# Some Determinants of $CO_2$ Emissions in Bangladesh

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## Abstract

*$CO_2$ emissions, industrial output growth, population growth and FDIinflows in natural log in Bangladesh for 1972 – 2008 are nonstationary in terms of both ADF and KPSS tests with different orders of integration. As a result, ARDL model and VECM are estimated. There are evidences of a cointegrating relationship among the variables, long-run causal flows from industrial output growth, population growth and FDI to $CO_2$ emissions. FDI seems to marginally reduce $CO_2$ emissions. Furthermore, short-run interactive feedback effects among the variables are also evidenced.*

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### I. Introduction

Among a host of environmental pollutants, $CO_2$ emission is a serious problem in developing countries. This increases at an early stage of industrial expansion as a transition from overdependence on agriculture. Such industrial transformation is heavily dependent on energy-intensive technologies. Knowingly, they also allow foreign dirty firms to migrate from developed countries where environmental standards are comparatively much higher resulting in high regulatory compliance costs of production. The motivation is to entice foreign direct investment (FDI) for job creation to exit abject poverty that is an outcome of rising income inequality. Moreover, the degree of environmental awareness is very low in developing countries.

Once a developing country's per capita real income approaches a certain level, the country has resources to invest in costly environment friendly technologies to mitigate the level of $CO_2$ emission. As the country's economic structure later gradually transforms from manufacturing to expanding services sector, $CO_2$ emission continues to abate. Meanwhile, people become growingly environmentally conscious for health reasons and continue to press the home country government to raise environmental standards. This phenomenon is described by Kuznet's inverted environmental U-curve. A similar analogy is drawn for China.

Bangladesh is a developing poor country where the main stay of living is still agriculture, although its percentage share in GDP continues to fall over time. Bangladesh is 1/5$^{th}$ the size of the state of Texas in USA with over 150 million people that is near 50 percent of US population. This necessitates an increased emphasis on industrialization for domestic consumption and exports to earn hard foreign currencies. Bangladesh also endeavors to attract FDI for job creation. At an early stage of industrialization, the above factors are likely to contribute to significant emissions of $CO_2$. Additionally, the level of environmental awareness is yet relatively low in Bangladesh.

The primary objective of this study is to investigate the roles of industrial production, FDI and rising population in determining the level of $CO_2$ emission in Bangladesh by implementing the Autoregressive Distributed Lag (ARDL) model for cointegration and long-run causality with short-run interactive feedback effects. The remainder of the paper is structured as follows. Section II briefly reviews the related literature. Section III outlines the ARDL empirical methodology. Section IV reports results. Section V offers conclusions and remarks.

## II. Brief Review of Related Literature

Grossman and Krueger (1991) found that the long-term relationship between economic growth and environment quality was an inverted U-shaped curve. The phenomenon has been labeled as Environmental Kuznets Curve (EKC) by Panayotou (1993). The EKC hypothesizes that environment quality deteriorates with the increase of per capita income at the early stage of economic growth and gradually improves when the country reaches a certain level of affluence. Since then, extensive empirical studies have been conducted to test the EKC hypothesis and the effect of economic growth on environmental quality is in much disputes.

