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Carbon Dioxide (CO_2) Emission in Three SAARC Countries: Determinants, Economic Growth and Environmental Policy Implications

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Abstract

ARDL model and VECM are estimated in the study as time series data on all variables are nonstationary in terms of both ADF and KPSS tests with different orders of integration. Bangladesh, Nepal and Maldives among SAARC countries have been selected for the study. There are evidences of cointegrating relationship among the variables, long-run causal flows from industrial output growth, population growth and FDI to carbon emissions in Bangladesh and Nepal. However, similar inferences are weak for Maldives as the associated t-value of the error- correction term (ECM_{t-1}) is not statistically significant. Short-run net positive interactive feedback effects among the variables are also evidenced. For abatement of carbon emissions and improvement in environmental quality, these three countries should adopt cost-effective and feasible short-term and medium-term strategies. At the same time, they should develop indigenous research capability to invest home-grown environment friendly technologies in the long run.

Keywords: carbon, emission, environment, cointegration.

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I. Introduction

Carbon emissions among all pollutants pose a serious problem for environmental degradation in developing countries. As hypothesized, it increases at an early stage of industrial expansion as a transition from overdependence on agriculture to manufacturing. Such 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 and regulatory compliance costs are exorbitant. The motivation for allowing foreign direct investment (FDI) is to promote job creation to exit extreme poverty. Moreover, the degree of environmental awareness is very low in developing countries. According to the recently disclosed Environmental Performance Index 2012, Bangladesh has been categorized as a modest improver country. Nepal is among the strongest performers (epi.yale.edu).

Once a developing country's per capita real income approaches a certain threshold, the country gains resources to invest in costly environment friendly technologies to mitigate the level of carbon emissions. As the country's economic structure later gradually transforms from manufacturing to expanding services sector, carbon emissions continue to decline. 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.

All the eight South Asian Association for Regional Cooperation (SAARC) countries (Bangladesh, Nepal, Bhutan, India, Maldives, Sri Lanka, Pakistan and Afghanistan) are low-carbon emitting countries due mainly to their slow transition toward industrialization. Being a densely populated area, this region should place added emphasis on industrialization to meet growing consumption demand and to create exportable surplus. This region also endeavors to entice FDI for job creation. At an early stage of industrialization, the above factors are likely to contribute to significant emissions of carbon in the region. Additionally, the level of environmental awareness is still relatively low in the region.

Although SAARC is a low carbon-dioxide emitting region, countries of this region particularly Bangladesh, Nepal and Maldives are likely to be worst sufferers of climate change. Considering the severity of potential adverse impacts of environmental change, policy makers should come up with policies to take necessary actions at least for minimizing internal causes for carbon emissions. There is an overwhelming consensus that these challenges are human-induced. As a result, industrialization, population growth and FDI are individually and collectively responsible for posing such enormous challenges.

The primary objective of this study is to find out the determinants of Carbon Dioxide (CO_2) Emission giving emphasis on variables associated with the economic growth in Bangladesh, Nepal and Maldives. To address this objective, the paper has taken endeavor to explore the roles of industrial production, FDI and rising population in determining the level of carbon emissions in these three countries in SAARC region by implementing the Autoregressive Distributed Lag (ARDL) model for cointegration, and long-run causality with short-run interactive feedback effects by estimating Vector Error-Correction Model (VECM). The remainder of the paper proceeds as follows. Section II briefly reviews the related literature.

Section III outlines the empirical methodology. Section IV reports results. Section V offers conclusions and policy measures.

II. Brief Review of Related Literature

Grossman and Krueger (1991) found that the long-term relationship between economic growth and environmental quality is an inverted U-shaped curve. The phenomenon has been labeled as Environmental Kuznets Curve (EKC) by Panayotou (1993). The EKC hypothesizes that environmental 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. The effect of economic growth on environmental quality is in much disputes in these studies.

Most of the empirical studies are based on multi-countries. In fact, EKC hypothesis is fundamentally a within-country story, but cross-sectional analyses assume that all 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 regulations and so on, although most of the empirical studies merely focused on income level. A growing world needs more inputs 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 trade-off 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).

International trade and FDI also 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 environmental awareness under greater 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

The nature of the data distribution of each variable is examined by a set of standard 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 in the Autoregressive Distributed Lag (ARDL) model.

In the event of non- stationarity of variables, the most commonly used procedures for cointegration include Engle and 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), and I(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 (Pesaran and Shin, 1999; Pesaran et al., 2001). Assuming a unique long–run relationship among the weakly exogenous independent variables, the following estimating Vector Error-Correction Model (VECM) is specified:

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

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

where, Car = carbon emissions, 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 model and 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:

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

$$\text{Ha: } \lambda_1 \neq \lambda_2 \neq \lambda_3 \neq \lambda_4 \neq 0 \text{ for cointegration}$$

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 variables. 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:

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

The optimum lag orders for the above are selected by the Akaike Information Criterion (AIC), as found in Akaike (1969). The optimum lags are selected appropriately to reduce residual serial correlation and to avoid over parameterization.

