International Journal of Business and
General Management (IJBGM)
ISSN(P): 2319-2267; ISSN(E): 2319-2275
Vol. 4, Issue 5, Aug - Sep 2015, 39-48

International Academy of Science, Engineering and Technology
Connecting Researchers; Nurturing Innovations

VECTOR ERROR CORRECTION MODELLING TO ESTIMATE THE LONG-RUN AND SHORT-RUN EFFECTS OF MACRO ECONOMIC VARIABLES FOR FDI PREDICTION IN INDIA

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ABSTRACT

This work examines the role of various macro-economic factors such as GDP, inflation, exchange rate, export, import, energy generation, capital account as percentage of GDP, coal generation and trade balance in estimating the foreign direct investment (FDI) in India. The statistical approaches; Regression, Autoregressive Integrated Moving Average(ARIMA), ARIMAX and Vector Error Correction Modeling (VECM) have been used to obtain the suitable/causal relationships within/among the variables under study. Regression equations with an apparently high degree of fit, as measured by the coefficient of multiple correlation R^2, but with a low value of the Durbin-Watson statistic, couldn't provide adequate predictive accuracy because of the non-stationary behaviour of most of the series. To improve the predictive accuracy, the analysis was further extended by following ARIMA, ARIMAX and VECM approaches. The emphasis is given to see whether ARIMA model including other time series as input variables or VECM helps in estimating FDI as ARIMA models alone (unlike regression) couldn't provide convincing results. Thus, for this empirical study, we found that VECM model with energy generation, coal exraction and capital account as explanatory variables outperformed the Regression/ ARIMA/ARIMAX models for estimating the value of FDI in India. However, ARIMA(1,1,0) model with GDP as explanatory variable showed the superiority over Regression/ ARIMA models for estimating the same.

KEYWORDS: Multiple Linear Regression, Dummy Variable, ARIMA, ARIMAX, VECM, FDI Forecasts

INTRODUCTION

Foreign Direct Investment plays a vital role in underdeveloped and developing countries. These countries are always deficient in funds for development/welfare projects. They need funds to sustain the economy. FDI brings in technology in addition to much need of funds. India is identified as one of the most attractive investment destinations. Foreign investment is of two forms i.e. Foreign Direct Investment (FDI) and portfolio investment. Further FDI can be categorized into outward and inward FDI. By recent reforms in retail, telecom, insurance sector, investment regime facilitates easy entry of foreign capital in almost all areas subject to specific limits on foreign ownership. Entry options have become simpler. Further boost to FDI will depend significantly on further liberalization of its foreign investment regime.

India after liberalizing and globalizing the economy to the outside world in 1991, observed a massive increase in the flow of FDI. FDI has played an important role in the process of development during the past two decades. At the macro-level, FDI is a non-debt-creating source of additional external finances. At the micro-level, FDI is expected to boost output, technology, skill levels, employment and linkages with other sectors and regions of the host economy. India is the largest democracy and third largest economy in terms of GDP (PPP) in the world. With its consistent growth performance and high-skilled manpower, it provides enormous opportunities for foreign investment. India is the second most attractive destination among transnational Corporations for FDI 2007-09 (UNCTAD's World Investment Report, 2007). Though, India has an overall market-friendly and liberal policy towards foreign investment, but foreign capital still does not enjoy equally easy access in all parts of the economy. The manufacturing sector is still untapped accompanied by lack of access in certain services and agriculture.

Singhania and Gupta (2011) have used GDP, inflation rate, interest rate, patents, money growth and foreign trade to find the best fit model ARIMA (p,d,q) to explain variation in FDI inflows into India. Maggon (2012) examined the economic policy determinants of FDI and suggested the improvements that can be made in the current policy framework. Anitha (2012) has conducted a study on foreign direct investment and economic growth in India. Just to cite a few; Laura *et al.* (2004), Ewing and Yang (2009), Pardeep (2011) etc. have worked on the determinants of FDI.

