Proceedings of the Australasian Conference on Business and Social Sciences 2015, Sydney
(in partnership with The Journal of Developing Areas)
ISBN 978-0-9925622-1-2

FORECASTING CARBON EMISSION AND INDUSTRIAL PRODUCTION WITH VECM: THE CASE OF BANGLADESH

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ABSTRACT

The key objective of this study is to forecast and analyse the causality and long run association between carbon dioxide (CO_2) emissions and industrial production using Vector Error Correction Model (VECM). Other econometric techniques, such as unit root test and Granger causality test have also been used to achieve the objective in a comprehensive way. The empirical results reveal that for Bangladesh there is no Granger causality between industrial production and CO_2 emission in any direction. The results from VECM reveal for Bangladesh that any disequilibrium between CO_2 emission and industrial production could take approximately 54 years to converge to the long-run equilibrium. The adjustment rate for the country's industrial production is positive, as it should be, as well as relatively faster at the rate of 83 percent a year. So any disequilibrium will be corrected mostly by the adjustment in the country's industrial production. The study concludes that the current CO_2 emission in Bangladesh is below the equilibrium level, which is an advantageous situation for the country. Therefore, it is expected that the Bangladesh's industrial sector will not face stricter CO_2 emission controlling policies and regulations in the near future.

JEL Classifications: Q510, Q530, Q560
Key words: CO_2 emissions; industrial production; Granger causality; long-run equilibrium; Bangladesh
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INTRODUCTION

It is apparent that carbon dioxide (CO_2) emissions arising from industrialised and industrialising countries' industrial processes are substantial. The industrial processes combine input and raw materials to produce goods and services, which result in large amounts of CO_2 emissions. Evidence suggests that nearly a third of the world's energy consumption and 36% CO_2 emissions are attributable to manufacturing industries (International Energy Agency, 2007). The bulk of these CO_2 emissions are related to the large primary materials industries, such as chemicals and petrochemicals, iron and steel, cement, pulp and paper, and aluminium. Even though over the last decade global industrial energy efficiency has improved and CO_2 emission has declined substantially in many sectors, this progress has been more than offset by growing industrial production worldwide. Consequently, total industrial energy consumption and CO_2 emissions have continued to rise. Scientists predict that over the next 40 years, demand for industrial materials in most sectors is expected to double or triple. Therefore, CO_2 emission reductions are vital across the whole of industry, but action is particularly crucial in the five most energy-intensive sectors, namely iron and steel, cement, chemicals and petrochemicals, pulp and paper, and aluminium. Therefore, these industrial sectors in any country need to play a greater role to reduce CO_2 emissions in the country.

Some studies have analysed the relationship between industrial/manufacturing production and CO_2 emissions for various countries/regions including the United States, European Union, Great Britain, Korea, and Taiwan. All these studies have revealed the fact, among others, that industrial/manufacturing activities result in significant volumes of CO_2 emissions. In fact, manufacturing and industrial processes all combine to produce large amounts of each type of greenhouse gas but specifically large amounts of CO_2 because of the following two reasons: first, many manufacturing facilities directly use fossil fuels to create heat and steam needed at various stages of production and second, their energy intensive activities use more electricity than any other sector so unless they are using renewable sources the energy that they use is responsible for vast amounts of emissions (United States Department of Energy 2005, 2002). Since the industrial/manufacturing sectors have apparently been proven as the significant contributors to the CO_2 emissions, they reasonably have substantial potential in reducing the same. A study by International Energy Agency reveals that the industrial CO_2 emissions reduction potential amounts to 1.9 to 3.2 gig tonnes per year, about seven to 12% of today's global CO_2 emissions (International Energy Agency, 2007).

