CHAPTER VIII

FORECASTING OF THE EXOGENOUS VARIABLES

8.1 Forecasting Approach

To simulate the model, all exogenous variables have to be forecasted by specifying a definite timeline. In this dissertation, 2001 to 2010 has been considered as a forecasted period. Econometrically, ARIMA/ ARMA model has been widely used for forecasting exogenous variables of a macroeconomic model.

In ARIMA (autoregressive integrated moving average) forecasting, it is possible to assemble a complete forecasting model by using combinations of the three steps of building blocks. The first step in forming an ARIMA model for a series of residuals is to look at its autocorrelation properties. One can use the correlogram view of a series for this purpose. This phase of the ARIMA modeling procedure is called identification (not to be the same with the concept used in the simultaneous equations model). The nature of the correlation between current values of residuals and their past values provides guidance in selecting an ARIMA specification. The autocorrelations are easy to interpret-each one is the correlation coefficient of the current value of the series with the series lagged a certain number of periods. If it is suspected that there could be a distributed lag relationship between the dependent (left-hand) variable and some other predictors, the thesis has experimented their cross correlations before carrying out estimation.

The next step is to decide what kind of ARIMA model to use. If the autocorrelation function dies off smoothly at a geometric rate, and the partial autocorrelations were zero after one lag, then a first-order autoregressive model [AR(1)] is appropriate. Alternatively, if the autocorrelations were zero after one lag and the partial autocorrelations declined geometrically, a first-order moving average process [MA (1)] would seem appropriate (Eviews Manual, 2005). If the autocorrelations appear to have a seasonal pattern, this research has considered the situation as presence of a seasonal ARMA. Precisely, the goal of ARIMA analysis is a parsimonious representation of the process governing the residual. The thesis has used only enough AR and MA terms to fit the properties of the residuals. Furthermore, the Akaike Information Criterion (AIC) has been considered with each set of estimates for using as a guide for the appropriate lag order selection. After fitting a ARIMA specification, one should verify that there are no remaining autocorrelations that the concerning model has not accounted for. Hence, the thesis has examined the autocorrelations and the partial autocorrelations of the residuals from the ARIMA model to see if any important forecasting power has been overlooked.

To specify the model, it is needed to check whether exogenous data are stationary or non-stationary. If a data series is stationary, ARMA Model has to be adopted for forecasting. On the contrary, ARIMA (autoregressive integrated moving average) Model is very effective for forecasting purpose if and only if a data series follows the properties of non-stationary behaviors.

To check the stationarity, at first the data series has been plotted in a two dimensional graph to verify whether there is any trend in the data with respect to time. After that, Unit root test has been accomplished through Augmented-Dickey Fuller (ADF) approach by selecting intercept (if there is no trend) values under Akaike Info Criterion (AIC) with the maximum lags.

If the absolute value of ADF test statistic is greater than the absolute Critical value at 5% Level, then a data series has been treated as a Stationary in this dissertation. The opposite is true in case of non-stationary. The process has helped to identify which model (i.e. ARIMA vs. ARMA) should be applied to forecast the data.

8.2 Forecasting the Future

Based on the above procedure, each exogenous variable has been forecasted respectively. At first, consumer credit rate (CCR) has been selected to do unit root test. It is found that Absolute value of ADF test statistic for CCR is 8.11, which is greater than the absolute critical value at 5% level (i.e. 3.18). Furthermore, as MacKinnon (1996) one-sided p-value is 0.0001 in this context, data series for CCR is stationary that suits ARMA model to forecast out-of-samples (i.e. from 2001 to 2010). To specify the ARMA model, Correlogram has been drawn by measuring partial correlation [that gives AR term] and autocorrelation [that gives MA term]. If the spikes go beyond the lines, then econometricians define AR and MA based on the total number of out-sided spikes. In this regard, AR(1) and MA(1) have given the ARMA model best estimate with adjusted R-squared value 0.68. By equation,

Box 8.1: Consumer Credit Rate

CCR	**= 8.13 + 0.43*CCR(-1) + [MA(1)=0.97, Backcast =1982]**				
t	= (2.58)	(1.91)	(17.09)		
p value	= (0.02)	(0.07)	(0.00)		
F-statistic	= 20.25	P (F-statistic)	= 0.00	Adjusted R2	= 0.68