A lot of methods and techniques are being used to analyze and forecast the time series. One of the most popular methodologies is based on ARIMA model by Box and Jenkins (1976). This method uses historical data of univariate time series to analyze its own trend and forecast future values. Time series are often affected by special events such as legislative activities, policy changes, environmental regulations and similar events, which is referred to as intervention events. Thus, one or more time series can be incorporated in a model to predict the value of another series by using a transfer function. Transfer functions can be used both to model and forecast the response series and to analyze the impact of the intervention. The general transfer function model employed by the ARIMA procedure was discussed by Box and Tiao (1975). When an ARIMA model includes other time series as input variables, the model is sometimes referred to as an ARIMAX model. Pankratz (1991) refers to the ARIMAX model as dynamic regression.

It is very common to see in applied econometric literature the time series regression equations with an apparently high degree of fit, as measured by the coefficient of multiple correlation R^2 but with an extremely low value of the Durbin-Watson statistic. The experience of Granger and Newbold (1974) has indicated just how easily one can be led to produce a spurious model if sufficient care is not taken over an appropriate formulation for the autocorrelation structure of the errors from the regression equation. In a situation, the variables are non-stationary; estimating the relationship using the Ordinary Least Squares method does not allow for valid statistical inferences. There are, in fact, as is well-known, three major consequences of autocorrelated errors in regression analysis: i) Estimates of the regression coefficients are inefficient, ii) Forecasts based on the regression equations are sub-optimal and iii) The usual significance tests on the coefficients are invalid. In such situations, Vector autoregressive (VAR) models and cointegration analysis are the most suitable econometric analyses and these analyses solve the endogeneity problems among variables and are able to separate short-run and long-run effects.

The broad objective of this study was to analyze the factors which discourage and encourage or influence FDI inflows into India. Factors under consideration were GDP, exchange rate, inflation, export, import, energy generation and trade balance. The qualitative factor i.e. Government policies (1991) was included as a dummy variable focusing towards FDI inflow into the country during the post liberalization period. In this article, four different statistical procedures have been used to obtain the suitable relationships for estimating the FDI inflow into country and a comparative performance of the selected relationships is also evaluated.

In subsequent sections, we first present the data used and methodology applied for the model building. Further, the FDI estimation derived from the fitted models and related discussion have been given accordingly.

Data Description and Methodology Used

The time-series data of FDI, GDP, exchange rate, inflation, export, import, energy generation and trade balance (export-import) from 1978-79 to 2009-10 were collected for the purpose. (**Source**: Handbook of Statistics on the Indian economy, various issues of RBI, Economic Survey, Database of IndiaStat, various issues of Central Statistical Organization). In accordance with the objectives formulated, the statistical analysis was carried out to develop the suitable relationships by following multiple linear regression, ARIMA, ARIMAX and VECM analyses for FDI prediction.

The standard linear regression model considered may be written in the form $\mathbf{Y}=\mathbf{X}\mathbf{b}+\boldsymbol{\varepsilon}$; where $\mathbf{Y}$ is an (n×l) vector of observations (i.e. dependent variable), $\mathbf{X}$ is an (n×p) matrix of known form(i.e. explanatory variables), $\mathbf{b}$ is a (p×l) vector of parameters, $\boldsymbol{\varepsilon}$ is an (n×l) vector of errors with the assumptions $E(\boldsymbol{\varepsilon})=\mathbf{0}$ and $V(\boldsymbol{\varepsilon})=\mathbf{I}\sigma^2$, so the elements of $\boldsymbol{\varepsilon}$ are uncorrelated. The normal equations $(\mathbf{X}'\mathbf{X})\,\mathbf{b} = \mathbf{X}'\mathbf{Y}$ are fitted by least squares technique (here $\mathbf{Y}$, $\mathbf{X}$ & $\mathbf{b}$ are same as above and $(\mathbf{X}'\mathbf{X})$ is the dispersion matrix) providing the solution $\hat{b}=(X'X)^{-1}X'Y$.

