Iranica Journal of Energy & Environment 3 (4): 354-360, 2012
ISSN 2079-2115
IJEE an Official Peer Reviewed Journal of Babol Noshirvani University of Technology
DOI: 10.5829/idosi.ijee.2012.03.04.10

BUT

FDI, Population Density and Carbon Dioxide Emissions: A Case Study of Pakistan

[1]*Haider Mahmood and* [2]*A.R. Chaudhary*

[1]GC University, Katchery Road, Lahore, Pakistan
[2]NCBA&E, Gulberg III, Lahore, Pakistan

(Received: January 18, 2011; Accepted in Revised Form: August 14, 2012)

Abstract: The study attempts at finding the impact of foreign direct investment on carbon dioxide emissions in Pakistan. It takes carbon dioxide emissions as dependent variable and foreign direct investment, share of manufacturing value added and population density as independent variables. ADF, PP, Ng-Perron and Zivot-Andrews Unit root tests were used to find the unit root problem. ARDL and its error correction model were used to find the long run and short run relationships. The study found the long run relationship in the model but short run relationship did not exist. Foreign direct investment, manufacturing value added and population density have positive impact on carbon dioxide emissions.

Key words: FDI · Carbon Dioxide Emissions · Population Density · Cointegration

INTRODUCTION

Foreign direct investment (FDI) can have three kinds of effects on environmental quality of developing countries. First is a scale effect, which can be positive if there is economic growth and there has been demand for environmental goods which can help in tackling the environmental problems. Negative scale effect occurs when a country experiences economic growth without considering environmental management and regulations. Second is technological effect which is positive when foreign investors use environmental friendly technology and also have spillovers on domestic investment through competition. Third is the policy effect which can be positive if host government makes tight regulations for the protection of environment and also enforces the foreign investors to follow such regulations. Negative policy effect can occur when there is competition amongst developing countries to attract FDI and host government relaxes the environmental regulations for FDI.

FDI is usually done in those countries where there are less environment laws to save the cost of production. FDI is done in manufacturing sector as well. So, FDI and production of manufacturing sector simultaneously can affect the environment of a country. Population growth and its density are responsible for environmental degradation. As population rises, the demand for energy and fuel, demand for industrial good and transportation would also rise. Secondly, better employment opportunities will attract the labor to migrate from rural to urban areas. It increases the population density and economic activities in urban area.

Literature Review: According to Dunning [1], the cultural, political and environmental effects of FDI depended on the government policies. Jaffe*et al.* [2] and Beghin[3] found that the dirty industries moving from the developed countries to the developing countries were proof of pollution-heaven hypotheses and in some cases the developing countries also purposely relaxed the environmental policies to attract the foreign investment. In such countries, pollution level would rise with expansion of foreign investment in dirty industries and composition effect would emerge with increasing share of dirty goods in Gross Domestic Product (GDP).

Copeland and Taylor [4] found that capital intensive country would produce and trade a pollution intensive product increasing world's pollution level. Similarly, capital rich country also did investment in poor countries and again increased pollution level. Organization of Economic Cooperation and Development's [5] report investigated the impact of globalization including FDI on environment. Report claimed that FDI activities generated environmental degradation in the host countries even though foreign investors followed greater environmental standards than local firms.

Corresponding Author: Haider Mahmood, GC University, Katchery Road, Lahore. Tel: +92 321 4546369,
E-mail: haidermahmood@hotmail.com.

Kolstad and Xing [6] collected data from manufacturing industries located in developing and developed countries. They found that relaxing environmental standards was the major determinant of FDI. The countries which attracted FDI by relaxing environmental regulation would have to face heavy cost in term of pollution. Goldenman[7] and Zarsky[8] stated that foreign investors used better production technologies than local manufacturers. So FDI seemed good for the environment. Dean [9] found that scale effect would emerge with increasing foreign investment and there would be greater economic activities which resulted in depletion of environmental resources and greater pollutant emissions.

