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Comparison of VECM and GMDH-Neural Network Algorithm approaches to estimating FDI inflows in Pakistan.

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Abstract

The study uses the comparison of Group Method of Data Handling (GMDH)-type neural network algorithm with Vector error correction model to predict the value of FDI on the basis of accuracy of prediction and to model the determinants of FDI in Pakistan. It was estimated in the times series data during the time period 1971-2013 and the time period 2014-2018 has been utilized to predict FDI. The Augmented Dickey-Fuller (ADF) test suggests that all variables data are of I (1) and Johansen co-integration test proved nexus of the variables FDI and its determinants in the long run. Nonetheless, the error correction-term of the vector error correction model (VECM) indicates that around 3 % of cumulative disequilibrium was expunged in every year in Pakistan. This paper compares two new methods Group Method of Data Handling (GMDH) Neural Network Algorithm and Vector Error Correction Model (VECM) in an attempt to obtain the more useful one based on accuracy of analysis when making predictions. Whereas, the effectiveness of VECM is then compared with a non parametric GMDH-like type neural network. An evaluation of forecasting model accuracies in terms of FDI was done using Root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Diebold Mariano (DM) test. The empirical outcomes are a clear indication that Group Method of Data Handling GMDH-type of neural network algorithm did very well in comparison with the vector error correction model based on forecasting.

1-Introduction

One of the key aspects in international economic integration is the Foreign Direct Investment which occurs when at least ten percent shareholding of a foreign based company involves an investment in a foreign firm. OECD (2008) places foreign direct investment (FDI) as the type of international investment that expresses the interest of a resident party in one economy to acquire an enduring interest in a business entity resident in another economy. FDI is considered to be, as posed by Gilpin.R (2002), when a nation wishes to establish economic establishments or the same business establishment in the lands of other countries and or wish to introduce the business in the lands of another nation. This was long felt that there has been a major change in the outlook towards Foreign Direct Investment which flows towards the developing countries. Particularly, the debate among scholars and policymakers does not center on whether Foreign direct investment should be promoted but on the ability of the developing countries to attract Foreign direct investment. Conclusively, indeed, several international-level development agencies, such as World Bank, contemplate FDI as one of the most vigilant tools globally which is the originator of eliminating poverty and in turn which

encourages developing countries to formulate guidelines with an intention to enhance FDI flows. Foreign Direct Investment can take place into two major forms, it is either in shape of "Greenfield investment" or merger and acquisition and it depends upon the nature of investment whether it takes the form of mainly newly produced assets or only a shift from domestic to overseas company. Though, FDI is more than adding to the stock of capital. Feldstein (1999) examined that FDI is the investment which is done with a view to bring 'advanced technology, up-to-date management and enlarge access to world market. Pakistan needs FDI, being a developing country which in turn promote its diverse sectors like Industrial Sector, Agricultural Sector, Science and Technology, and to decrease unemployment with a view to rise as a developed nation. The significance of Foreign Direct Investment can be indicated from the quick growth of the next-door nations of Pakistan i.e., China and India that are considered the economic center of Asia and they are getting a huge amount of Foreign Direct Investment. Political instability remained a major part in the history of Pakistan as the FDI inflows was affected by dictatorships and an ordinary law and order situations in Pakistan. Furthermore, that stressed circumstances on boundaries specially with Afghanistan after September 11, 2001 incident was happened and more presently the war against terror contributed more as well. As indicated by Pakistan Economic Survey 2001-2003, the Foreign Direct Investment of Pakistan declined by 66.6 % in 2001. Just in the short periods which is from October to December 2001, the loss of billions in exports and imports orders has been occurred in Pakistan which brought a rise in unemployment and worsening in capital and current account deficit (Khan, 2001). FDI contributes considerably in the requirements of funds necessary in setting up the productive projects, technology transfer, gaining addition to the raising living and incomes, formation of additional employment, enhancing the rules of production, enrichment of the skills of the management expertise, and gaining competitive benefits in the export sector. The massive increase in FDI is the most evident stage of globalization since the last couple of decades. The world average growth rate of FDI is twice as compared to the international trade in the last two decades. FDI is not only perceived because of the fact that it plays a central role in economic growth across the entire countries but can also have the capacity to regulate key impediments including lack of financial resources, technology and skills. It is because of the reason that policy makers in developing countries such as those found in Africa and South Asia have made it the center of their attention.

The conventional linear regression methods have failed to generate conceptually and statistical reliable results. The study conducted by us is different in many ways compared to earlier work. The first relates to building univariate and multivariate time series forecasting models both by employing Group Method of Data Handling (GMDH) type of neural network and econometrics respectively. This is done by joining the concept of FDI and some selected determinants variables which will prove to be significant in determining FDI as indicated by a previous literature. Second, we evaluate differences in performance of nonlinear GMDH model and linear (VECM) model using a different criterion to capture the out of sample forecasting namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Diebold Mariano (DM) test. The existing research complemented by the current study incorporates FDI as one of the important factors that plays significant role in the economy of a nation and introduces complex econometric model like VECM, Group Method of Data Handling (GMDH) Algorithm Neural Network and Diebold Mariano (DM) Test. This research conducts error corrections procedures according to Group Method of Data Handling (GMDH) Neural Network Algorithm to estimate the amount of FDI and juxtaposes the two models considering the accuracy of predictions made in each. The estimation was carried out using the time series data between 1971 and 2013 whereas the prediction was made by using the time series data between 2014 and 2018 to track out which model is doing a better job in predicting. Previously, the nexus between FDI and its determinants was tested and there was a test of the long-run relationship and short-run relationship but this study shall first predict the value of the FDI and compare the results of Vecm and GMDH Neural Network Algorithm based on RMSE, MAE and MAPE and Diebold Mariano (DM) test to predict on the basis of accuracy. Some of the empirical

tests and methodologies of the determinants of FDI in Pakistan have been carried out; most of these researches have been done through linear basically regressions to evaluate a set of major variables and their influence on FDI flows in the Pakistan. This paper seeks to provide such a different and possibly pathbreaking new methodology where Group Method of Data Handling (GMDH) type neural network modelling approaches to the prediction of the value of FDI is presented in the paper. The study has addressed the gap of other researcher in Pakistan. The study has used the latest technique and modelling that have never been employed by a researcher in the kind of research in Pakistan. The present paper uses Vector Error Correction Model (VECM) as compared with Group Method of Data Handling (GMDH) Algorithm neural network (NN), Diebold Mariano (DM) Test, Augmented Dickey Fuller tests and Johansen Co- Integration tests.