Box –Jenkins ARIMA Modeling Procedure

The univariate ARIMA approach was first popularized by Box and Jenkins and the models developed through this approach are referred to as univariate Box-Jenkins (UBJ) models. The strategy adopted for univariate time series model is identification, parameter estimation, diagnostic checking and forecasting. The general functional form of ARIMA (p,d,q) model is :

$$\phi_p(B)\Delta^d y_t = c+\theta_q(B)a_t$$

where y = Variable under forecasting

B = Lag operator

a = Error term (Y-$\hat{Y}$, where $\hat{Y}$ is the estimated value of Y)

t = time subscript

$\phi_p(B)$ = non-seasonal AR i.e. the autoregressive operator, represented as a

polynomial in the back shift operator

$\theta_q(B)$ = non-seasonal MA i.e. the moving-average operator, represented as a polynomial in the back shift operator

ϕ's and θ'$_s$ are the parameters to be estimated

ARIMA Models with Input Series (ARIMAX)

When an ARIMA model includes other time series as input variables, the model is sometimes referred to as an ARIMAX model i.e. in addition to past values of the response series and past errors, the response series is modeled using the current and past values of input series.

An ARMAX form of the model is presented as:

$$\phi(B)y_t = \beta x_t + \theta(B)a_t \text{ or } y_t = \frac{\beta}{\phi(B)}x_t + \frac{\theta(B)}{\phi(B)}a_t$$

where x_t is a covariate at time t and β is its coefficient.

β can only be interpreted conditional on the value of previous values of the response variable.

$\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ and

$\theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q$

For ARIMA errors in case of non-stationary data, $\phi(B)$ is simply replaced with $\nabla^d \phi(B)$ where $\nabla = (1 - B)$ denotes the differencing operator.

Johansen Methodology

Johansen and Juselius (1992) developed a procedure to estimate a co-integrated system involving two or more variables. This procedure is independent of the choices of the endogenous variables, and it allows researchers to estimate and test for the existence of more than one cointegrating vectors in the multivariate system. The general vector error correction model is described as follows:

p-1

Δ Yt = Σi=1 Γi ΔYt-i + Π Yt-1 + εt

where Π = αβ’. Γ and Π are the parameter matrices and ΔYt is a vector of first differences of Yt i.e. the column vector of the current values of all the variables in the system (integrated of order one), εt is the vector of errors assuming E(εt εt’) = Ω for all t, p is the number of lag periods included in the model,

which is determined by using the Akaike Information Criterion and Schwartz Bayesian Criterion. p-1 The first element in the right hand side of above equation Σi=1 Γi ΔYt-i captures the short-run relationshipsamong the variables, while the long-run effects are captured by the second term Π Yt-1 . The matrix Π is amatrix of order k×k, where k is the number of endogenous variables. If the rank r of Π matrix is less thank, the vector of endogenous variables is integrated of order 1, I(1)or higher. The matrix Π may be factored as αβ’ where α is a matrix of equilibrium coefficients that captures the speed of adjustment to a shock in the long-run and β’ is a cointegrating matrix that quantifies the long-run relationships among the variables, matrix β is such that β’Yt is I(0) even though Yt itself is I(1).The cointegration rank is usually tested by the

maximum eigen value and trace statistics proposed by Johansen (1988,91,92). When the variables in the VAR model are at least I(1), there is the possibility of existence of at least one cointegrating relationship. So, one has to determine the number of r possible cointegrating vectors and estimate the above equation(s) restricting Π to the r cointegrated variables.

RESULTS AND DISCUSSIONS

The analysis has been carried out on the time-series data ranging from 1978-79 to 2009-10 of all the variables under consideration. First of all, the correlation and multiple linear regression analyses were performed to see the various factors' effects on FDI inflows into India. Dummy variable was created keeping in mind the 1990-91 policy change and used as a qualitative variable focusing towards FDI inflow into the country during the pre and post liberalization period. The analysis was done using SPSS/SAS softwares.

Multiple Linear Regression Based Output

The correlation coefficients among most of the variables except with that of inflation rate were observed significant. The regression analysis was performed by taking FDI as dependent variable and rest of the variables under consideration as explanatory variables. The best subsets of input variables were obtained using the stepwise regression method (Draper and Smith, 1981). Finally, the best supported regressor variables were retained in the model (Tables 1-a & b) if they had the highest adjusted R^2 and lowest standard error (SE) of estimate at a given step.