Most of the empirical studies are based on multi-countries. In fact, EKC hypothesis is fundamentally a within-country story, but cross-countries analysis assumes that all cross-section countries react identically no matter how different in income, geographical conditions, culture and history (Dijkgraaf and Vollebergh, 1998). In recent years, some researchers have begun to use individual countries to test the EKC hypothesis (i.e., De Bruyn, 2000; Unruh and Moomaw, 1998; Lekakis, 2000; Stern and Common, 2001; Cole, 2003). Besides the income factor, environmental quality is also affected by other factors, such as economic structure, international trade, FDI, environmental regulation and so on, although most of the empirical studies merely focused on income level. A growing world needs more input to expand outputs, which implies that wastes and emissions as by-products of the economic activities will increase (Grossman and Krueger, 1995). With the economic growth, the production structure will change, from clean agrarian economies to polluting industrial economies and further to clean service economies (Arrow, et. al., 1995). As Panayotou (1993) points out, when the production of an economy shifted mainly from agriculture to industry, pollution intensity increases. It is because more and more resources are exploited and the exhaustion rate of resources begins to exceed the regeneration speed of resources. When the industrial structure enhances further, from energy-intensive heavy industry to service and technology-intensive industries, pollution falls as income grows. The upgrading of industrial structure needs the support from technology. Technical progress makes it possible to replace the heavily polluting technology with cleaner technology. It is the tradeoff between scale effect and technology effect that the environment deteriorates at the first industrial structural change and improves at the second industrial structural change. So the relationship between environment and economic growth looks like inverted-U curve. The downward sloping portion of the environment and economic growth may be facilitated by advanced economies exporting their pollution-intensive production processes to less-developed countries (Suri and Chapman, 1998).

In another vein, international trade and FDI help explain the EKC hypothesis. International trade and FDI have contradictory impacts on environment. International trade, especially exports and inflows of FDI lead to increased use of land and natural resources, as well as encouraging consumption, which will cause more pollution due to more production and/or consumption, while international trade and FDI also have positive effects on environment via composition effect and/or technology effect which are attributed to *Displacement Hypothesis* and *Pollution Haven Hypothesis* (Dinda, 2004). To developing countries, FDI might bring in improved efficiency and cleaner technology, which offers opportunities to improve the most damaging phases of industrialization (Goldemberg, 1998). Pollution emissions may drop due to trade openness, since the economies gain more environment awareness under grater competitive pressure. But trade and FDI might facilitate advanced economies to export their pollution-intensive production processes to less-developed countries due to different environmental stringent policies (Suri and Chapman, 1998). This will speed up the pollution level of less-developed countries. As Arrow, et. al. (1995) and Stern, et. al. (1996) pointed out, if there was an EKC type relationship, it might be partly or largely a result of the effects of trade on the distribution of polluting industries.

## III. Empirical Methodology

To begin, the nature of the data distribution of each variable is examined by descriptive statistics. To examine the time series property of each variable, Augmented Dickey-Fuller Test (Dickey and Fuller , 1981;Fuller , 1996) and KPSS(Kwiattkowski, et al., 1992) tests have been applied, although such pre-testing is optional inthe Autoregressive Distributed Lag (ARDL) model.

In the event of non- stationarity of variables, themost commonly used procedures for ascertaining the cointegrating relationship include Engle – Granger (1987) residual –based procedure and Johansen-Juselius ( 1992, 1999) maximum likelihood-based procedure.Both procedures concentrate on cases in which the underlying variables are integrated of order one. But it is highly unlikely in the real world. To address the issue of unequal order of integration of non-stationary variables for long-term equilibrium relationship and causal flows, Autoregressive Distributed Lag (ARDL) model or bound testing procedure suggested by Pesaran et al. (2001) has been used in this study.It is applicable irrespective of whether the regressors in the model are purely I(0), andI(1) or mutually integrated. Another advantage of this approach is that the model takes sufficient number of lags to capture the data generating process (DGP) in a General to Specific (GETS) modeling framework (Laurenceson and Chai, 2003). A dynamic error-correction model (ECM) can also be derived from ARDL procedure through a simple linear transformation (Banerjee et al., 1993). The ECM integrates the short–run dynamics with the long run equilibrium relationship without losing long-term memory.