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

$$ECM_{t-1} = lnCar_t - (\widehat{\alpha_0} + \sum_{i=1}^{p1} \widehat{\alpha_1} \ln \mathrm{Car}_{t-i} + \sum_{i=0}^{q1} \widehat{\alpha_2} \ln \mathrm{Ind}_{t-i} + \sum_{i=0}^{q2} \widehat{\alpha_3} \ln \mathrm{Fdi}_{t-i} + \sum_{i=0}^{q3} \widehat{\alpha_4} \ln \mathrm{Pop}_{t-1} \qquad (3)$$

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

$$\Delta lnCar_t = \beta_0 + \sum_{i=1}^{p} \beta_{1\ \Delta \ln \mathrm{Car}_{t-i}} + \sum_{i=0}^{p} \beta_{2\ \Delta \ln \mathrm{Ind}_{t-i}} + \sum_{i=0}^{p} \beta_{3\ \Delta \ln \mathrm{Fdi}_{t-i}} + \sum_{i=0}^{p} \beta_{4\ \Delta \ln \mathrm{Pop}_{t-1}} + \psi \mathrm{ECM}_{t-1} + \mu_t \quad (4)$$

Where, β's are the coefficients relating to the short –run dynamic elasticities and ψ is the speed of adjustment to the long-run equilibrium associated with the error-correction term, ECM_{t-1}. The expected sign of $\hat{\psi}$ 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 2010 are employed for Bangladesh and Nepal. For Maldives, annual data from 1984 to 2010 are used since data availability is limited. The number of sample observations seems 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). Carbon emissions data are in per capita term and 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.

IV. Results

The standard data descriptors are reported, as follows:

Table 1: *Descriptive Statistics*

Variables	Bangladesh				Nepal				Maldives			
Descriptors	LnCAR	LnIND	lnFDI	LnPOP	LnCAR	LnIND	lnFDI	LnPOP	LnCAR	LnIND	lnFDI	LnPOP
Mean	-2.06	22.17	197.86	4.70	-4.11	20.09	13.32	16.77	-1.15	20.64	16.45	12.42
Median	-2.01	21.99	7.00	4.70	-4.61	20.11	13.42	16.76	-1.08	20.50	16.21	12.44
Std. Dev.	0.51	0.67	300.13	0.24	0.56	0.73	2.44	0.26	0.72	0.75	1.13	0.16
Skewness	-0.04	-0.03	1.36	0.01	0.34	-0.22	1.54	-0.01	-0.30	0.20	2.10	-0.42
Kurtosis	1.78	2.23	3.78	1.84	1.30	1.63	4.95	1.76	1.83	1.96	6.96	2.00
Jarque-Bera	2.31	0.93	12.36	2.06	5.18	3.22	20.52	2.37	1.80	1.29	34.68	1.78
Probability	0.32	0.63	0.00	0.36	0.08	0.20	0.00	0.31	0.41	0.52	0.00	0.41

A cursory inspection of Table 1 reveals that all descriptive statistics including Jarque-Bera support normal distribution of each variable excepting ln FDI in each country .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						
Variables	**Bangladesh**		**Nepal**		**Maldives**	
Excluded	**Chi-sq**	**Prob.**	**Chi-sq**	**Prob.**	**Chi-sq**	**Prob.**
LNIND	28.36	0.00	4.42	0.11	7.50	0.02
LNFDI	34.34	0.00	5.22	0.07	7.21	0.03
All	36.85	0.00	9.58	0.05	10.51	0.03

Considering population (lnPop) as exogenous to the system and treating LnIND and Ln FDI as weakly exogenous, the parameter of the conditional scalar variable (LnCar) is meaningfully estimated independently of the marginal distribution of LnIND and LnFDI following (Johansen 1992; Pesaran et al., 2001). The Chi-Square value from the underlying VAR model is 36.85 with P-value of 0.00 for Bangladesh. The Chi-Square values for Nepal and Maldives are also significant with P-values of 0.05 per cent and 0.03 percent, respectively. These indicate that all level variables are exogenous, globally. The individual Chi-Square values for all variables excepting LnIND for Nepal also reaffirm 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)*

