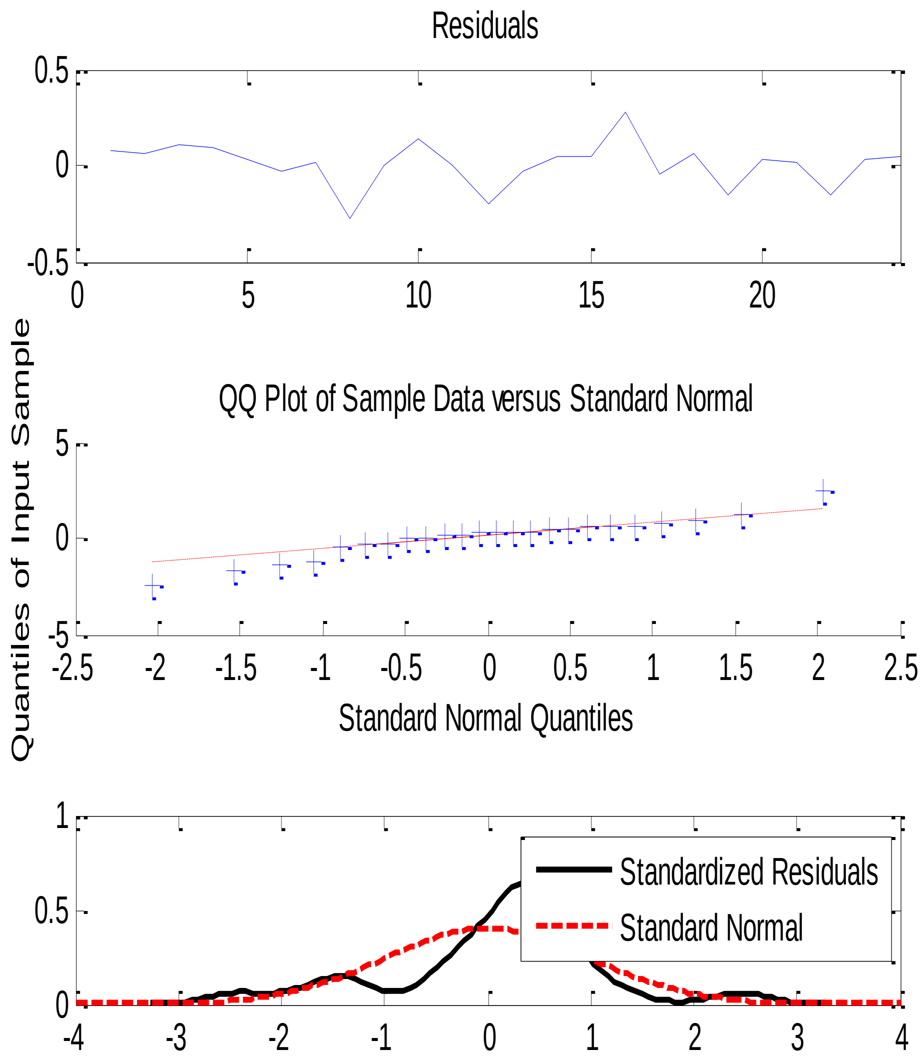


Figure 2.3 a. Plots of the residual-diagnosis-check. The Q-Q and Kernel density functions plots exhibit no obvious violation of the normality assumption.