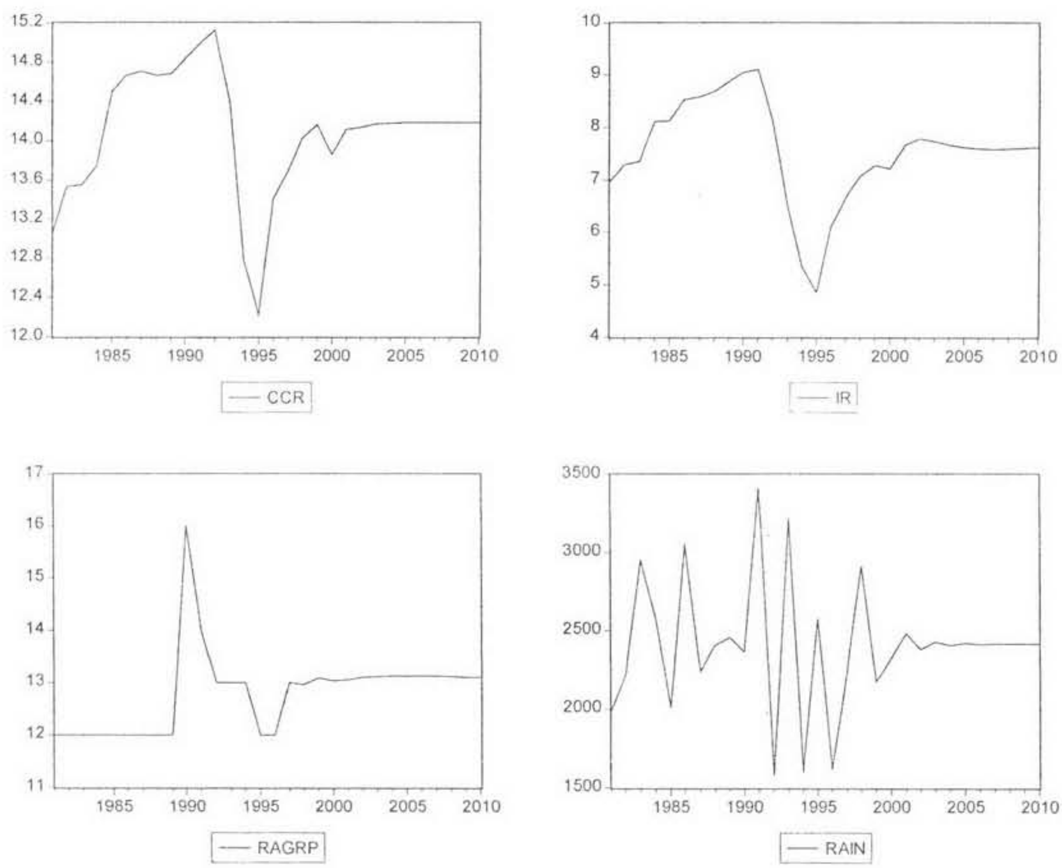
For the exogenous variable 'Currency Outside Banks' (COB), absolute value of ADF statistic (1.31) is less than the critical value (i.e. 3.18) that defines the data series as non-stationary. ARIMA model has been applied with AR(1). Symbolically,

Box 8.2: ARIMA Model with AR (1)

D(COB)	**=2668.08 + 0.58*D(COB(-1))**				
t	= (1.88)	(2.08)			
p value	= (0.08)	(0.05)			
F-statistic	= 4.35	P (F-statistic)	= 0.05	Adjusted R2	= 0.16