2.Brief Literature Review

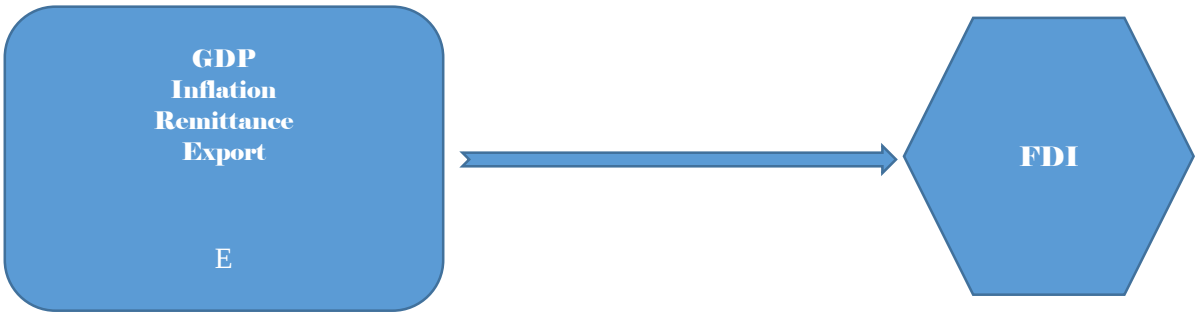
Analysis and forecasting the changes in FDI over time have been research studies that have been conducted in the various countries. In the research study conducted by Al-Abdulrazag & Bataineh (2007), there was expected increment of the FDI volume over the next 21 years i.e. between 2004 and 2025 on the basis of their analysis done on the period of 1976 to 2003 in India. These had been utilizing the ARIMA models, which were based on the Box -Jenkins method of forecasting the FDI inflows. Similarly, the forecasting technique of Box Jenkins ARIMA model by biswas (2015) also depicted that the FDI inflows in India is increasing within the forecasted phase (2015-2034) based on the analysed data set (1992-2014). Other similar Indian research studies that have been reviewed by Dhingra et al (2015) on the inflow foreign institutional investments executed during January 2004 to September 2012 using the ARIMA models (based on the box-Jenkins modelology) found inflows or out flows of the foreign institutional investment being influenced by the numerous AR terms and MA terms. Outside of India, such study was conducted by Prasanna (2015) in the SAARC and the total FDI amount in the subsequent 25 years (2013-2037) will be anticipated as US 1672895.8 million and average FDI will be anticipated as US 66915.81 million. The ARIMA models (as applied by Box and Jenkins) had been applied by him also, during the period between the years 1970 and 2012. FDI inflows have also been forecasted based on the ARIMA models (as a method based on Box Jenkins technique) using a study conducted in Zambia by Jere et al (2017) over a 197014, period and the annual net FDI inflows were forecasted to be increasing slowly at about 44.36 percent by 2024. The same study has not been conducted in Pakistan until now so the empirical literature lacks the realization of the same form. Thus, the present paper will review the dynamics of FDI inflows in Pakistan.

There has been also a large volume of studies conducted by academic scholars and organizations on the topic of the determinants of FDI determinants with variable and dimensions. The amount of inflation is regarded as a leading indicator of economic stability. This is explored by many scholars such as Demirhan & Masca (2008) that the low inflation demonstrated the stable economy and that it gives a space to grow the economy. The stable economy of the country has the ability of drawing in the numerous foreign investors since the economy is stable and they too will be in a position to expand the business and expand on their activities. These arguments were derived through findings of regression models that showed that there is negative relationship between inflation and FDI. Ibrahim and Hassan (2013) analyzed the fact that Inflation is a determinant element of foreign direct investment. They used research through period of 1970-2010 in Sudan and utilised the Johansen co integration to come up with conclusion that the FDI is negatively related to inflation. An article by Fayyaz and Hussain, (2012) also utilized panel data on the years 2009 to 2009 in 57 developing countries. They reasoned out that there is a stable macroeconomic environment, that is, low and sustained inflation and it can embolden FDI inflows. Mohamed and Sidiropoulos (2010) conduct another study in an area, the MENA (Middle East North African countries) to investigate the elements that offer impact on FDI where they concur with the traditional literature of economic liberty and FDI. To make comparisons of more variations of FDI, they add on domestic, financial, institution,

policy and other external variables of fixed-effects model and estimating MENA countries as compared to other established countries. They replace the domestic variables with market size (log GDP); financial variables with national stock index; institutional variables with investment profile and the corruption levels; policy variables with rate of inflation and government expenditure and external variables with measure of world liquidity and ease of trade. They thus find that the market size and freedom in trade which generates coefficient of 98.15 and 12.43 is one of the biggest factors in predicting the FDI whereas the other influential factors are not big such as investment profile, the level of corruption, inflation rates, government expenditure, natural resources and the growth expectation. However, compared to such findings, in the case of the MENA countries, the freedom of trade becomes immaterial. Dritsaki & Stiakakis, (2014) carried out an economic study that focused on the connection between foreign direct investments, exports and the economic growth in Croatia where the work relied on time series data sets throughout the years 1994-2012 of annual analysis. The estimation was conducted by performing bounds testing (ARDL) and also the estimation was carried out using ECM-ARDL model. The outcome suggested that it possesses a short and a lengthy run correlation amid FDI as well as the GDP. The exciting issue is that the long and the short run GDP functions have the negative sign with foreign direct investments hence interpreting that foreign direct investments fail to result in growth in Croatia whether in the short run or long run period. Gebrewold, (2012) carried out a study on the determinants of the inflow of foreign direct investment into African states using estimation of a panel regression model between the years 1985 to 2009. The study had explanatory variables as GDP per capita, GDP growth rate, Exports, openness to trade, human capital and the growth rate of labor force, number of telephone lines per 1000 persons, exchange rate, inflation and the proportion of oil and minerals in total exports. According to the findings, export is found to be a positive FDI driver of the overall balance of all nations as well as to the two sets of the middle income nations whereas, GDP per capita, labor force growth rate and inflation prove significant in the case of aggregate and Lower Middle-income groups. As a de facto test, Coon and Neumann (2016) examine Follow the Money: Remittance Responses to FDI Inflows by utilizing time period 1980-2010. The researchers used panel data consisting of 118 countries given the Instrumental Variables strategy two-stage with random effects in the study. The results of the study indicated that there was a positive and significant nexus between the remittances and FDI flows. In this regard, PALAMULENI (2018) conducted research on the topics Do remittances really attract foreign direct investments? Using time period 1980-2014, evidence can be based on panel cointegration. ADF test was used in the study to verify the stationarity of the variables whereas padroni test was used in exploring long-term association. Using 47 data points of developing countries, the research conducted DOLS approach as an estimation. The results showed that the correlation between remittance and FDI flows is positive though small in value.