The ARDL procedure based on bound testing approach uses the following unrestricted model as found in Pesaranand Shin,1999, Pesaran, Shin, and Smith, 2001.Assuming a unique long –run relationship among the weakly exogenous independent variables, the following estimating Vector Error-Correction Model (VECM) is specified:

$$\Delta lnCar_t = \alpha_0 + \sum_{i=1}^{p} \mathrm{b}_{\Delta \ln \mathrm{Car}_{t-i}} + \sum_{i=0}^{p} \mathrm{c}_{\Delta \ln \mathrm{Ind}_{t-i}} + \sum_{i=0}^{p} \mathrm{d}_{\Delta \mathrm{lni\,fdi}_{t-i}} + \sum_{i=0}^{p} \mathrm{e}_{\Delta \ln \mathrm{Pop}_{t-i}}$$

$$+\lambda_1 lnCar_{t-1} + \lambda_2 lnInd_{t-1} + \lambda_3 lnFdi_{t-1} + \lambda_4 lnPop_{t-1} + \varepsilon_t \qquad (1)$$

where, Car = carbon dioxide ($CO_2$) emission, lnd = industrial output, Fdi = foreign direct investment and Pop = population size. All first-differenced variables here are in natural logs. To implement the bound testing procedure,the following steps are outlined:

First, testing for weak exogeneity, Autoregressive Distributed Lag (ARDL) procedure is implemented through VAR pair-wise Granger Causality/Block Exogeneity Wald Tests.Johansen

(1992) stated that the weak exogeneity assumption influences the dynamic properties of the modeland must be tested in the full system framework.

Second,equation (1)has been estimated by Ordinary Least Squares (OLS) in order to test for the existence of a cointegrating relationship among the variables through conducting F-test for the joint significance of the coefficients of the lagged variables in levels. The null and the accompanying alternative hypotheses for the cointegrating relationship are

Ho: $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ for no cointegration

Ha: $\lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 = 0$ for cointegration

If the calculated F-statistic is above its upper critical value, the null hypothesis of no long-run relationship can be rejected irrespective of the orders of integration for the time series. Conversely, if the calculated F-statistic falls below its lower critical value, the null hypothesis cannot be rejected. If the calculated F-statistic falls between its lower and upper critical values, the inference remains inconclusive.

Third, on the evidence of cointegrating relationship, the following conditional ARDL ($p_1$, $q_1$,$q_2$, $q_3$)is estimated:

$$lnCar_t = \alpha_0 + \sum_{i=1}^{p1} \alpha_{1\,\ln \mathrm{Car}_{t-i}} + \sum_{i=0}^{q1} \alpha_{2\,\ln \mathrm{Ind}_{t-i}} + \sum_{i=0}^{q2} \alpha_{3\,\mathrm{fdi}_{t-i}} + \sum_{i=0}^{q3} \alpha_{4\,\ln \mathrm{Pop}_{t-i}} + \omega_t$$

(2)

The optimum lag orders in the above are selected by the Akaike Information Criterion(AIC)as found in Akaike (1969). The optimum lagsare selected appropriately to reduce residual serial correlation and to avoid overparameterization. According to the recommendation of Pesaran and Shin (1999) for annual data, a maximum of two lags are selected.

For subsequent use in the vector error-correction model, the error-correction term ($ECM_{t-1}$) is obtained from the following equation:

$$ECM_{t-1} = lnCar_t - (\widehat{\alpha_0} + \sum_{i=1}^{p1} \widehat{\alpha_1}\ {}_{\ln Car_{t-i}} + \sum_{i=0}^{q1} \widehat{\alpha_2}\ {}_{\ln Ind_{t-i}} + \sum_{i=0}^{q2} \widehat{\alpha_3}\ {}_{lnfdi_{t-i}} + \sum_{i=0}^{q3} \widehat{\alpha_4}\ {}_{\ln Pop_{t-i}}$$

(3)

Finally, the short –run and long-run dynamics are captured by estimating the following vector error-correction model:

$$\Delta lnCar_t = \beta_0 + \sum_{i=1}^{p} \beta_{1\ \Delta\ln Car_{t-i}} + \sum_{i=0}^{p} \beta_{2\ \Delta\ln Ind_{t-i}} + \sum_{i=0}^{p} \beta_{3\ \Delta lnfdi_{t-i}} + \sum_{i=0}^{p} \beta_{4\ \Delta\ln Pop_{t-i}} + \psi ECM_{t-1} + \mu_t \qquad (4)$$

Where, β's are the coefficients relating to the short –run dynamic elasticities and $\psi$ is the speed of adjustment to the long-run equilibrium associated with the error-correction term, $ECM_{t-1}$. The expected sign of $\bar{\psi}$ is negative. Its statistical significance is reflected through the associated t-value and its numerical magnitude indicates the speed of adjustment toward long-run convergence.