Talukdar and Meisner [10] used the carbon dioxide emissions as proxy for the environment and FDI in developing countries. The study found a negative relationship between FDI from developed countries and carbon dioxide emissions. It was an evidence to use cleaner technology by developed countries. Smarzynska and Wei [11] collected data from 534 Multinational Enterprises (MNEs) from different economies and tested the Pollution-Heaven Hypothesis of FDI. They found a positive but insignificant relationship between FDI and lax environmental regulations. Bora [12] investigated the pollution intensity of United States owned MNEs and found that developed countries had the highest proportion of pollution-intensive production in foreign production activities. Xing and Kolstad [13] stated that developing countries used relax environmental laws to attract FDI from developed countries in dirty industries. They also found that US's FDI had bad impact on environmental quality of developing countries.

Yang [14] used the provincial level data of China and found a negative relationship between FDI and sulfur dioxide emissions. Liang [15] used the panel data of 260 major cities of China and tested the environmental effects of FDI and per capita GDP and found a negative relationship between FDI and sulfur dioxide (SO_2) emissions. The finding suggested that FDI was helpful in reducing sulfur dioxide emissions in China. He [16] claimed that bad impact of FDI on environment was due to lenient environmental regulation and also claimed that environmental quality would improve with technical and knowledge spillovers with FDI.

Merican *et al*. [17] investigated the impact of FDI on carbon dioxide emissions. The study found that FDI did not have any impact in enhancing carbon dioxide emissions in Indonesia and Singapore. The case for Singapore also showed that major foreign investment was in tertiary sector which did not usually contribute in pollutant emissions. Baek and Koo [18] investigated data of India and China. They found the long run relationships amongst FDI, SO_2 emissions and economic growth and a unidirectional causality from FDI to economic growth and SO_2 emissions in these countries. Acharyya [19] used the data of India for 1980-2003 and found that FDI had a positive and significant impact on the economic growth and carbon dioxide emissions.

Model Specification and Methodology: To capture the impact of FDI on pollution level, the study uses carbon dioxide emissions as percentage of Gross Domestic Product (GDP) as dependent variable and uses FDI and manufacturing value added as percentage of GDP and population density as independent variable.

Model of study is as follows:

$$COG_t = f\,(FDIG_t, PD_t, MVAG_t) \quad (1)$$
$$t = 1972, 1973, \ldots\ldots, 2005$$

where,

COG_t = Carbon Dioxide Emissions in kg as percentage of GDP at time t.

$FDIG_t$ = Foreign Direct Investment inflow in constant year 2000 US $ as percentage of GDP at time t.

PD_t = Population Density, people per square KM at time t.

$MVAG_t$ = Manufacturing Value Added as percentage of GDP at time t.

At first, study discusses the Augmented Dickey-Fuller (ADF) test, which was produced by Dickey and Fuller [20] to check the stationarity in the time series. This test proposed the following equation with intercept to detect the non-stationarity.

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \gamma_2 \Delta Y_{t-2} + \ldots\ldots + \gamma_m \Delta Y_{t-m} + u_t \quad (2)$$

where, Δ is a difference operator, t refers to the time period and u_t is a residual at time period t. Y_t denotes the variable, which is investigated for stationarity. $\gamma_1\Delta Y_{t-1} + \gamma_2\Delta Y_{t-2} + \ldots\ldots + \gamma_m\Delta Y_{t-m}$ is used to correct the correlation problem among u_t and regressors of equation (2). The equation (2) includes intercept α and can also be assumed with intercept and time-trend T as follows:

$$\Delta Y_t = \alpha + \lambda T + \delta Y_{t-1} + \gamma_1 \Delta Y_{t-1} + \gamma_2 \Delta Y_{t-2} + ... + \gamma_m \Delta Y_{t-m} + u_t \quad (3)$$

where λ is the coefficient of time-trend (T). ADF test checks the null hypothesis (δ=0), if δ is statistically significant and it is not zero, then time series has no unit root problem. A time-series variable is stationary with two conditions. At first, δ should be statistically non-zero and it should be negative.