2.1 Conceptual Framework

The following is the conceptual framework of the study.



Explanatory Variables Dependent Variable

3.Research Methodology

3.1 Data

The present paper seeks to compare Vector Error Correction Model (VECM) and the Group Method of Data Handling (GMDH) Algorithm Neural Network in measures to establish the FDI in Pakistan in sample forecasting value. Besides, the study will examine how determinants affect FDI and forecast the value of FDI in Pakistan. FDI, Inflation, Remittance, GDP and exports data are obtained using World Development Indicators (WDI). FDI is employed as a dependent variable and it is presented as net inflows as a % of GDP. Remittances are quantified in millions of US dollar. Consumer price index is taken to be inflation. The gross domestic product is GDP. The exports also have a ratio calculated against GDP. We carry on in two ways since on the one hand, Vecm is implemented to study the short -run as well as long -run relation between FDI and its determinants with time frame of 1971-2013. The approximated model was calculated, in which a five-year forecast was made and comparison was made with GMDH type Neural Network Algorithm over time period of 2014-2018. The R software was employed in the data analysis and management.

3.2 Methodology

The determinants of Foreign Direct Investment have normally been examined in earlier works using an ordinary time series technique associated with the auto-distributive lag model (ARDL) analysis of co-integration and error correction and Granger causality. Nonetheless, econometric approaches were conducted on the presence of long-term relationships that are coupled with short term associations with the consideration given to the nexus of FDI and its determinants. In a study conducted recently, error correction techniques that were performed were as per GMDH Neural Network Algorithm in forecasting the value of FDI and compared both the models based on the basis of the prediction accuracy. There is the use of this new approach of modeling. To investigate the determinants and causes of FDI in Pakistan, to has taken the approach of the Neural Network Algorithm methodology. More effective method of prediction accuracy in terms of accuracy is attempted in the paper through GMDH Neural Network Algorithm and VECM. The technique is unorthodox to such a study (in relation to orthodox linear-vector error correction model) and is used mainly on the FDI dynamics of Pakistan. The study recommends certain nonconventional ways of managing the current complexities of the FDI markets. The objective of the comparison of VECM model and Group Method of Data Handling (GMDH) Neural Network Algorithm is to determine the model used in the prediction (Plikynas and Akber, 2005). The notion of non linear dynamics started to penetrate the financial investment markets after the release of such well know publications; e.g., Peters (2000), Chorafas (1998), Friedman (1995) Mandelbrot had made some significant contributions to the same. New approaches only came in handy when modern information technologies were capable of modeling real-time nonlinear dynamics aided by modern information technologies and Group Method of Data Handling (GMDH) Neural Network Algorithm. Forecasting models accuracy as far as FDI is concerned was established by: root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Diebold test. The empirical analysis and parameterization are delineated as follows: The interrelation between FDI and the determinants of FDI is exhibited in the following long-term regression before the complete description of the GMDH type Longitudinal and RI-type-Neural Network Algorithm and VECM has been presented:

$$FDI = f(GDP, Inflation, Remittances, Exp) \quad (1)$$

$$\Delta yt = a1 + a2ect - 1 + a3\Delta yt - 1 + a4\Delta xt - 1 + et \quad (2)$$

$$\Delta FDI_t = \alpha_0 + \sum_{i=1}^{t} \beta_{1i}\Delta(GDP)_{t-1} + \sum_{i=0}^{u} \beta_{2i}\,\Delta(Inf)_{t-1} \quad (3)$$
$$+ \sum_{i=0}^{v} \beta_{3i}\,\Delta(Exp)_{t-1} + \sum_{i=0}^{w} \beta_{4i}\,\Delta(REM)_{t-1} + \theta(ECM)_{t-1} + \mu_t$$

The initial distinctions Represented by 7 are that the term delta, GDP is the growth domestic product,

Exp is the export, the price inflation proportionality denoted by the proxy of consumer price index (CPI) and Rem is the remittance. Definition Here epsilon cm -1 is a delayed error correction term describing the error in the cointegrating vectors equation that was created when using the Johansen cointegration test. To forecast the value of FDI, Group Method of Data Handling (GMDH) Algorithm may be organized as followed,

$Y = b_0 + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} \sum_{j=i}^{n} b_{ij} x_i x_j + \sum_{i=1}^{n} \sum_{j=i}^{n} \sum_{k=j}^{n} b_{ijk} x_i x_j x_k + \ldots$

3.3 Augmented Dicky Fuller test –Unit Root Test

Time series data first involves checking to see whether it is stationary. They are non-stationary by and large. Consequently, one has to examine the possible non-stationary issue (unit- root) in the first place and to examine the degree of integration of each variable. Failure to consider a unit root problem would result into a spurious regression. Prior to estimating the cointegration space and the calculation of cointegration rank, one should, as a first step, test the order of-integration of each of the variables, or alternatively examine whether all the variables have unit roots by following (Dickey & Fuller, 1979):

$\Delta z_t = \rho z_{t-1} + \sum_{i=1}^{p} \delta \Delta z_{t-i} + \varepsilon_t$ (4)

$\Delta z_t = \beta + \rho z_{t-1} + \sum_{i=1}^{p} \delta \Delta z_{t-i} + \varepsilon_t$ (5)

$\Delta z_t = \beta + \gamma_t + \rho z_{t-1} + \sum_{i=1}^{p} \delta \Delta z_{t-i} + \varepsilon_t$ (6)

Where is the difference operator; is the intercept; is the time index; is the coefficient that shows process root i.e focus on testing, is the coefficient of a time trend, is the number of lag of the autoregressive process and is random error.