Annual data from 1972 through 2008 are employed in this study. The number of sample observations is relatively small for meaningful cointegration analyses. But large sample period can partially overcome this problem (Hakkio and Rush, 1991). In contrast, when sample period is relatively small, high frequency data may partially compensate for this deficiency (Zhou, 2001). $CO_2$ emission data are in per capita term in metric tons excluding emissions from land use and agriculture, obtained from the Carbon Dioxide Information Analysis Center at the Oak Ridge National Laboratory (2009), Tennessee. Industrial production data are at constant 2000 (US dollar) and obtained from World Development Indicators (2009), World Bank. FDI data are nominal and in US dollar, obtained also from World Development Indicators (2009), World Bank. Population data are obtained from various issues of International Financial Statistics, IMF.

## III. Results

The data descriptors are reported as follows:

*Table 1: Descriptive Statistics*

| Descriptors | LnCAR | LnIND | lnFDI | LnPOP |
|---|---|---|---|---|
| Mean | -2.055147 | 22.06820 | 197.8619 | 4.696007 |
| Median | -2.009915 | 21.99266 | 7.000000 | 4.698296 |
| Maximum | -1.241329 | 23.25308 | 1086.300 | 5.075174 |
| Minimum | -2.995732 | 20.53408 | -8.000000 | 4.282068 |
| Std. Dev. | 0.512581 | 0.668197 | 300.1324 | 0.238232 |
| Skewness | -0.044043 | -0.025962 | 1.361373 | 0.006122 |
| Kurtosis | 1.780291 | 2.225368 | 3.776772 | 1.844811 |
| | | | | |
| Jarque-Bera | 2.305483 | 0.929240 | 12.35910 | 2.057524 |
| Probability | 0.315770 | 0.628374 | 0.002071 | 0.357449 |
| | | | | |
| Sum | -76.04045 | 816.5233 | 7320.889 | 173.7523 |
| Sum Sq. Dev. | 9.458613 | 16.07352 | 3242861. | 2.043155 |
| | | | | |
| Observations | 37 | 37 | 37 | 37 |
| | | | | |

A cursory inspection of Table 1 reveals that all descriptive statistics including Jarque-Bera corroborate normal distribution of each variable except lnFDI.Weak exogeneity test results are reported in Table 2 as follows.

*Table 2: Weak Exogeneity Tests (VAR Pair wise Granger Causality / Block Exogeneity Wald Tests)*

| Dependent variable: LNCARBON | | | |
|---|---|---|---|
| Excluded | Chi-sq | Df | Prob. |
| LNIND | 28.36388 | 3 | 0.0000 |
| LNFDI | 34.33534 | 3 | 0.0000 |
| All | 36.85419 | 6 | 0.0000 |

Considering population (lnPop) as exogenous to the system and treating Ln IND and Ln FDI as weakly exogenous, the parameter of the conditional scalar variable (LnCar) is meaningfully estimated independently of the marginal distribution ofLnIND and LnFDI following (Johansen 1992; Pesaran & Shin & Smith 2001). The Chi-sq value from the underlying VAR model is 36.85419 with P-value 0.0000. This indicates that all level variables are exogenous globally. The individual Chi-sq value values also support this finding.