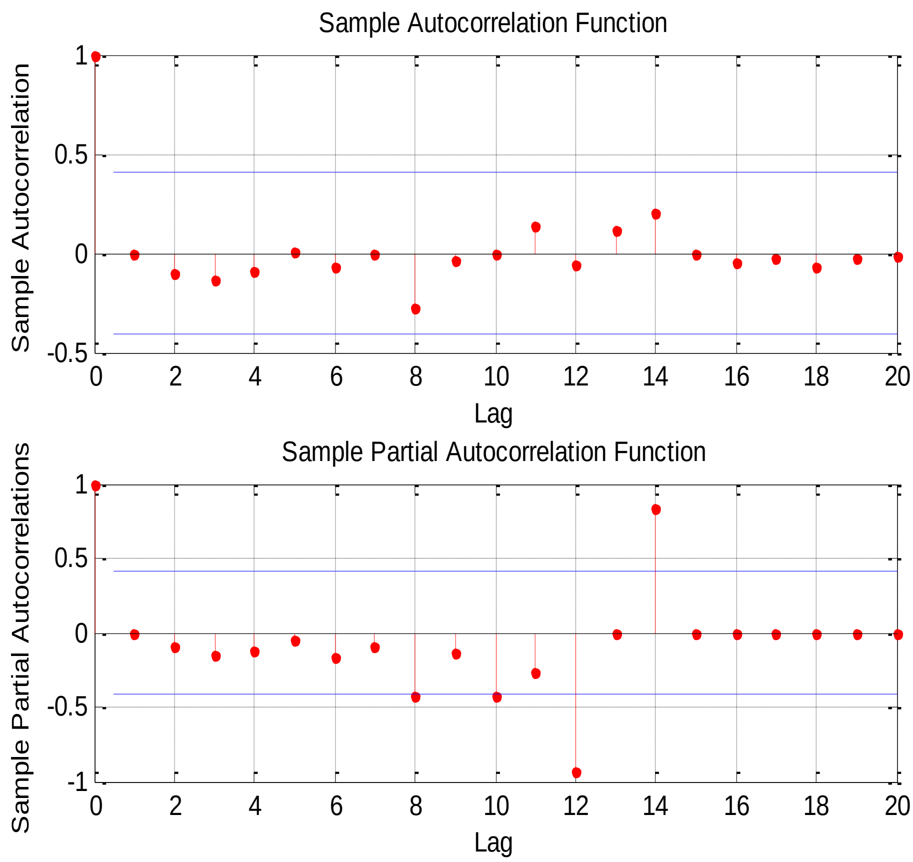


Figure 2.3 b. Plots of the residual-diagnosis-check. The ACF and PACF plots confirm that the residuals are uncorrelated.

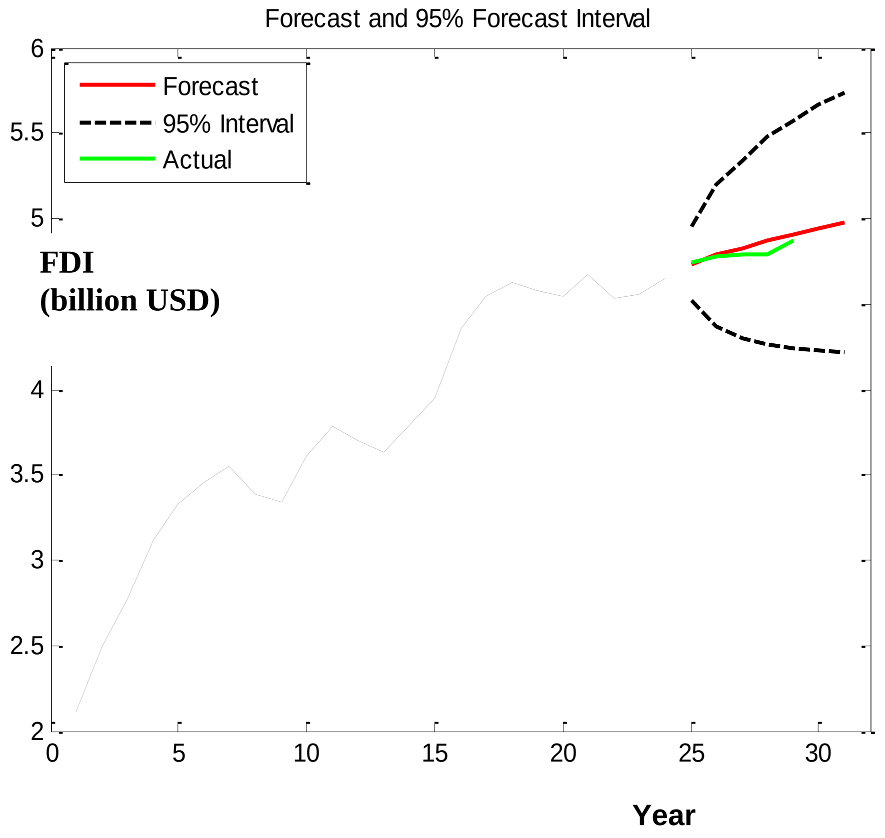


Figure 2.4: Forecasting plot for 7 years (5 testing years and 2 upcoming years)

Supplementary File

MATLAB KPSS Test Results:

The time series is non-stationary; it fails in the unit root test.

The time series is not trend stationary; it fails the trend stationarity test.

The log differenced time series is stationary; it passes the unit root test.

The log-differenced time series is stationary; and passes the trend stationarity test.

MATLAB Results of ARIMA (3,1,4) Model Fitting:

Conditional Probability Distribution: Gaussian

Parameter	Value	Standard Error	t Statistic
-----------	-----------	------------	-----------
Constant	0.00341865	0.0486006	0.0703418
AR{1}	-0.412404	0.438749	-0.939953
AR{2}	0.729312	0.208313	3.50103
AR{3}	0.47868	0.468284	1.0222
MA{1}	1	0.759065	1.31741
MA{2}	-0.613957	0.970342	-0.632723
MA{3}	-1	0.98175	-1.01859
MA{4}	-0.386042	0.672484	-0.574055
Variance	0.0126039	0.00612632	2.05734

AIC score computed by MATLAB:

AIC= -18.8610

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