Phillips and Perron [21] developed the unit root test which is different from ADF tests in dealing with heteroscedasticity and serial correlation. They ignore the $\gamma_1\Delta Y_{t-1}$ + $\gamma_2\Delta Y_{t-2}$ +......+$\gamma_m\Delta Y_{t-m}$ from ADF equation (3) which is for any serial correlation amongst error terms. Phillips-Perron (PP) test removes the serial correlation by giving ranks to the residuals. Equation of PP test is as follows:

$$\Delta Y_t = \alpha + \lambda T + \delta Y_{t-1} + u_t \quad (4)$$

u_t may have heteroscedasticity, so for correction of serial correlation and heteroscedascity. PP test uses the modified statistic Z_t and Z_δ which are as follows:

$$Z_t = \left(\frac{\hat{\sigma}^2}{\hat{\pi}^2}\right)^{1/2} .t_{\delta=0} - \frac{1}{2}\left(\frac{\hat{\pi}^2 - \hat{\sigma}^2}{\hat{\pi}^2}\right).\left(\frac{T.SE(\hat{\delta})}{\hat{\sigma}^2}\right) \quad (5)$$

$$– \qquad Z_\delta = T\hat{\delta} \quad \frac{1}{2}\frac{T^2.SE(\hat{\delta})}{\hat{\sigma}^2}\left(\hat{\pi}^2 \quad \hat{\sigma}^2\right) \quad (6)$$

where, $SE(\hat{\delta})$ is the standard error of $\hat{\delta}$. $t_{\delta=0}$ is the test statistic under the estimates of $\hat{\sigma}^2$ and $\hat{\pi}^2$, which are given below:

$$\hat{\sigma}^2 = \lim_{T\to\infty} T^{-1}\sum_{t=1}^{T} E\left[u_t^2\right], \quad (7)$$

$$\hat{\pi}^2 = \lim_{T\to\infty} \sum_{t=1}^{T} E\left[T^{-1}S_T^2\right], \quad (8)$$

where $S_T = \sum_{t=1}^{T} u_t$ and T is the time-trend. Z_t and Z_μ of PP test follows the same distribution as the t-statistic of ADF test under the null hypothesis (δ=0). PP test has an advantage over ADF test that that PP test robust heteroscedasticity in the error term (u_t). Secondly, it does not need to specify the lag length for its estimation.

Ng and Perron [22] developed efficient and a modified version of PP test by using generalized least square detrending data. This procedure is also efficient for large negative errors and can do better estimation than PP test. The efficient and modified PP tests are as follows:

$$MZ_\alpha^d = (T^{-1}(y_T^d)^2 - f_0)/2k \quad (9)$$

$$MSB^d = \left(k/f_0\right)^{1/2} \quad (10)$$

$$MZ_t^d = MZ_\alpha^d \times MSB^d \quad (11)$$

$$MPT_T^d = ((\bar{c})^2 k + (1-\bar{c})T^{-1})(y_T^d)^2/f_0 \quad (12)$$

where, the statistics MZ_α^d and MZ_t^d are efficient versions of PP test and

$$k = \sum_{t=2}^{T}(y_{t-1}^d)^2/T^2, \bar{c} = -13.5.$$

$$f_0 = \sum_{j=-(T-1)}^{T-1} \theta(j).k(j/l) \quad (13)$$

where l is a bandwidth parameter (which acts as a truncation lag in the covariance weighting) and $\theta(j)$ is the j-th sample auto covariance of residuals.