The time series property of each variable is examined by both ADF test and its counterpart KPSS test. The results are reported in Table 3 as follows:

*Table 3: Unit Root Tests (ADF and KPSS)*

| Variables | ADF | | KPSS | |
|---|---|---|---|---|
| | Level | 1st Difference | Level | 1st Difference |
| lnCAR | -0.694050 | -5.970553* | 0.732201* | |
| lnIND | 1.810694 | -2.429028 | 0.745831 | 0.184255* |
| lnFDI | 0.248215 | -6.241580* | 0.611091* | |
| lnPop | -1.075871 | -6.127511* | 0.729319* | |

The Mackinnon (1996) ADF critical values are -3.752946 and - 2.998064 at 1 percent and 5 percent levels of significance, respectively. The KPSS critical values (Kwiatkowski, et al., 1992, Table 1) are 0.73900 and 0.46300 at 1 percent and 5 percent levels of significance, respectively. * indicates stationarity of the variables.

Table 3 reveals nonstationarity of each variable with different orders of integration. Subsequently, the estimates of equation (1) for cointegration are reported in Table 4 as follows:

*Table 4: F-Statistics for Cointegration Relationship*

| Dep. Var. | F Statistics | Probability | Out come | |
|---|---|---|---|---|
| $F_{CAR}$ (CAR\|IND, FDI,POP) | 4.640954 | 0.001 | Cointegration | |
| $F_{IND}$ (IND \| CAR, FDI,POP) | 3.72323 | 0.004 | No cointegration | |
| $F_{FDI}$ (FDI (\| CAR, IND,POP) | 2.08841 | 0.067 | No Co integration | |
| $F_{POP}$ (POP \| CAR, IND,POP) | 1.26949 | 0.306 | No Cointegration | |

The asymptotic critical Value bounds are min F= 2.86 & Max F=4.01 at 5% (Table C1 iii. unrestricted intercept and no trend, Pesaranet al. (2001).

Table 4 illustrates the results of the calculated F-statistics when each variable is considered as a dependent variable (normalized) in the ARDL-OLS regressions. The calculated F-statistics, F car (Car| Ind, FDI, POP) = 4.640954 is higher than upper bound critical value of 4.01 at the 5% level. Moreover, none of the estimated coefficients of LnCar, LnInd, LnFdi and LnPop as represented by $\lambda_1$, $\lambda_2$ ,$\lambda_3$ and $\lambda_4$respectively is equal to 0. This is an affirmation of presence of a long-run equilibrium relationships among the variables. Thus, the null hypothesis of no cointegration is rejected, implying a long–run cointegrating relationshipamong the variables when regressions are normalized on $CO_2$ variable.

On the evidence of a cointegrating relationship, equation (2) is estimated using the following ARDL (2,2,1,1) specification to unveil the long-run relationship. The results obtained by normalizing on per capita $CO_2$emissionin the long run are reported in Table 5, as shown below:

*Table 5: ARDL Long Run Estimation of LnCAR (2,2,1,1).*

| Variables | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -14.62797 | 0.949170 | -15.41133 | 0.0000 |
| lnIND | 0.235969 | 0.093491 | 2.523979 | 0.0166 |
| lnFDI | -8.79E-05 | 5.41E-05 | -1.623435 | 0.1140 |
| lnPOPU | 1.572144 | 0.256271 | 6.134686 | 0.0000 |

The estimated coefficients show that both industrial production as well as population havestatistically significanthigh positive impacts on $CO_2$ emissions in Bangladesh.Growing industrialization shows a serious threat to environment. Toxic wastes from industries and factories, mostly established on the banks of the rivers, contaminate the water of the rivers as wastesare not being treated by affluent treatment plants (ATP) which is although mandatory for factories that dispose of toxic wastes. Population growth contributes to the degradation of environment through contaminating drinkable water and clogging the sanitation pipes. Also, numerous vehicles and traffic congestions in the capital city, increasing uses of refrigerators, and air coolers are prone to $CO_2$ emissions.Furthermore, lnFDI has negative effect on $CO_2$emissions, although it is statistically insignificant. It means inflow of Foreign Direct Investment (FDI) in Bangladesh contributes marginally in reducing $CO_2$ emissions in Bangladesh. This is a result of foreign-owned enterprises'compliances with the environmental standards set by the Department of Environment (DoE).