3.4 Co-integration Analysis

Then, cointegration test to determine long run relationship between FDI and its determinants would have been conducted after integrating all series of variables on the first difference. Johansen test is a procedure that configure cointegrating a set of time series. This methodology is favoured over the others since it discerns the basic characteristics of the time series data and it is the system equation test that looks at all the co-integrating associations that can be established in a vector of nonstationary variables or a combination of stationary and nonstationary variables (Harris, 1995). In this way the hypothesis that the maximal number of r cointegrating vectors exist can be estimated by employing two likelihood test statistics as depicted by Johansen and Juselius (1990) as follows: This multivariate cointegration test can be expressed as:

$J_{trace}(r) = -T \sum_{i=r+1}^{m} \ln(1-\hat{\lambda}_i)$ (7)

$J_{max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+1})$ (8)

In which, the highlighting of the greatest estimated i th characteristic root (eigvalue); r = 0, 1, 2,…,k-1, is represented by 1 (hat) and spotlights T, the sample size of estimated pi matrix. The J-trace statistic would follow the null hypothesis which states that the number of integrated vectors equal to r against the general alternative hypothesis. On the other hand, the Jmax statistic is an estimate of the null hypothesis of the no. of cointegrating vectors, r against the alternative hypothesis of the no. of cointegrating vectors, r + 1.

3.5 Vector Error Correction Model (VECM)

In case, co- integration exists between both the series, we have long term equilibrium between these two series and VECM is used as a means to analyse properties of short run of the co-integrated series. When a group of variables is discovered to have one or more cointegrating vectors, a VECM (Vector Error Correction Model) would be appropriate to apply as it adapts to short run fluctuations of variables as well as shocks to equilibrium.

$\Delta FDI_t = \alpha_0 + \sum_{i=1}^{t} \beta_{1i} \Delta(GDP)_{t-1} + \sum_{i=0}^{u} \beta_{2i} \Delta(Inf)_{t-1} + \sum_{i=0}^{v} \beta_{3i} \Delta(Exp)_{t-1} + \sum_{i=0}^{w} \beta_{4i} \Delta(REM)_{t-1} + \theta(ECM)_{t-1} + \mu_t$ (9)

Already explained above

3.6 Group Method of Data Handling (GMDH) Algorithm

The approach was initiated in 1968 by Prof. Alexey G. Ivakhnenko in the Institute of Cybernetics in

Kiev (then in the Ukrainian SSR). Effectively neural computing has come in as a usable technology in the recent years with a successful application in so many areas as varied as finance, medicine, engineering, geology, physics, economics and biology. The Group Method of Data Handling (GMDH) model is a self- organized model whose structure of the model was optimized with respect to the data provided. Lastly, GMDH can overcome the issue of overfitting that usually happens to Artificial Neural Network (ANN) by the use of objectively chosen models of optimum complexity. Usually, there are three components of GMDH models: input variables, internal criteria, and external criteria. Coefficients of the equation (representation of how input variables are linked with the predictor variable) were found using the value of the input variables, and they are called internal criteria. They fail to use alternative information. The selection of the model on the other hand comes with external basis. Group method of data handling involves the use of Kolmogorov-Gabor polynomial to describe the relation between the predicted dependent variable and the predictive variables. In the term of discreteness, the following of more first order of the Kolmogorov Gabor polynomial was taken into consideration by us:

$f(x_1, x_2, \ldots, x_n) = a_0 + a_1x_1 + a_2x_2 + \ldots + a_nx_n$ (10)

With n denoting the number of inputs, x being a known vector of inputs, and, a.sub.1, a.sub.2, …, a.sub.n being the vector of coefficients. Terms are for the most part used in calculation to the square terms as below,

$y = a_0 + a_1x_1 + a_2x_2 + a_4x_1x_2 + a_5x_1^2 + a_6x_2^2$ (11)

Group method of data handling constructs its system on the self- organization process. The nodes in the input layer are known as the predictor variables. Middle candidate models are obtained by combining two of these nodes in pairs. The coefficients a prime in the equation (3.8) are estimated using internal criteria. Ordinary least square (OLS) is normally used as internal criterion. Following this, a number of middle-range candidate models could be designed in the next tier. The external criterion selects some of these models of middle candidates.