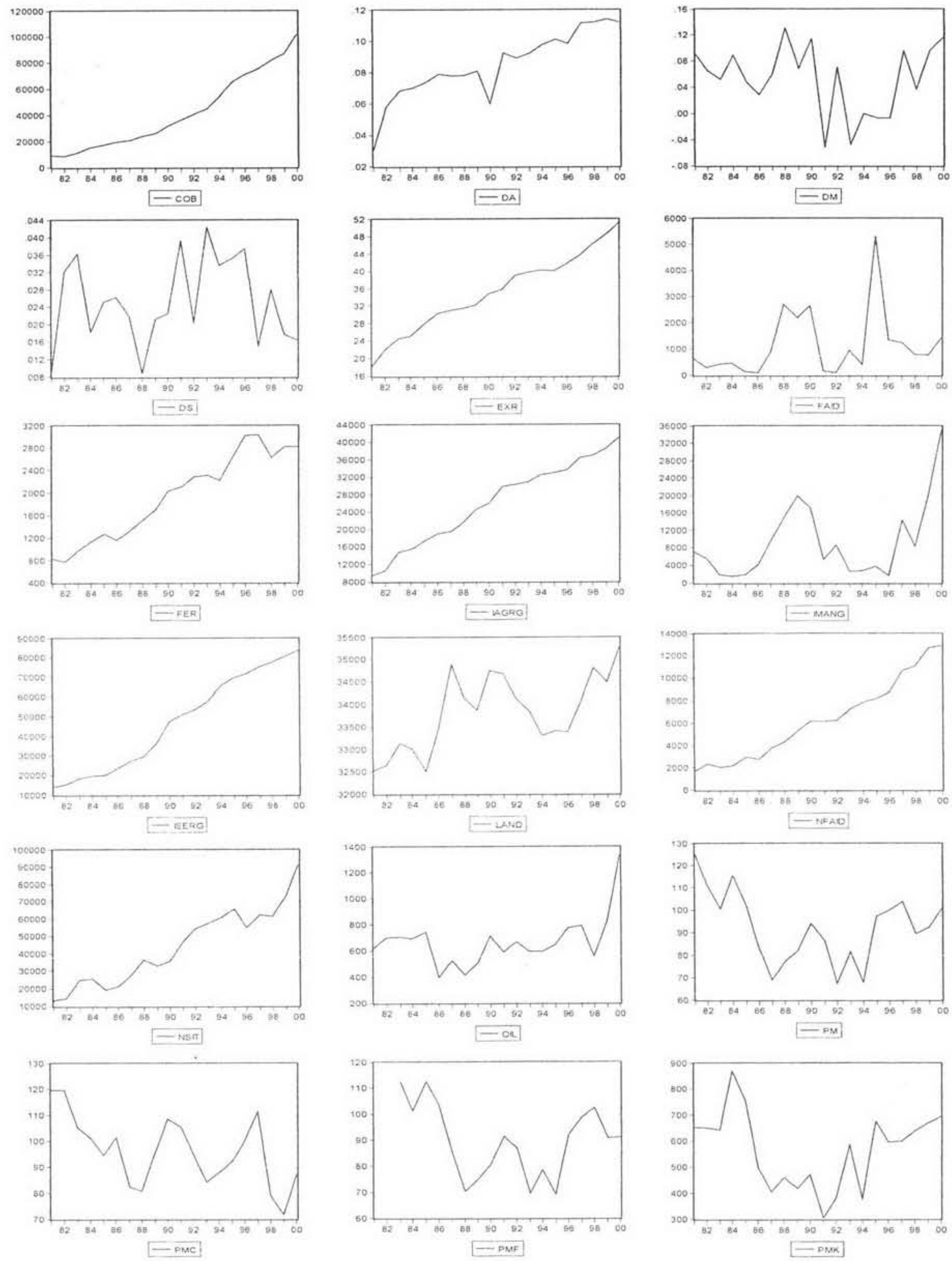
By using the same technique, all of the exogenous variables in the model have been forecasted up to 2010. At the bottom, it has been visualized that in total only 4 exogenous variables have satisfied the criteria of being stationary. These include consumer credit rate (CCR), interest rate (IR), interest rate in agriculture (rAGRp), and rainfall index (RAIN). Therefore, ARMA model has been applied for these 4 variables to forecast for the sake of running the model out-of-samples. **Figure 8.1** has forecasted for the period 2001 – 2010 based on ARMA model.