	Bangladesh				**Nepal**					**Maldives**				
	ADF		**KPSS**		**ADF**			**KPSS**		**ADF**			**KPSS**	
Variables	Level	1^{st} Diff.	Level	1^{st} Diff.	Level	1^{st} Diff.	2^{nd} Diff.	Level	1^{st} Diff.	Level	1^{st} Diff.	2^{nd} Diff.	Level	1^{st} Diff.
lnCAR	-0.69	-5.97*	0.73*		-0.82	-2.17	-9.80*	0.60*		-1.42	-7.60*		0.72*	0.27
lnIND	1.81	-2.43	0.75	0.18*	-2.89	-4.47	-6.21*	0.71*	0	1.07	-4.05*		0.73	0.20*
lnFDI	0.25	-6.24*	0.61*		-2.21	-12.97*		0.32*		6.61	-0.29	0.32	0.59*	
lnPop	-1.08	-6.13*	0.73*		-3.37*	-2.02		0.73*		0.48	-8.64*		0.72*	

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 of three countries 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*

Country	Dependent Variable	F-Statistics	Probability	Findings
Bangladesh	FCAR (CAR|IND, FDI,POP)	4.64	0.001	Cointegration
Nepal	FCAR (CAR|IND, FDI,POP)	25.07	0.000	Cointegration
Maldives	FCAR (CAR|IND, FDI,POP)	73.17	0.000	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, Pesaran, et al. (2001).

Table 4 illustrates the results of the calculated F-statistics when carbon emissions is considered as a dependent variable (normalized) in the ARDL-OLS regressions. The calculated F-statistics, F car (Car| Ind, FDI, POP) for Bangladesh, Nepal and Maldives are 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 of three countries, as represented by λ_1, λ_2 ,λ_3 and λ_4, respectively is equal to 0. This confirms a long-run equilibrium relationship among the variables. Thus, the null hypothesis of no-cointegration is rejected, implying a long–run converging relationship among the variables when regressors are normalized on carbon emission variable.

On the evidence of a cointegrating relationship for Bangladesh, Nepal and Maldives, equation (2) is estimated using the following ARDL (2,2,1,1),(1,3,2,3) , (2,1,1,2) specification, respectively to unveil the long-run relationship. The results obtained by normalizing on per capita carbon emissions in the long run are reported in Table 5, as shown below:

Table 5: *ARDL Long-Run Estimation of LnCAR (2,2,1,1) (1,3,2,3)and(2,1,1,2) for Bangladesh, Nepal and Maldives, respectively.*

Variables	Bangladesh		Nepal		Maldives	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
C	-14.62797	-15.41133	-18.28504	-1.315347	-43.60645	-5.075393
lnIND	0.235969	2.523979	0.626985	1.291873	0.437340	1.058654
lnFDI	-8.79E-05	-1.623435	1.61E-08	2.291862	-4.01E-09	-0.974882
lnPOPU	1.572144	6.134686	0.096548	0.068855	2.711121	1.996263

The estimated coefficients show that both industrial production as well as population have positive impacts on carbon emissions in Bangladesh, Nepal and Maldives. However, associated t-values for Bangladesh are statistically significant for both industrial production and population. In Maldives, t-value is statistically significant only for population. For Nepal, t-values are statistically insignificant for both variables. Growing industrialization in Bangladesh 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 wastes are not being treated by effluent treatment plants (ETP), although mandatory for factories that dispose of toxic wastes. Population growths in both Bangladesh and Maldives contribute 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 carbon emissions. A similar inference is weak for Nepal, although both variables increase carbon emissions. Furthermore, lnFDI has a negative effect on carbon emissions in Bangladesh and Maldives despite statistical insignificance. It means that inflow of

FDI contributes marginally in reducing carbon emissions in Bangladesh and Maldives. This is a result of foreign-owned enterprises' compliances with the environmental standards set by the Environment authorities of these countries. Surprisingly, FDI has statistically significant positive impact on carbon emissions in Nepal. The estimates of VECM, as specified in equation (4), are reported in Table 6, as follows:

Table 6: *ARDL (2,2,1,1), (1,3,2,3) and (2,1,1,2) Vector Error-Correction Model of LnCAR for Bangladesh, Nepal and Maldives, respectively.*

Variables	**Bangladesh**		**Nepal**		**Maldives**	
	Coefficient	**t-Statistic**	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
Constant	0.036778	0.838287	-13.34850	-8.346039	0.971179	4.809651
ECM_{t-1}	-0.750210	-3.146169	-0.359413	-2.097907	-0.233687	-0.409930
Δ (LnCAR (-1))	0.212594	1.027629	0.510617	2.319404	0.185255	0.403678
Δ (LnCAR(-2))	0.025375	0.131834			0.170903	0.527416
Δ (LnIND)	0.265894	0.926548	0.296861	0.444817	-0.045947	-0.081328
Δ (LnIND(-1))	-0.043218	-0.294395	0.115450	0.214922	-0.203330	-0.304168
Δ (LnIND(-2))	0.102055	0.942202	-0.328096	-0.554911		
Δ (LnIND(-3))			-0.070949	-0.133191		
Δ (FDI)	1.84E-06	0.029674	5.54E-09	1.093337	4.34E-09	1.099252
Δ (FDI(-1))	8.59E-05	1.120598	5.54E-09	0.710142	-1.07E-10	-0.015804
Δ (FDI(-2))			6.63E-09	1.089212		
Δ (LNPOP)	1.098021	1.254519	5677.042	4.388610	-556.2310	-1.384827
Δ (LNPOP(-1))	-2.270883	-3.017656	-12102.33	-3.638930	921.1999	1.261507
Δ (LNPOP(-2))			10830.07	3.455577	-459.3220	-1.334988