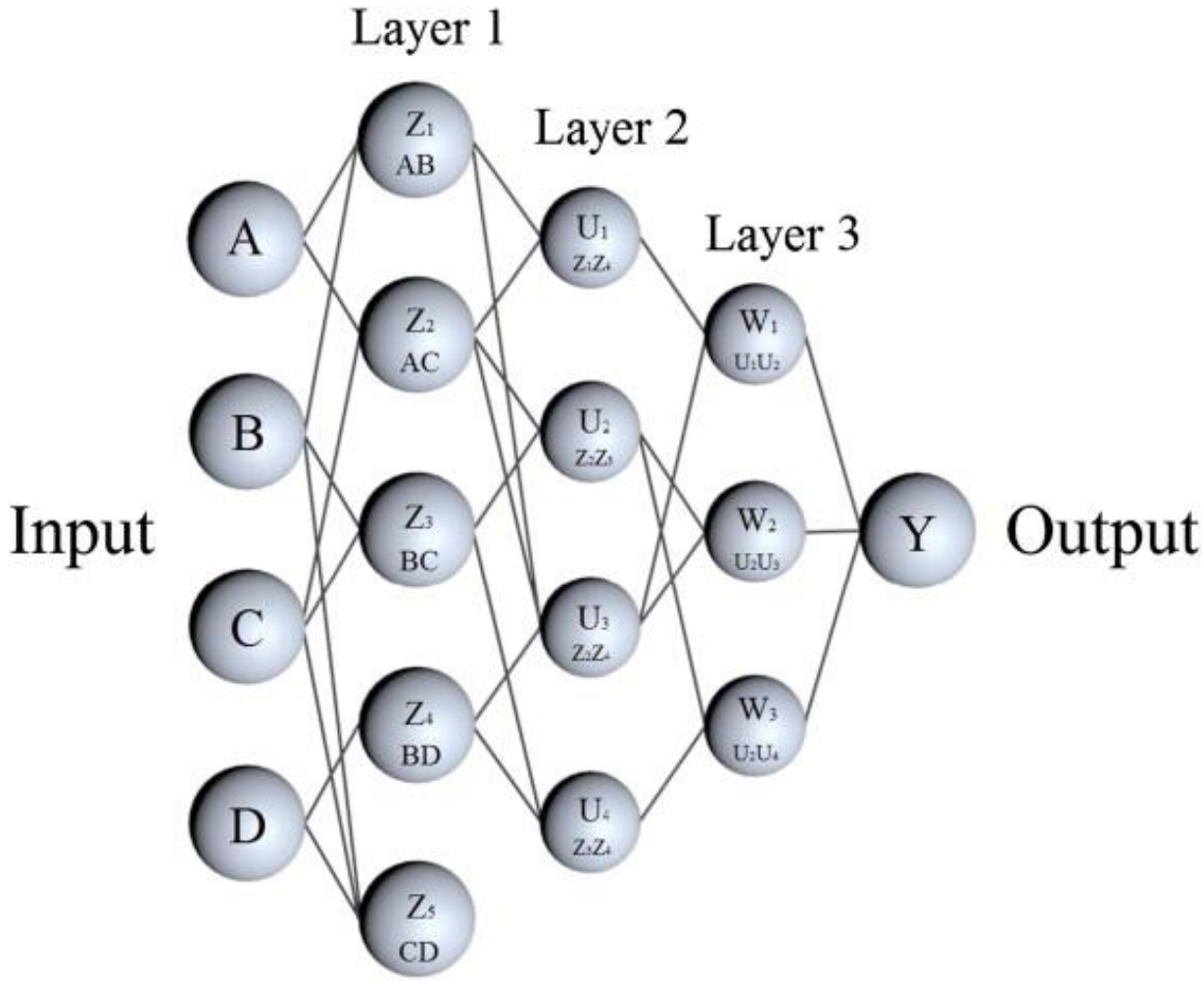


Figure 1 Group method of data handling (GMDH) algorithm

3.7 Error Metrics

So in statistical perspective, the forecast-error is more realistic tests to evaluate the ability of forecasting and deciding the most appropriate method. The common employed performance metrics in this field as RMSE (root mean square error), MAPE (mean absolute percentage error), MAE (Mean Absolute error) and Diebold Mariano test have been used in this study.

3.8 Root Mean Square Error (RMSE)

RMSE indicates the strength of error in the comparison of forecasts and RMSE is measure that is scaled quadratically. RMSE system places proportionately higher weights on large errors. Good forecast is expected with low RMSE value of the model. It is cited as

$$\text{RMSE} = \sqrt{\frac{1}{H}\sum_{t=1}^{H}\left(Y_t - \hat{Y}_t\right)} 2 \qquad (12)$$

3.9 Mean Absolute Percentage Error (MAPE)

Absolute mean of the percent errors (the mean absolute percentage error), the mean absolute percentage deviation (MAPD). Mean absolute percentage error (MAPE) is one of the most popular metrics of forecast accuracy which has desirable properties, scale-independency and interpretability. It can be described as

$$\text{MAPE} = \frac{1}{H}\sum_{t=1}^{H}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| * 100 \qquad (13)$$

The easiest method of measuring accuracy of a forecast is termed as Mean Absolute Error (MAE). MAE is basic, plain and simple as the name implies the derivative of the mean of the absolute errors. Absolute error is simply the difference between the actual and the predicted in absolute values. MAE

helps us know what can be expected of the forecast in terms of the size of average error.

$$MAE = \frac{1}{H}\sum_{t=1}^{H}\left|Y_t - \hat{Y}_t\right| \quad (14)$$

In RMSE equations of MAPE and MAE, Y t and Y t hat represent the actual and the predicted values respectively and H represents forecast horizon.

3.10 Diebold Mariano (DM) Test

In a case where various models are applied to predict one variable then it is best to verify which of the model has a better performance with regard to prediction. In this regard, Diebold and Mariano (1995) test can be applied. In addition, the test can be applied to the data in the event of non-zero mean, non-Gaussian, contemporaneously and serially correlated errors. There is a loss function which is used to test the error in the forecasting of losses in terms of, primarily, squared loss of forecast error and absolute loss of forecast error. DM test hypothetical specifications are referred to as

$H_0 : E(d_t) = 0,$

$H_1 : E(d_t) \neq 0.$

The hypothesis that two models exhibit the same degree of predictive performance is tested with the corresponding test statistics that takes the form of

$$DM = \frac{\bar{d}}{\sqrt{Var(\bar{d})}}$$

Where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$; where the asymptotic variance of the d has a form of;

$$Var(\bar{d}) = \frac{1}{T}[\gamma_0 + 2\sum_{i=1}^{T-1}\gamma_i]$$

$$\hat{\gamma_i} = \frac{1}{T}\sum_{t=i+1}^{T}(d_t - \bar{d})(d_{t-i} - \bar{d})$$

The Diebold-Mariano test statistic tends to standard normal distribution by increasing sample size. For small sample, the DM statistic was modified by Harvey et al., (1998). The modified test statistic approximately follows a t-distribution, which is given as

$$DM^* = \frac{DM}{[T+1-2j+T^{-1}\ j(j-1)]}$$

In the above test statistic, j denotes the forecast steps. Diebold-Mariano (1995) recommended that incorporate the autocovariance up to j-1 for j step-ahead forecasts.