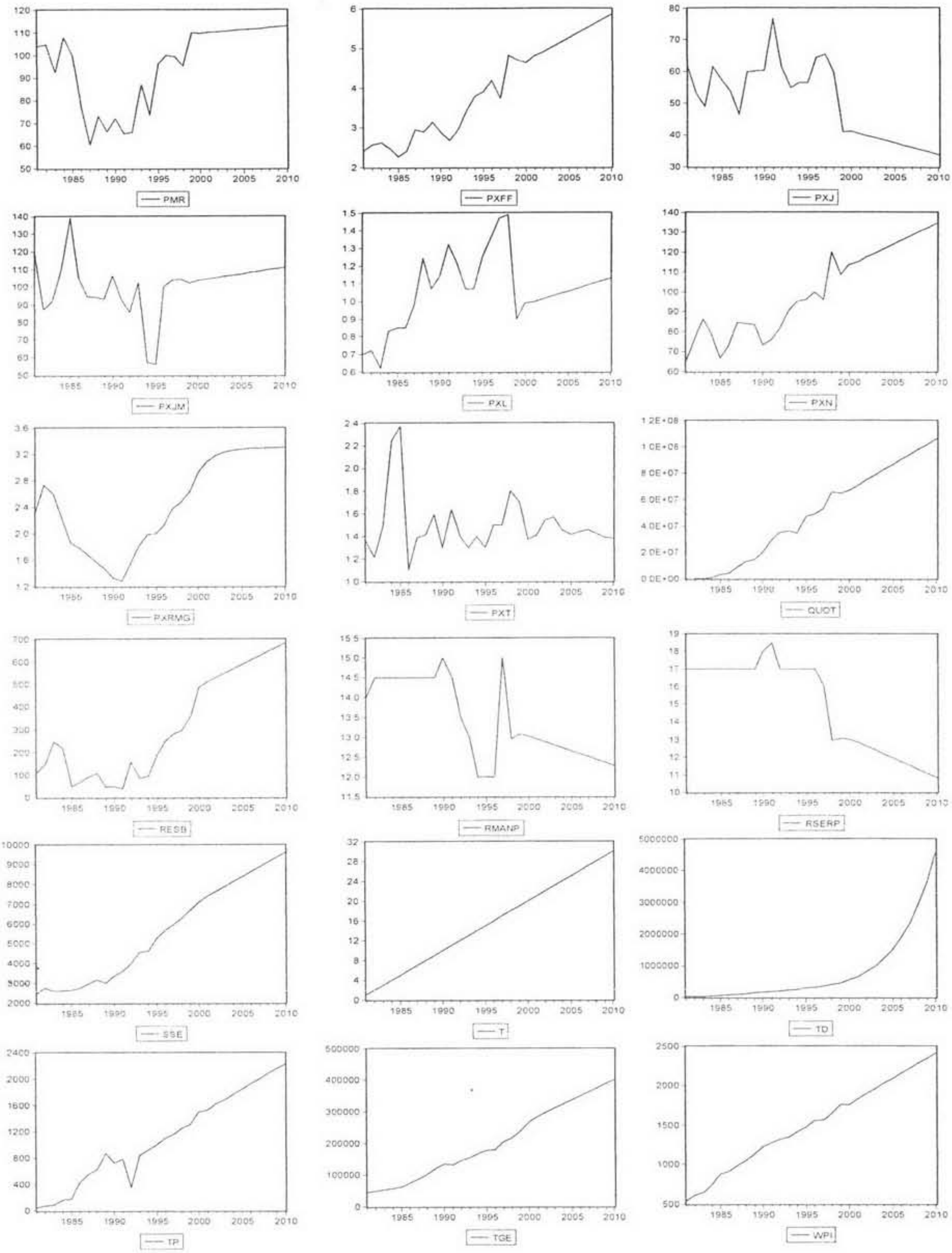
Figure 8.1: Exogenous variables forecasting based on ARMA model, 2001-2010



On the contrary, overall 49 exogenous variables have been found to be non-stationary with respect to their time series data. In this regard, the thesis has used ARIMA model for forecasting purpose respectively. Figure 8.2 demonstrated all exogenous variables of the model that have been forecasted based on ARIMA model.