Zivot and Andrews [23] modified the PP and ADF unit root test, which also considers the one-unknown structural break. The ADF test may fail in identifying the true result in the presence of a structural break whether time series is stationary or not. ADF and PP tests do not allow for structural break in data. Zivot-Andrews test uses the sequential ADF test to find the break with the following equations.

$$Model \quad A: \ \Delta Y_t = \mu_1{}^A + \gamma_1{}^A t + \mu_2{}^A DU_t(\lambda) + \alpha^A Y_{t-1} + \sum_{j=1}^{k}\beta_j \Delta Y_{t-j} + \varepsilon_t \quad (14)$$

$$Model \quad B: \ \Delta Y_t = \mu_1{}^B + \gamma_1{}^B t + \gamma_2{}^A DT^*{}_t(\lambda) + \alpha^B Y_{t-1} + \sum_{j=1}^{k-1}\beta_j \Delta Y_{t-j} + \varepsilon_t \quad (15)$$

$$Model \quad C: \ \Delta Y_t = \mu_1{}^C + \gamma_1{}^C t + \mu_2{}^C DU_t(\lambda) + \gamma_2^c DT_t^*(\lambda) + \alpha^C Y_{t-1} + \sum_{j=1}^{k-1}\beta_j \Delta Y_{t-j} + \varepsilon_t \quad (16)$$

where $DU_t(\lambda)$ is 1 and $DT^*_t(\lambda) = t - T\lambda$ if $t>T\lambda$, 0 otherwise. $\lambda = {}^{T_B}\!/_{T}$, T_B represents a possible break point. Equations (14), (15) and (16)are tested sequentially for T_B=2,3,....,T-1, where T is the number of observations after adjustment of differencing and lag length k. Model (A) allows for a change in the intercept of the series, Model (B) allows for a change in the trend of a series, while Model (C) allows changes in both intercept and trend.

After testing the unit root problem in the time-series variables, the cointegration test can be used to find the long-run relationship among the variables. Long-run relationship states the long-run equilibrium among variables, which may have the shock of disequilibrium in the short-run from long-run, but it will move again in long-run equilibrium Harris and Sollis [24]. Auto-Regressive Distributive Lag (ARDL) bound testing technique has been developed by Pesaran *et al*. [25]. ARDL can be applied if variables have mixed order of integration i.e. I(0) and I(1). This approach takes the optimum lag length for each variable separately in the model which helps in the data generating process from a general to a specific model. The problems resulting from non-stationarity of data can also be avoided by using an ARDL approach Laurenceson and Chai [26]. The study uses the SBC to find the maximum relevant lag length. To find the cointegration amongst variables of model (1), ARDL model is as following:

$$\Delta COG_t = \delta_0 + \delta_1 COG_{t-1} + \delta_2 FDIG_{t-1} + \delta_3 PD_{t-1} + \delta_4 MVAG_{t-1} + \sum_{i=1}^{p}\beta_{1i}\Delta COG_{t-i} + \sum_{i=0}^{q}\beta_{2i}\Delta FDIG_{t-i} + \sum_{i=0}^{r}\beta_{3i}\Delta PD_{t-i} + \sum_{i=0}^{s}\beta_{4i}\Delta MVAG_{t-i} + \lambda\, D_{COG} + \varepsilon_t \quad (17)$$

In equation (17), first difference of COG is the dependent variable, the null hypothesis is (H_0: $\delta_{o1}=\delta_{o2}= \delta_{o3}= \delta_{o4}= 0$) and alternate hypothesis is ($\delta_{o1}\neq\delta_{o2}\neq \delta_{o3}\neq \delta_{04}\neq 0$) which shows existence of long run relationship in the model, δ_{o0} is a constant and ε_{ot} is error term. D_{COG} is included in equation for possible structural break and to complete information in the model. This is also shown as $F_{COGt}(COG_t/FDIG_t,PD_t,MVAG_t)$. If cointegration exists in the model then long run and short run coefficients will be calculated. Error correction term can be used to find the short-run relationship in the model. Error correction model is as follows:

$$\Delta COG_t = \gamma + \sum_{i=1}^{p}\beta_{1i}\Delta COG_{t-i} + \sum_{i=0}^{q}\beta_{2i}\Delta FDIG_{t-i} + \sum_{i=0}^{r}\beta_{3i}\Delta PD_{t-i} + \sum_{i=0}^{s}\beta_{4i}\Delta MVAHG_{t-i} + \phi\, D_{COG} + \varphi\, ECT_{t-1} + \zeta_t \quad (18)$$

φ is showing the speed of adjustment from short run disequilibrium to long run equilibrium. Afterwards, diagnostic tests are used to check the normality, functional form, heteroscedasticity and serial correlation in the model. CUSUM and CUSUMsq statistics are used to ensure the stability of parameters.