The estimates of VECM as specified in equation (4) are reported in Table 6 as follows:

*Table 6: ARDL (2,2,1,1) Vector Error-Correction Model of LnCAR*

| Variables | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| Constant | 0.036778 | 0.043873 | 0.838287 | 0.4105 |
| $ECM_{t-1}$ | -0.750210 | 0.238452 | -3.146169 | 0.0045 |
| Δ (LnCAR (-1)) | 0.212594 | 0.206878 | 1.027629 | 0.3148 |
| Δ (LnCAR(-2)) | 0.025375 | 0.192480 | 0.131834 | 0.8963 |
| Δ (LnIND) | 0.265894 | 0.286973 | 0.926548 | 0.3638 |
| Δ (LnIND(-1)) | -0.043218 | 0.146802 | -0.294395 | 0.7711 |
| Δ (LnIND(-2)) | 0.102055 | 0.108315 | 0.942202 | 0.3559 |
| Δ (FDI) | 1.84E-06 | 6.19E-05 | 0.029674 | 0.9766 |
| Δ (FDI(-1)) | 8.59E-05 | 7.66E-05 | 1.120598 | 0.2740 |
| Δ (LNPOP) | 1.098021 | 0.875253 | 1.254519 | 0.2223 |
| Δ (LNPOP(-1)) | -2.270883 | 0.752532 | -3.017656 | 0.0061 |
| R-squared | 0.529096 | Mean dependent var | | 0.045752 |
| Adjusted R-squared | 0.324356 | S.D. dependent var | | 0.053969 |
| S.E. of regression | 0.044361 | Akaike info criterion | | -3.136711 |
| Sum squared resid | 0.045262 | Schwarz criterion | | -2.642888 |
| Log likelihood | 64.32408 | Hannan-Quinn criter. | | -2.968303 |
| F-statistic | 2.584227 | Durbin-Watson stat | | 2.089146 |
| Prob(F-statistic) | 0.028935 | | | |

The estimated coefficient ($\hat{\lambda}$) of the error-correction term ($\widehat{ECM}_{t-1}$) at -0.750210 is highly significant in terms of the associated t-value with the expected negative sign and its numerical magnitude indicates significant speed of adjustment toward long-run convergence.In the short–term,interactive feedback effects are positive, but statistically insignificant in terms of the insignificant associated individual t-value. The DW-value at 2.089146 indicates near absence of autocorrelation. The numerical value of $\bar{R}^2$ shows that only32% of the change of $CO_2$ emission in Bangladesh is explained by the changes in industrial production, foreign direct investment and population. The F-statistic at 2.584227 suggests moderate interactive feedback effects within the system.

Furthermore, figures (1) and (2) show that both the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) plots from a recursive statement of the model lie within the 5 per cent critical bound. Thus, parameters of the Vector Error-Correction Modeldo not suffer from any structural instability i.e. there is strong evidence in favor of stable parameters.