Figure 8.2: Exogenous variables forecasting based on ARIMA model, 2001-2010




PMR
PXFF
PXJ
PXJM
PXL
PXN
PXRMG
PXT
QUOT
RESB
RMANP
RSERP
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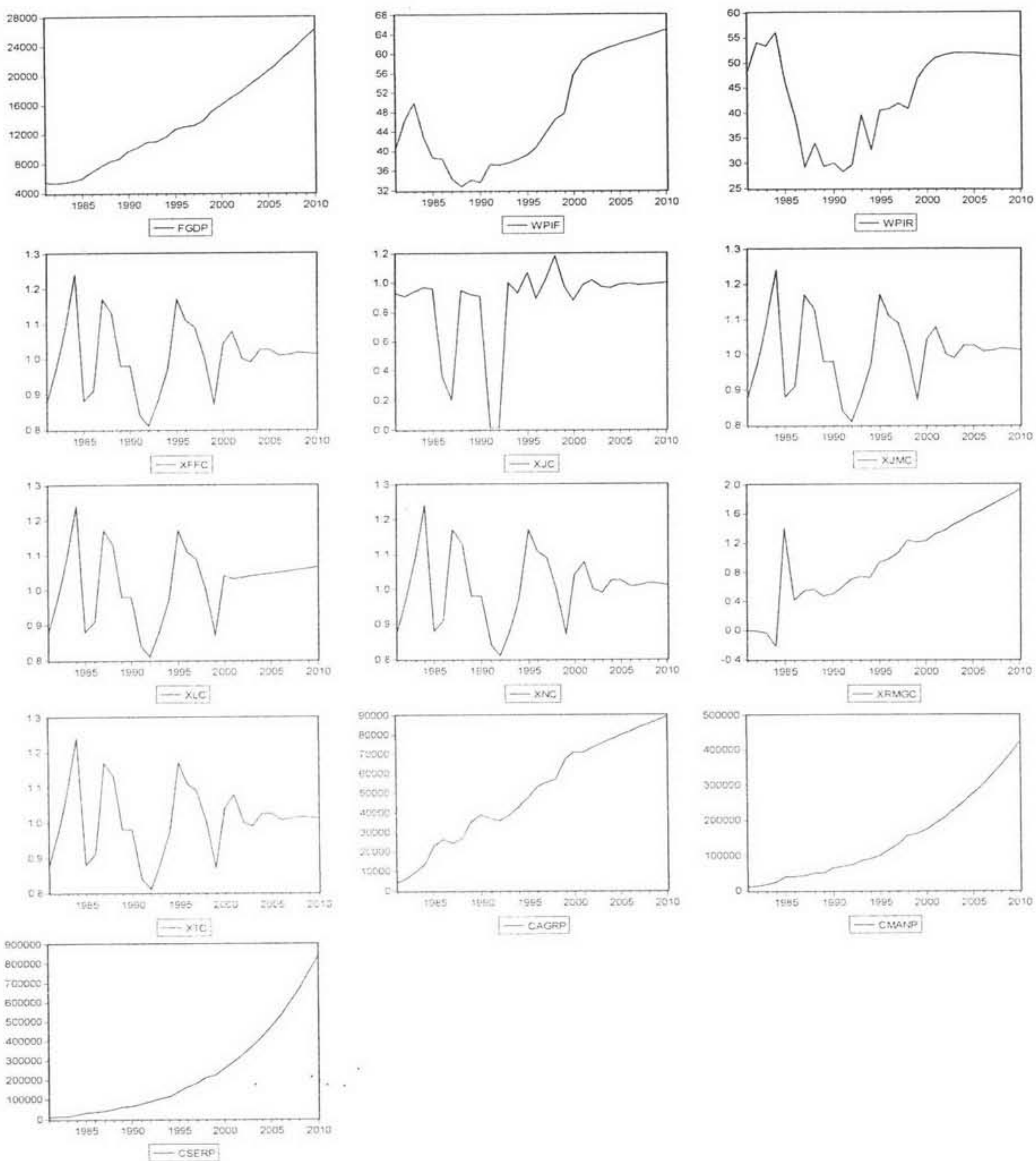
TD
TP
TGE
WPI



It is to be recalled that the above figures have been drawn based on ARIMA model where absolute values of Augmented Dickey-Fuller test statistic are less than absolute critical values at 5% level. Different data series has specified with different AR terms based on partial correlation spikes that has given the best fit to the baseline considering maximum adjusted R-squared values.