Data Source: Data on carbon dioxide emissions, manufacturing value added, foreign direct investment and population density is taken from World Bank [27] for the years 1972 to 2005. This study used EViews (Version 7) for data analysis.

Empirical Results: Table 1 shows the results of ADF, Phillip-Perron and Ng-Perron tests. The results show that that all variables of model are non-stationary at level with all tests.

Table (2) shows that COG_t is non-stationary with significant structural break for the year 1979 in intercept, significant break for the year 1981 in trend and significant break for the year 1979 in both intercept and trend. $FDIG_t$ become stationary with significant structural break for the year 1999 in trend and significant break for the year 1995 in both intercept and trend. PD_t is non-stationary with significant structural break for the year 1998 in intercept. $MVAG_t$ is non-stationary with significant structural break for the year 1997 in intercept and significant break for the year 1981 in both intercept and trend.

Table 3 shows that $dCOG_t$ is stationary at 1% level of significance in ADF, PP and Ng-Perron (MZ_a, MZ_t and MPT) tests and at 5% in Ng-Perron (MSB) test with intercept. $dCOG_t$ is stationary at 1% level of significance in ADF, PP and Ng-Perron (MZ_t and MPT) tests and at 5% in Ng-Perron (MZ_a and MSB) tests with both intercept and trend. $dFDIG_t$ is stationary at 1% level of significance in ADF, PP and Ng-Perron (Mz_t) tests and at 5% in Ng-Perron (MZ_t, MSB and MPT) tests with intercept. $dFDIG_t$ is stationary at 1% level of significance in ADF, PP and Ng-Perron (MZ_t) tests and at 5% in Ng-Perron (MZ_a,MSB and MPT) tests with both intercept and trend. dPD_t is stationary at 1% level of significance in PP tests and at 5% in ADF and Ng-Perron (MZ_a, MZ_t, MSB and MPT) tests with intercept. dPD_t is stationary at 1% level

Table 1: Unit Root Tests at Level

			Ng-Perron			
Variable	ADF	PP	MZ_a	MZ_t	MSB	MPT
Model Specification: Intercept						
COG_t	0.281(1)	0.406(5)	1.569(1)	1.707	1.088	9.999
$FDIG_t$	-2.022(0)	-2.044(2)	-1.888(0)	-0.875	0.464	11.814
PD_t	1.842(2)	1.623(4)	0.872(1)	2.274	3.652	12.724
$MVAG_t$	-1.287(0)	-1.742(1)	-5.568(1)	-1.251	0.275	5.447
Model Specification: Intercept & Trend						
COG_t	-2.992(0)	-2.875(1)	-10.321(1)	-2.269	0.219	8.838
$FDIG_t$	-2.668(1)	-2.512(3)	-11.085(1)	-2.157	0.195	9.159
PD_t	2.625(3)	2.623(5)	-6.628(1)	-1.524	0.528	11.273
$MVAG_t$	-2.647(0)	-1.561(1)	-1.282(0)	-1.041	0.512	5.189

Note: * and ** show stationarity at the 0.05 and 0.01 level respectively. Brackets contain the optimum lag length.

Table 2: Unit Root Test: Zivot-Andrews

Variable	k	Year of Break	α	t_α	Type of Model
COG_t	0	1979	-0.769	-4.154	A
	3	1981	-1.098	-4.478	B
	0	1979	-0.877	-4.065	C
$FDIG_t$	2	1999	-1.354*	-4.423	B
	3	1995	-1.487*	-5.139	C
PD_t	4	1998	-0.146	-3.602	A
$MVAG_t$	4	1997	-0.818	-3.716	A
	4	1981	-0.508	-3.511	C