**Plots of CUSUM and CUSUMSQ of Recursive Residuals (From ARDL, Vector Error Correction Model)**

Figure 1: CUSUM of Recursive Residuals

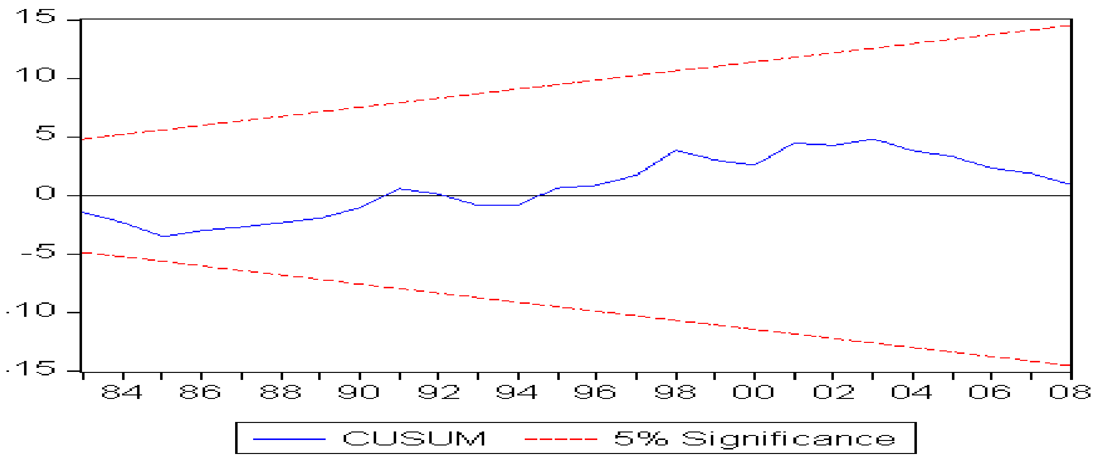
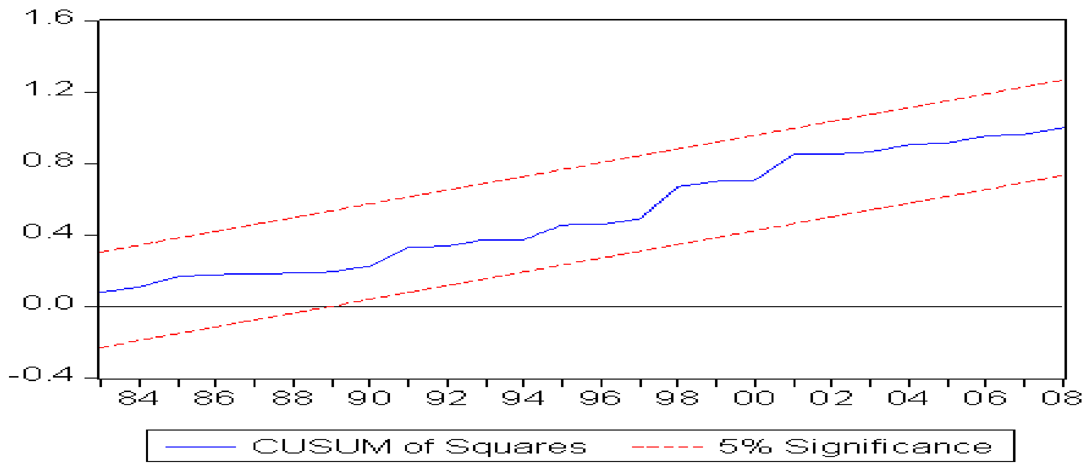



Figure 2: CUSUMSQ of Recursive Residuals



## IV. Conclusions and Remarks

All the variables under study are nonstationary in log-levels with different orders of integration. The estimates of ARDL model lend support to the existence of a cointegrating relationship among the variables. The estimates of the Vector Error-Correction Model depict a strong long-run causal flow from industrialization and population growth to $CO_2$ emissions in Bangladesh while that from growth in FDI is relatively subdued and statistically insignificant. There are evidences of short-run positive interactive feedback effects among the variables.

For policy implications, Bangladesh should be poised for larger emissions of $CO_2$ in an early phase of industrial expansion and in the face of rapid population growth in large cities. FDI inflow should be encouraged to mitigate the problem. Once achieving a certain prescribed level of per capita real GDP, the country should devote attention to improve environmental quality. At the same time, population growth should be kept in check in large cities by a wider geographic distribution of industries throughout the country. China can be a role model for Bangladesh in these respects.

In closing, environmental awareness in Bangladesh is surging slowly. Although $CO_2$ emissions have drawn worldwide attention, other common pollutants such as sulphur dioxide ($SO_2$), carbon monoxide (CO), nitrogen oxide ($NO_x$), ground-level ozone ($O_3$), hydrogen sulphide ($H_2S$), etc. should also be mitigated with due attention to improve the overall environmental quality in Bangladesh.

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