Δ (LNPOP(-3))			-4030.078	-3.737785		
Adjusted R-squared	0.324356		0.926101		0.946950	
F-statistic	2.584227		28.95608		38.48546	
Prob(F-statistic)	0.028935		0.000000		0.00000	
Durbin-Watson stat	2.089146		2.144061		1.754535	

Table 6 reveals that the coefficient of the error-correction term (ECM_{t-1}) for each country has expected negative sign. But the associated t-values for Bangladesh and Nepal are statistically significant. For Maldives, associated t-value is statistically insignificant. The aforementioned results imply a significant long–run causal flow to carbon emissions in Bangladesh and Nepal from the explanatory variables. In addition, numerical magnitudes of the coefficients of ECM_{t-1} (Bangladesh= - 0.750210, and Nepal= - 0.359413) indicate significant-to-moderate speed of adjustment toward long-run convergence in both Bangladesh and Nepal. For Maldives, such evidence is relatively weak. There also exists evidence of net positive feedback effects for each country in the short run, although mostly statistically insignificant. The DW-values indicate near absence of autocorrelation for Bangladesh and Nepal, but it shows mild positive autocorrelation for Maldives. The respective F-statistic is also significant excepting Bangladesh. The numerical values of $\bar{R}^2$ show that 32%, 92% and 94% of the changes in carbon emissions respectively in Bangladesh, Nepal and Maldives, are explained by independent variables.

V. Conclusions and Policy Measures

To sum up, all variables under study are nonstationary in natural log 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 carbon emissions in Bangladesh and only from population growth to carbon emissions in Maldives. A strong long-run causal flow is also observed from FDI to carbon emissions in Nepal. Long-run causal flows from other explanatory variables to carbon emissions are relatively subdued in all three countries. Short-run positive interactive feedback effects among the variables are also evidenced.

For policy implications, Bangladesh should expect larger carbon emissions in an early phase of industrial expansion and in the face of rapid population growth in large cities. FDI inflow of regulation complaint firms should be encouraged to mitigate the problem. Once achieving a certain prescribed level of per capita real GDP, the country should devote greater 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. In Nepal, enactment and implementation of suitable policies are necessary specially to stop relocating of polluting industries in Nepal from more stringent locales. At the same time, industrialization with balanced population growth and distribution is also a cause of concern for the country in this regard. Finally, growth and concentration of population are needed to be kept in check to reduce this problem in Maldives. Moreover, industrialization taking into account the environmental issues and enticement of more environment friendly FDI deserve due attention to mitigate this problem.

Environmental awareness in the region is surging slowly. Although carbon 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 emphases to improve the overall environmental quality in the region.

To add further, Bangladesh, Maldives and Nepal are classified as very low-income countries in the world. They all confront severe balance of payment constraints and inadequacies of external resources. These make them unlikely to embark upon adoption of the latest and costly green technologies that are to be imported from the developed countries subject to granted access to them. Despite such limitations, they have a host of feasible other options for pollution abatement. Some of these options may include i) revamping of environmental regulations with stricter enforcement, ii) support and subsidy programs for environment friendly firms, iv) discouragement for uses of black coal for cement production and bricks burning, v) massive programs for tree-plantation and recovery from deforestation, vi) gradual introduction of environment friendly ground transportation, vii) mitigation of traffic congestion in big cities, viii) creation of job opportunities in rural areas to lessen intense population pressures in large metropolies, ix) financial incentives for indigenous research for inventing cost-effective home-grown green technologies, and x) discontinuation of entry for foreign dirty firms.

Some of the aforementioned measures may create strains on domestic fiscal resources and cause erosion in global competitiveness for export firms in the short run. But the long-term gains will vastly outweigh short-run sacrifices. These three selected SAARC countries must adopt “go green” mantra before it is too late since they appear to be the most vulnerable countries in the region to climate change primarily caused by global warming and deforestation.

This paper has several limitations. One of them is the utilization of annual data over a relatively short sample period for meaningful cointegration analyses. To overcome this problem partially, panel cointegration methodology can be applied in future research with pooled data for all eight SAARC countries.

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