Table 1a: Model Summary

Model	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.958	.955	2248.04	1.86

Table 1b: Parameter Estimates of the Selected Model

Model 1	Unstandardized Coefficients		t	Sig.
	B	Std. Error		
Constant	-1621.48	627.92	-2.58	.015
Trade balance	-0.33	0.01	-23.18	.000
Dummy	1526.12	869.47	1.76	.070

Predictors: (Constant), tradebalance, dummy
Dependent Variable: FDI

ARIMA and ARIMAX Based Output

The FDI data was found to be non stationary and differencing of order one was sufficient for getting an appropriate stationary series. After experimenting with different lags of the moving average and autoregressive processes; ARIMA (1,1,0) with GDP/ trade balance (Table 2) as input series were taken for estimating FDI in India. Several combinations of ARIMA(1,1,0) with altering order of numerator, denominator and differencing of the explanatory variables were tried. To be more clear; i) a numerator order of 1 specifies that the value of an independent series one time period in the past as well as the current value of the independent series is used to predict the current value of dependent series ii) a denominator order of 1 specifies that deviations from the mean value of an independent series one time period in the past be considered when predicting the current value of dependent series and iii) the order of differencing applied to the selected independent series before estimating the model. Marquardt algorithm (1963) was used to minimize the sum of squared residuals. Log Likelihood, Akaike's Information Criterion, AIC (1969), Schwarz's Bayesian Criterion, SBC (1978) and residual variance decided the criteria to estimate AR and MA coefficients in the model. The residual acf along with the associated 't' tests and Chi-squared test suggested by Ljung and Box (1978) were used for the checking of random shocks to be white noise (Table 3).

Table 2: Parameter Estimates of Fitted ARIMAX Models

					Estimate	SE	t	Sig.
FDI Model-1	FDI		Constant		1247.69	1033.32	1.21	.239
			AR	Lag 1	0.36	0.20	1.82	.061
			Difference		1			
	GDP		Numerator	Lag 0	-24.40	5.32	-4.59	.000
			Difference		1			
			Denominator	Lag 1	-0.91	0.08	-11.16	.000
FDI Model-2	FDI		Constant		1399.23	1131.589	1.24	.229
			AR	Lag 1	0.48	0.19	2.56	.018
			Difference		1			
	GDP		Numerator	Lag 0	-28.12	6.21	-4.53	.000
			Difference		1			
			Denominator	Lag 1	-0.83	0.10	-8.22	.000
	Tradebal		Numerator	Lag 0	-0.20	0.08	-2.64	.015
			Difference		1			

Explanatory variable: GDP

Table 3: Model Fit Statistics and Diagnostic Checking of Residual Autocorrelations: FDI

Model	Number of Predictors	Model Fit statistics						
		Stationary R-squared	R-squared	RMSE	MAPE	Normalized BIC	Ljung-Box Q Statistics	Sig.
FDI (1,1,0)	0	.001	.836	4527.91	1435.39	17.06	5.88	.994
FDI (1,1,0) with GDP	1	.444	.908	3576.68	961.64	16.84	19.62	.294
FDI (1,1,0) with GDP & Trade bal	2	.575	.930	3195.04	806.73	16.73	15.40	.566

Table 4: FDI Estimates Based on ARIMA and ARIMA(X) Models

Models	FDI (1,1,0) (million US $)			FDI (1,1,0) with GDP (million US $)			FDI (1,1,0) with GDP & Trade bal		
	2010-11	2011-12	2012-13	2010-11	2011-12	2012-13	2010-11	2011-12	2012-13
Estimate	37072.9	38140.9	39533.8	31690.9	38299.6	33017.1	35288.1	57853.3	41178.3
UCL	46363.4	51252.9	55326.2	39068.7	54576.8	50587.2	41886.3	59644.3	57508.5
LCL	27782.4	25346.3	23741.4	24313.1	29705.1	21447.1	28689.7	36062.4	24848.1

Observed FDI : 26502 (2010-11); 36498 (2011-12); 22400 (2012-13)
UCL & LCL - Upper and lower confidence limits (95%)