1. RESULT AND DISCUSSIONS

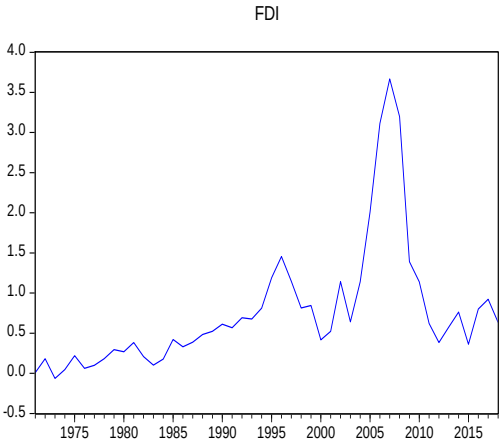
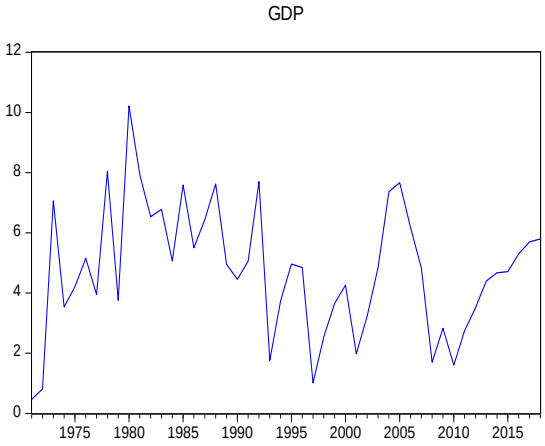


Figure 2



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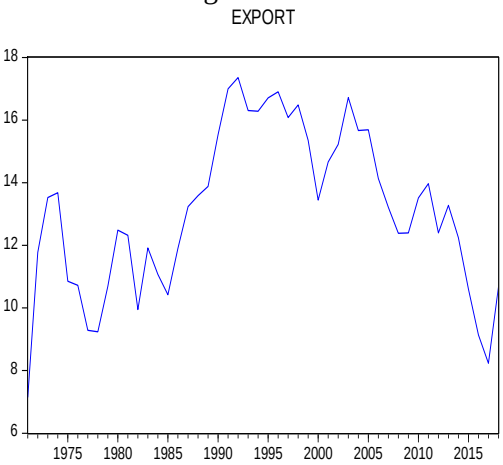

Figure 4

Figure 5

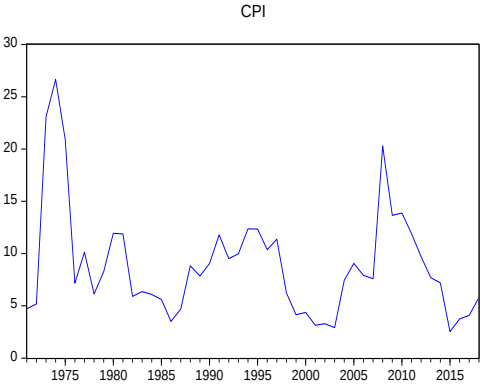

Figure 6

Table 1 Descriptive Statistics

	FDI	GDP	INFL	EXP	IMP	REM
Mean	4.722842	8.587721	15.91153	28.40305	0.761511	4.739808
Median	4.772638	8.818121	16.49136	29.40916	0.546401	4.450276
Maximum	10.21570	12.47198	19.23542	38.74397	3.668323	10.24763
Minimum	0.468373	2.139167	11.43511	10.20433	-0.063242	1.453638
Std. Dev.	2.191843	2.365712	1.932538	6.396734	0.811768	2.300180
Skewness	0.134208	-0.515700	-0.555909	-1.453981	2.141477	0.410154
Kurtosis	2.634535	3.193805	2.285164	5.243372	7.458016	2.158313

A careful description statistical analysis of the selected variables is conducted before resorting to multivariate analysis of the time series data. The descriptive statistics revealed in Table 1 indicate that the mean GDP growth is 4.72 as compared to 2.19 being its standard deviation. The mean of import is 19.65 and standard deviation is 2.77, and M of export is 13.26 followed by standard deviation of 2.49, M of remittance is 4.73 with standard deviation of 2.30, and mean real effective exchange rate is 143.68 and standard deviation of 50.53