Note: * and ** show stationarity at the 0.05 and 0.01 level respectively

Table 3: Unit Root Tests at First Difference

			Ng-Perron			
Variable	ADF	PP	MZ_a	MZ_t	MSB	MPT
Model Specification: Intercept						
$dCOG_t$	-8.246**(1)	-8.254**(2)	-13.999**(0)	-2.642**	0.189*	1.763**
$dFDIG_t$	-8.346**(1)	-8.614**(1)	-13.974**(0)	-2.546*	0.188*	2.027*
dPD_t	-3.121*(1)	3.181**(2)	-8.326*(1)	-2.172*	0.194*	2.182*
$dMVAG_t$	-4.928**(1)	-4.897**(2)	-15.836**(1)	-2.772**	0.173**	1.703**
Model Specification: Intercept & Trend						
$dCOG_t$	-8.170**(0)	-8.153**(1)	-18.498*(0)	-3.586**	0.152*	4.818*
$dFDIG_t$	-7.031**(1)	-10.392**(3)	-18.974*(1)	-3.499**	0.154*	5.284*
dPD_t	-3.481*(1)	-3.782*(3)	-19.625*(1)	-3.182**	0.149*	5.412*
$dMVAG_t$	-5.007**(1)	-4.977**(2)	-18.865*(0)	-3.791**	0.145*	4.488*

Note: * and ** show stationarity at the 0.05 and 0.01 level respectively. Brackets contain the optimum lag length.

Table 4: ARDL Bound Test Using ARDL(2,2,1,1)

		At 0.05		At 0.01	
VARIABLES (when taken as a dependent)	F-Statistic	I(0)	I(1)	I(0)	I(1)
$D(CO_t)$	10.524**	3.615	4.913	5.018	6.610

** Means at 5%, 10% significant levels reject the null hypotheses of no cointegration

* Means at 10% significant level reject the null hypotheses of no cointegration

Table 5: Long Run Results: Dependent Variable is COG_t

Regressor	Parameter	S. E.	t-Statistic	P-value
$FDIG_t$	5.328*	2.661	2.002	0.057
PD_t	1.727***	0.264	6.543	0.000
$MVAG_t$	1.772*	1.005	1.764	0.091
C	32.515***	4.809	6.762	0.000
D_{COG}	7.694***	1.924	3.998	0.000

Note: *, ** and *** show statistical significance of parameters at the 0.10, 0.05 and 0.01 respectively. S. E. is standard error.

Table 6: Error Correction Model: Dependent Variable is $dCOG_t$

Regressor	Parameter	S. E.	t-Statistic	P-value
dCO_{t-1}	0.339*	0.169	-2.003	0.056
$dFDI_t$	0.861	1.712	0.503	0.619
$dFDI_{t-1}$	-3.543*	2.009	-1.764	0.090
$dMVA_t$	1.398*	0.753	1.858	0.075
dPD_t	1.538**	0.464	3.315	0.003
dC	5.471*	2.872	1.905	0.067
dD_{CO}	0.612**	0.241	2.536	0.018
ECT_{t-1}	-0.124	0.080	-1.553	0.133

Note: *, ** and *** show statistical significance of parameters at the 0.10, 0.05 and 0.01 respectively. S. E. is standard error.

Table 7: Diagnostic Tests

	LM version	P-value
Serial Correlation (x^2)	0.354	0.552
Functional Form (x^2)	2.267	0.132
Normality (x^2)	1.678	0.209
Heteroscedasticity (x^2)	2.117	0.146

of significance in Ng-Perron (MZ_t) tests and at 5% in ADF, PP and Ng-Perron (MZ_a,MSB and MPT) tests with both intercept & trend. $dMVAG_t$ is stationary at 1% level of significance in all tests with intercept. dPD_t is stationary at 1% level of significance in ADF, PP and Ng-Perron (MZ_t) tests and at 5% in Ng-Perron (Mz_a, MSB and MPT) tests with both intercept and trend. There is evidence for mix order of integration I(0) and I(1). So, ARDL model is suitable to apply here. The study finds the optimum lag length for ARDL model by using SBC and then includes dummy variable D_{COG} in the ARDL model to complete the information in the model. Optimum lag length is 2 for $dCOG_t$, 2 for $dFDIG_t$,1 for dPD_t and 1 for $dMVAG_t$. The study selects the year 1979 for break period and puts 0 from 1972 to 1979 and 1 afterward in D_{COG}. The calculated F-statistic for selected ARDL model is given in Table (4).