The predictive performance of the three contending models observed in terms of the estimated values of FDI in relation to observed FDI, differed markedly. The level of accuracy achieved by ARIMA (1,1.0) with GDP as input series was considered adequate for estimating FDI whereas the level of accuracy attained by the regression model was too low to be useable (Estimated values of FDI : 38506(2010-11) and 55160(2011-12). Though GDP, energy generation, exchange rate, trade balance and dummy variables were statistically significant predictors of FDI giving R^2- value more than 0.90 but the relative percent deviations were too wide for practical purposes for the sample period itself, rendering the fitted regression models unsuitable for predicting FDI. In an effort to improve the predictive performance; ARIMA and ARIMAX models were tried. Neither of the regression/ARIMA model could provide the suitable relationship to reliably estimate the FDI. However ARIMA with input variables i.e. ARIMAX could better explain the FDI data. Three-steps ahead (out–of-model development period i.e. 2010-11, 2011-12 and 2012-13) estimated values of FDI shown in Table 4. favour the use of ARIMA(1,1,0) model with GDP as explanatory variable to get short-term forecast estimates of FDI in India.

Vector Error Correction Modeling

If each element of a vector of time series Y_t achieves stationarity after differencing, but a linear combination $\beta' Y_t$ is already stationary, the time series Y_t are said to be cointegrated with co-integrating vector β. There may be several such co-integrating vectors so that β becomes a matrix. Interpreting $\beta' Y_t = 0$ as a long run equilibrium, co-integration implies that deviations from equilibrium are stationary, with finite variance, even though the series themselves are non stationary and have infinite variance. Thus, the first step was to explore the univariate properties and to test the order of integration of each series. The Augmented Dickey Fuller (ADF) test (Dickey and Fuller, 1979, 81) was used to perform unit root tests for checking the stationarity of the variables. The following results show that the series are integrated at the first order, I(1). Since all the series under consideration were integrated at the same order as shown below, the dataset was appropriate for co-integration analysis.

Variable\Augmented Dickey Fuller Test	At Level		At First Difference	
statistic	(t-Statistics	Prob*)	(t-Statistics	Prob*)
FDI	2.51	0.99	-7.42	0.00
Energy (energy generation)	6.05	1.00	-2.56	0.11
Capacc (capital account as %age of GDP)	-2.39	0.25	-7.12	0.00
Coal (coal extraction)	3.58	1.00	-3.02	0.04
Exchange (exchange rate Rs/$)	-0.85	0.78	-4.67	0.00
Inflation	-3.07	0.03		
GDP	5.41	1.00	1.56	0.99
Import	3.89	1.00	-0.12	0.93
Export	3.84	1.00	0.00	0.94

Null Hypothesis : FDI has a unit root
*MacKinnon (1996) p-values.

From the above tabular presentation, it can be seen that the series FDI, energy generation, capital account, coal extraction and exchange rate became stationary after the first difference. Inflation data is stationary where as GDP, Import and Export couldn't become stationary even after the first differencing. So only FDI, energy generation, capital account, coal extraction and exchange rate variables were considered for Johansen Cointegration Test as descried below:

Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace) was performed and the Trace test indicated 2 cointegration equations at 0.05 probability level. Subsequently, the model-1 based on FDI, energy generation, capital account and coal extraction, and the model-2 based on FDI, energy generation, capital account and exchange rate were obtained:

Model-1: $\Delta FDI_t = C(1)*(FDI_{t-1} - 0.06*Energy_{t-1} + 275.82*Capacc_{t-1} + 111.36*Coal_{t-1} - 9058.68) + C(2)*\Delta FDI_{t-1} + C(3)*\Delta FDI_{t-2} + C(4)*\Delta Energy_{t-1} + C(5)*\Delta Energy_{t-2} + C(6)*\Delta Capacc_{t-1} + C(7)*\Delta Capacc_{t-2} + C(8)*\Delta Coal_{t-1} + C(9)*\Delta Coal_{t-2} + C(10)$

Model-2: $\Delta FDI_t = C(1)*(FDI_{t-1} - 0.27*Energy_{t-1} - 101.17*Exchange_{t-1} + 35570.87*Capacc_{t-1} + 149473.17) + C(2)*\Delta FDI_{t-1} + C(3)*\Delta FDI_{t-2} + C(4)*\Delta energy_{t-1} + C(5)*\Delta energy_{t-2} + C(6)*\Delta Exchange_{t-1} + C(7)*\Delta Exchange_{t-2} + C(8)*\Delta Capacc_{t-1} + C(9)*\Delta Capacc_{t-2} + C(10)$

(Δ - stands for 1st difference and (t-1), (t-2) indicates the variable(s) value at lag1, lag 2)

From the following statistics, it is clear that the model-1 is preferred over the model-2 as AIC, SBC of the former is smaller, where as the log-likelihood and adj. R^2 is higher. DW statistics shows that there is no problem of auto-correlation in either of the models.