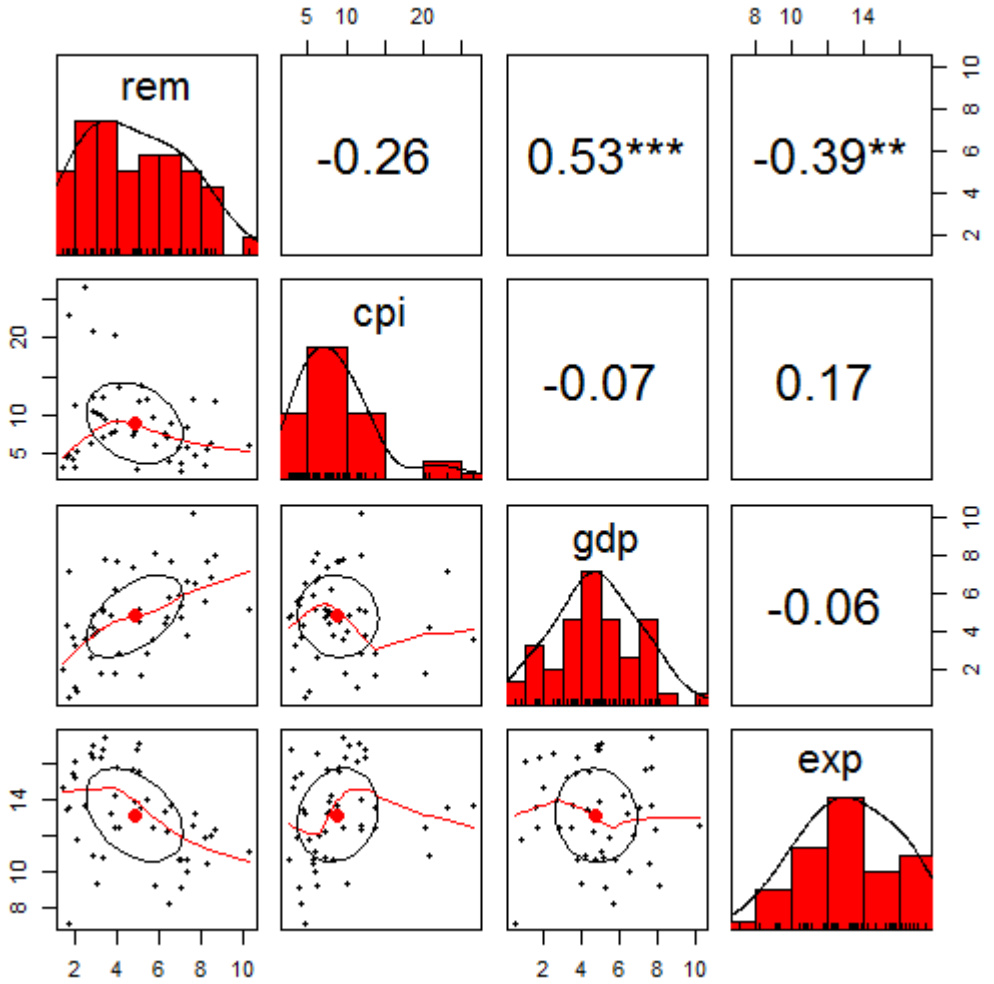

Figure 7

4.1 Correlation Matrix

Correlation Matrix is essentially aimed at computing the power or the degree of linear relation between variables. This matrix is useful in addressing certain econometric issues such as multicollinearity among the explanatory variables. Based on the above graph, we can infer that there is negative correlation between REM and CPI as well as the strength -0.26. The correlation value between the REER and the GDP is 0.53 and this shows that the two variables are moving in the same direction. The correlation between REER and EXP is -0.39 implying that, the higher the value in one of the variables, the lower will be the value in the other variable. The relationship between CPI and GDP is negative with coefficient equal to -0.07, CPI and EXP are positively correlated as well. Graphically indicated the GDP and EXP are having the same direction of change of magnitude of 0.02.

Table 2 Augmented Dicky-Fuller Test

	At level		At first difference		
Variables	Constant	Constant with trend	Constant	Constant with trend	Conclusion
FDI	-2.754	-3.116	-4.356*	-4.357*	I (1)
REM	-1.716	-1.697	-4.537*	-4.499*	I (1)
GDP	-2.486	-2.655	-5.262*	-5.182*	I (1)
EXP	-2.002	-1.900	-5.455*	-5.340 *	I (1)
IR	-2.699	-2.043	-6.564*	-6.407*	I (1)

Note: * represent significance levels at 5% percent.

On table 2, the test, using ADF unit root, was established on two sets (that is, constant and constant along time trend). According to them, they found all the series are non-stationary both under constant and constant with time trend at the level. And, each of them has been found integrated at I(1). The response variable is of order one integration and this is essential in cointegration analysis.

Table 3 Johansen Co-integration Test Result

	Test statistic	10pct	5pct	1pct
r <= 4	2.55	6.50	8.18	11.65
r <= 3	8.03	12.91	14.90	19.19
r <= 2	14.25	18.90	21.07	25.75
r <= 1	26.79	24.78	27.14	32.14
r = 0	44.62	30.84	33.32	38.78

Table 4 Co-integration Rank Test (Max –Statistics)

	Test statistic	10pct	5pct	1pct
r <= 4	2.55	6.50	8.18	11.65
r <= 3	10.59	15.66	17.95	23.52
r <= 2	24.84	28.71	31.52	37.22

r <= 1	47.64	45.23	48.28	55.43
r = 0	98.25	66.49	70.60	78.87

Our Tabulated findings of Johansen cointegration tests are as indicated in the above Table 3 and 4. Johansen cointegration test results have two fundamental criteria namely; trace test and maximum eigenvalue test. The results of both the maximum eigenvalues test and the trace test of the test have indicated the presence of the cointegration. In other words, there exists a long run potential relationship between the variables. The outcome of the trace test suggested that cointegration of rank one is present between the variables and the maximum statistics also suggested that there would be one co-integrating vector. In the null hypothesis, the value of trace statistic is 44.62; this exceeds the critical value i.e., 33.32 at 5 percent. In the same way, in the null hypothesis, the maximum eigenvalue test statistic value is 98.25, greater than the critical value i.e., 70.60 at 5 percent. This has the implication that the long run correlation is stable where remittance, economic growth, inflation, export and foreign direct investment have a relationship of 5 percent level of significance.

Table 5 Vector Error Correction Model (VECM)- Short-run coefficients

Variable	Coefficient	Std. Error	T-Statistic	P>|T|
ECT (-1)	-0.028	0.0123	-2.311	0.026
ΔFDI (-1)	0.275	0.143	1.924	0.061
ΔREM(-1)	0. 056	0.063	0.888	0.379
ΔCPI (-1)	-0.026	0.011	-1.989	0.049
ΔGDP (-1)	0.007	0.028	0.265	0.791
ΔEXP (-1)	0.009	0.045	0.197	0.844
CONS	-0.969	0.420	-2.303	0.026

4.2 Short-run Results

The Table 5 gives short-run outcomes, and the coefficient of ECM is representing the rate of convergence to equilibrium. Banerjee (1998) provides evidence on a stable long-run nexus based on the negative coefficient of ECM which is found to be statistically significant. The negative value of ECM coefficient in the model tend toward equilibrium and the positive one sign go away equilibrium.

The approximate value of the coefficient of ECM is -0.028; thus, nearly three percent of deviation of the long-run equilibrium is corrected within one year. The overall conclusion revealed that the effect of remittance inflow on FDI are both positive and insignificant in the short run. Consumer price index influences the economic growth negatively and remarkably at 5 percent critical value. The GDP and Export as an influence on FDI is only significant at 10 percent level of significance and to the positive side. The F-statistic tests the hypothesis that all the coefficients of the regression in the model are false, that is, have a zero value in the same point. In Table 4.5, F-value is given as 2.57 and the corresponding P-value is 0.04 and this shows that fitted model is significant at 5 percent. The goodness of fit statistic (R2) of VEC model is 0.28 implies that the 28 percent changes due to regressors in the dependent variable. The test results on diagnostics show that the absence of any significant problem of autocorrelation and normality of the estimated model is present.