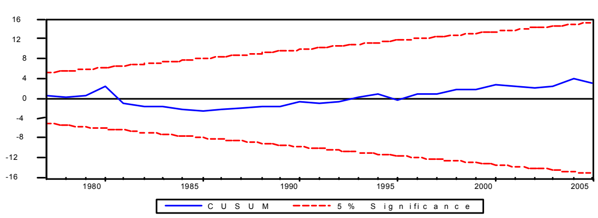

Fig. 1(a): CUSUM test

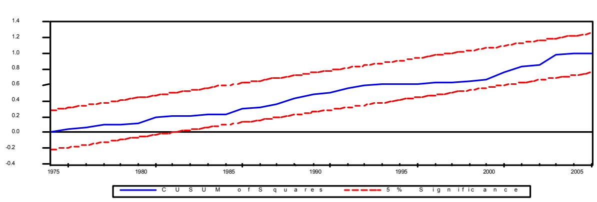

Fig. 1(b): CUSUMsq test

Table 4 shows that F-statistic is 10.524. It is greater than upper bound both at 1% level of significance, so null hypothesis of no cointegration is rejected and alternate hypothesis of cointegration is accepted. The long run relationships exist amongst variables of the model.

Table 5 shows that the coefficients of $FDIG_t$, PD_t and $MVAG_t$ are positive and statistically significant. FDI, population density and manufacturing value added significantly contributed to carbon dioxide emissions. Intercept (C) is positive and significant. Coefficient of D_{COG} is positive and significant at 1% level of significance. So, intercept has changed after the year 1979.

Table 6 shows that coefficients of all differenced variables at specified lags are statistically significant except $dFDIG_t$. The coefficient of ECT_{t-1} is negative and statistically insignificant. So, there is no evidence for short run relationships amongst the variables in the model.

Results of Table (7) show that P-values of serial correlation, functional form, normality and heteroscedasticity are greater than 0.1 so there are no problem of serial correlation, functional form, normality and heteroscedasticity.

Figure 1(a) and 1(b) show that CUSUM and CUSUMsq did not exceed the critical boundaries at 5% level of significance. This means the model of environment is correctly specified and long run coefficients of regressors are reliable.

CONCLUSIONS

To check the impact of foreign direct investment on carbon dioxide emissions, this study used FDI and manufacturing value added as percentage of GDP and population density as independent variables and carbon dioxide emissions as dependent variable. The study used ARDL cointegration technique and its error correction model to check the long run and short run relationships. The long run relationship exists in environment model and short run relationship does not exist in the model. FDI, population density and manufacturing value added have the positive impact on carbon dioxide emissions. Results give evidence that all variables in the environment model contribute to the pollution in Pakistan.