Model(s)	Model-1	Model-2
R-squared	0.85	0.60
Adj. R-squared	0.79	0.43
Log likelihood	-266.63	-281.98
Akaike AIC	18.44	19.46
Schwarz SBC	18.90	19.93
Durbin-Watson stat	2.06	2.15

It is observed from Table 5 that C(1), the error correction term is negative (that is desirable) and was found significant. C(1) is one period lag residual of cointegrating vector between FDI and energy generation, capital account, coal extraction thus indicating that these variables have long run causality on FDI. The dependent variable ΔFDI is 1st difference (VECM converts the variables into 1st difference automatically). Further, the coefficients; C(2), C(3), C(4), C(6) and C(8) were found significant and Wald-test showed that the joint short-run effect of these parameters is significant i.e. FDI_{t-1}, FDI_{t-2}, Energy $_{t-1}$, Capacc $_{t-1}$, coal $_{t-1}$ jointly influence FDI so there exists short-run causality from these variables to FDI (Table-6). The coefficients C(5), C(7), (C9) i.e. energy generation, capital account and coal extraction at lag 2 are not significant pertaining to Model 1 and hence they do not cause short run variation.

Table 5: Parameter Estimates of Long-Run and Short-Run Effects of Macro Economic Variables to FDI

	MODEL 1			MODEL 2		
	Coefficient	**Std. Error**	**Prob.**	**Coefficient**	**Std. Error**	**Prob.**
C(1)	-0.42	0.18	0.00	0.03	0.03	0.38
C(2)	1.35	0.24	0.00	0.13	0.31	0.67
C(3)	1.86	0.28	0.00	-0.23	0.32	0.47
C(4)	0.04	0.02	0.11	0.11	0.06	0.06
C(5)	-0.001	0.04	0.97	0.09	0.07	0.20
C(6)	-247.45	99.37	0.09	-1022.78	382.75	0.01
C(7)	-108.93	482.60	0.82	399.63	445.27	0.38
C(8)	145.65	90.00	0.12	170.43	1189.00	0.88
C(9)	-41.72	92.49	0.65	45.71	892.63	0.95
C(10)	-6209.37	1293.64	0.00	-3710.68	2903.76	0.21

Table 6: Wald-Test for Joint Short-Run Effect of Parameters

Models			Model-1		Model-2	
Test statistic	Value	df	Probability	Value	df	Probability
	14.27	(8, 20)	0.00	3.85	(8, 20)	0.00

Using AIC and SBC for optimal lags, Durbin-Watson, Breusch-Godfrey serial correlation LM test , ARCH for heteroscedastic residuals, and Jargue-Bera for normality tests; we recommend Model 1 for estimating FDI in India. The diagonostic checking results are as follows:

Model(s)	H_0 : Residuals are Normally Distributed		H_0 : There is no Serial Correlation		H_0 : There is no ARCH Heteroskedasticity	
	Jarque-Bera	Probability	F-statistic	Prob. Chi-Square	F-statistic	Prob. Chi-Square
Model-1	0.03	0.98	0.24	0.53	0.33	0.55
Model-2	5.11	0.07	6.73	0.005	0.85	0.34

The results obtained in this empirical study support our theoretical acceptance where energy generation, coal extraction positively affect the FDI in India where as deficit doesn't promote FDI inflow in the country. Reviewing and analyzing such relationships are essentially important for a country like India because FDI plays a vital role not only in getting the funds but also the new technologies. Among the major reasons, which discourage the international investors from investing in India despite of its consistent economic growth; include politics and corruption, lack of infrastructure, inadequate legal system, instability of Indian social and political environment, absence of corporate governance practices and maturity of the financial markets etc.

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