Table 6

R-squared = 0.28	DW stat = 1.91
S. Error = 0.39	F-statistic = 2.57
Diagnostic tests result	
Serial correlation LM test	2.26 [0.32]
Normality test	1.76 [0.41]

4.3 Selection of best GMDH Algorithm

One of the computing techniques or artificial intelligence have been extensively studied and used in time series forecasting, which is known as Group Method of Data Handling (GMDH). After using VECM model, now we use GMDH algorithm for prediction of FDI. It is used for short term prediction. In GMDH algorithm, 2 inputs and 1 hidden layer are selected with 1 output layer of neurons using trial and error method. Figure (3.13) shows that residuals of GMDH are white noise because residuals have zero mean and constant variance.

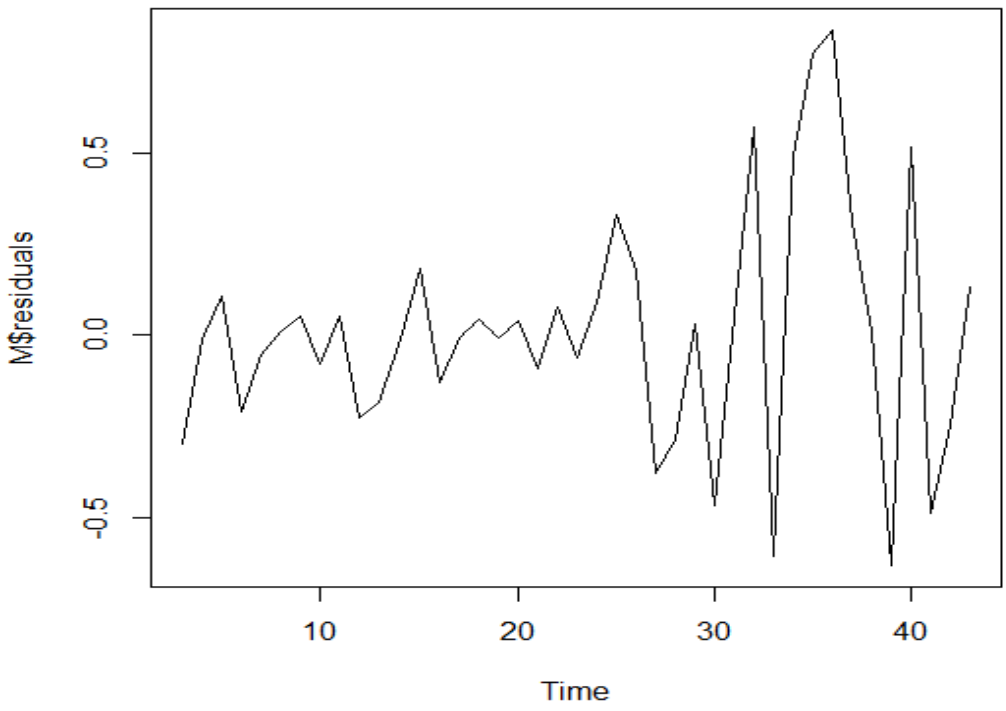

Figure 8

Forecasting

Table 7 Forecasting Results

Year	Actual FDI	GMDH	VECM
2014	**0.7640**	0.6211	0.6497
2015	**0.3611**	0.6662	0.6921
2016	**0.8000**	0.7104	0.1380
2017	**0.9230**	0.7537	0.6055
2018	**0.6346**	0.7960	0.6604

Table 8 Forecast comparison

Criteria	GMDH	VECM
RMSE	0.187	0.363
MAPE	0.316	0.455
MAE	0.173	0.290

Table 9 Diebold Mariano (DM) Test

DM test statistic = -2.85	P-value = 0.004

Based on root mean square error, mean absolute percentage error, mean absolute error and Diebold-Mariano test the forecast results remarkably suggest that GMDH-type neural network algorithm outperforms in terms of prediction than VECM model, in the sense that having lowest forecast errors in one-step ahead forecast for the period (2014 to 2018).

Conclusion

To predict the value of FDI, this paper compares GMDH-type neural network algorithm and Vector error correction model on the basis of the accuracy of prediction as well as to examine the determinants of FDI in Pakistan. The paper has established the fact that Group Method of Data Handling (GMDH) Neural Network Algorithm is a useful tool compared to Vector error correction model in predicting FDI in the Pakistani economy. As can be seen in the paper there is evidence that it can be extracted or can be deduced the hidden information in FDI and can be used to predict the future concerning FDI inflows in Pakistan. FDI forecasting is extremely important to every Investor and the large ones in particular. GMDH-type neural network algorithm is organic as compared to other methods and this approach develops a learning algorithm to more predictive results. The research is about Pakistan economy and has relied on the dataset over the period (1971-2013) to estimate the model and a forecast (2014-1018) in Pakistan. The particular empirical analyses are performed through the recently emerged VECM approach to cointegration. Also, we calculate the in sample forecast accuracy under VECM and GMDH-type neural network algorithm. The accuracy of forecasting models was determined with the use of the Root mean square error, mean absolute error, mean absolute percentage error and Diebold Mariano test. The empirical findings clearly prove that GMDH-type neural network algorithm has done exceptionally great when compared to vector error correction model with the reference to FDI forecasting. The outcome of the ADF test illustrated that the variables in question are stationary at I(1) and provides space to use Johansen method of co-integration. The Johansen approach to cointegration established the cointegrating relationship as observed in the long-run nexus of all variables that made certain the lasting relationship amid the variables FDI and GDP, Exp, Rem and Infl.

The recent estimation of a vector error correction model is estimated to track short run and long-run dynamics among the variables and error correction-term (ECT) indicates that about 3 per cent disequilibrium per year was averted in 1. Moreover, the parameter of adjustment has negative value and is statistically significant. Vector error correction model illustrated that inflation is very significant and negatively connected to FDI in the short-run. The findings have implied that inflation is a crucial element in Foreign Direct Investment. Thus, a short-run connection is shown between the Inflation and the FDI. This is attributed to high price level in the country and it escalates production costs because of escalation of the prices of input like wage rate, cost of raw materials, land and capital expenses. The positive positive impact of Remittance, economic growth and export on FDI is however not significant. However, there is a negative and significant coefficient in error correction term to ensure that there is a stable long-term association between FDI and all the determinants. Given the results that were predicted, policy-makers ought to be in a position to understand the better investment promotion policy and respond to the demands of such inflow with regards to infrastructure and skilled labor.

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