REFERENCES

1. Dunning, J.H., 1993. MNEs, the Balance of Payments and the Structure of Trade. In: Dunning, J.H. (ed.). Multinational Enterprises and the Global Economy. Addison-Wesley. Wokingham, UK and Reading, MA.
2. Jaffe, A.B., S.R. Peterson, P.R. Portney and R. Stavins, 1995. Environmental Regulation and The Competitiveness of US Manufacturing. Journal of Economic Literature, 33(1): 132-163.
3. Beghin, J., 1996. Computable General Equilibrium Model Analysis of Economy Wide Cross Effects of Social and Environmental Policies in Chile. Ecological Economics, 5(4): 447-472.
4. Copeland, B.R. and M.S. Taylor, 1997. A Simple Model of Trade, Capital Mobility and the Environment. NBER Working Paper No. 5898, National Bureau of Economic Research, Cambridge, MA.
5. Organization of Economic Cooperation and Development. 1997. Economic Globalisation and the Environment. OECD, Paris.
6. Kolstad, C.D. and Y. Xing, 1998. Do Lax Environmental Regulations Attract Foreign Investment? Departmental Working Paper No. 28-98, University of California, Department of Economics, Santa Barbara, California.
7. Goldenman, G., 1998. The Environmental Implication of Foreign Direct Investment: Policy and Institutional Issues. OECD Paper. CCNM/EMEF/EPOC/CIME (98)3, Paris
8. Zarsky, L., 1999. Havens, Halos and Spaghetti: Untangling The Evidence about Foreign Direct Investment and The Environment. OECD Paper: CCNM/EMEF/EPOC/CIME (98)5, Paris.
9. Dean, J., 1999. Testing the Impact of Trade Liberalization on the Environment: Theory and Evidence. in P.G. Fredriksson, ed., Trade, Global Policy and the Environment. World Bank Discussion Paper No. 402, World Bank, Washington DC.
10. Talukdar, D. and C.M. Meisner, 2001. Does The Private Sector Help or Hurt The Environment? Evidence from Carbon Dioxide Pollution in Developing Countries. World Development, 29: 827-840.
11. Smarzynska, B.K. and S.J. Wei, 2001. Pollution Havens and Foreign Direct Investment: Dirty Secret or Popular Myth? NBER Working Paper No. 8465, Cambridge, MA.
12. Bora, B., 2002. FDI and the Environment–The Link between FDI and the Environment. Foreign Direct Investment– Research Issues. London and New York: Routledge, pp: 211-229.
13. Xing, Y. and C. Kolstad, 2002. Do Lax Environmental Regulations Attract Foreign Investment? Environmental and Resource Economics, 21: 1-22.
14. Yang, H., 2005. Impact on EKC by Trade and FDI in China. China Population, Resources and Environment, 15(3): 99-103.
15. Liang, F.H., 2006. Does Foreign Direct Investment Harm the Host Country's Environment? Evidence from China. Working Paper, Haas School of Business, UC Berkeley.
16. He, J., 2006. Pollution Haven Hypothesis and Environmental Impacts of Foreign Direct Investment: The Case of Industrial Emission of Sulfur Dioxide (SO_2) in Chinese Province. Ecological Economics, 60: 228-245.
17. Merican, Y., Z. Yusop, Z.N. Mohd and L.H. Siong, 2007. Foreign Direct Investment and Pollution in Five ASEAN Nations. Journal of Economics and Management, 1(2): 245-261.
18. Baek, J. and W.W. Koo, 2008. A Dynamic Approach to the FDI-Environment Nexus: The Case of China and India. Associated Annual Meeting, American Agriculture Economics, Orlando, FL.
19. Acharyya, J., 2009. FDI, Growth and Environment: Evidence from India on CO_2 Emission during the Last Two Decades. Journal of Economic Development, 34(1): 43-58.
20. Dickey, D. and W. Fuller, 1981. Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root. Econometrica, 49: 1057-1072.
21. Phillips, P.C.B. and P. Perron, 1988. Testing for Unit Roots in Time Series Regression. Biometrika, 75: 335-346.
22. Ng, S. and P. Perron, 2001. Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. Econometrica, 69: 1519-1554.
23. Zivot, E. and D.W.K. Andrews, 1992. Further Evidence on the Great Crash, the Oil-Price Shock and the Unit Root Hypothesis. Journal of Business and EconomicStatistics, 10(3): 251-270.
24. Harris, R. and R. Sollis, 2003. Applied Time Series Modelling and Forecasting. John Wiley, West Sussex.
25. Pesaran M.H., Y. Shin and R. Smith, 2001. Bounds Testing Approaches to the Analysis of Level Relationships. Journal of Applied Econometrics, 16: 289-326.
26. Laurenceson, J. and J.C.H. Chai, 2003. Financial Reform and Economic Development in China. Edward Elgar, Cheltenham.
27. World Bank. 2010. World Development Indicators. World Bank, Washington, DC.