Also a very recent study by the United States Environmental Protection Agency reveals that the largest source of CO_2 emissions globally is the combustion of fossil fuels such as coal, oil and gas in power plants, automobiles, industrial facilities and other sources (United States Environmental Protection Agency, 2011). This study further reveals that a number of specialised industrial production processes and product uses such as mineral production, metal production and the use of petroleum-based products can also lead to CO_2 emissions. Studies on the European Union and the Great Britain also reveal similar findings. Referring to Britain, a study by the Committee on Climate Change stated that as the economy and industrial production return from recession to growth, CO_2 emissions will rise again (Committee on Climate Change, 2010). The study on European Union reveals that global downturn is forcing industrial installations to cut back on production and therefore on their CO_2 emissions (Singh, 2007).

The empirical findings from some studies on Asian countries are also found to have matched with those obtained on the United States, European Union, and Great Britain. For example, the rate of growth of industrial CO_2 emissions has drastically decreased since the 1998 financial crisis in Korea (Lim *et al.*, 2009). This study further reveals that of all the individual factors, economic growth accounted for the largest increase in CO_2 emissions in Korea. The empirical results of a similar study conducted on Taiwan indicate that industrial production has the closest relationship with aggregate CO_2 emission changes (Chang & Lin, 1999). Also the empirical results obtained by another study on Taiwan indicate that the primary factor for the increase of CO_2 emission is the level of domestic final demand and exports (Chang & Lin, 1998). Moreover, some recent studies have studied the link between firms' CO_2 emission strategy and their performance in a comprehensive way. The results of one of those studies conducted by Lee (2012) indicated a significant relationship between a firms' carbon strategy and its sector and size. But a significant relationship between the carbon strategy and firm performance was not confirmed by that study. Another study by Sariannidis *et al.* (2013) revealed that a firm's financial performance is closely related to its environmental behaviour. The empirical findings of the study have also revealed that the performance of socially responsible firms is negatively related to an increase of global CO_2 emissions. That means firms' commitment to do corporate social responsibility does help decrease global CO_2 emissions. In fact, many firms are facing increasing pressure by governments, shareholders and other stakeholders to reduce their CO_2 emissions in order to mitigate climate change. The importance of managing CO_2 emissions and crafting adequate CO_2 strategies has increased for those firms affected (Weinhofer & Hoffmann, 2010). This study found that firms with different CO_2 emissions reduction strategies significantly differ in terms of company size and absolute amount of CO_2 emissions they contribute.

Furthermore, the study by Alvarez (2012) found an interesting finding revealing that CO_2 emission variation is a significant but negative variable for firm's rate on asset (ROA). This study, on the other hand, also revealed that CO_2 emission variation is insignificant but positive variable for rate on equity (ROE). A similar but very recent study conducted by Fujii *et al.* (2013) at Japanese context added further to the literature. The study argued that environmental performance increases ROA through both returns on sales and improved capital turnover and that there exists a significant positive relationship between financial performance and environmental performance based on CO_2 emissions. The authors of the Japanese study also argued that these findings may provide evidence for the consequences of firms' environmental behaviour and sustainable development. Another study by Boiral *et al.* (2012) argued that there is win–win relationship between the commitment to reduce greenhouse gas emissions and financial performance. But an earlier study by Sprengel and Busch (2011) found that firms' response strategies do not actually relate to individual stakeholder groups, but rather the firms' level of pollution measured as its greenhouse gas intensity is identified to have an influence on the environmental strategy. Nevertheless, stakeholders' influences on and their close associations with firms are still important for firms to get motivation to undertake sound environmental strategies will help reduce CO_2 emissions from their productions and operations. In fact, the firms that are close-to-consumers are more likely to undertake environmental activities for which there was no explicit cost-reduction benefit, suggesting that reputation with consumers/society may be a particular business motivator for them (Haddock-Fraser & Tourelle, 2010).

It is apparent from the above introductory context and reviews of extant and relevant studies that analysis and forecast of the causality and long-run relationship between carbon emission and industrial production are important for undertaking effective policies to tackle emission related problems and to minimise the emission to a tolerable level. Bangladesh, which has been growing considerably over the decade producing more industrial output than ever in history, is believed to have been significantly contributing to carbon emission, especially by its industrial production. This study is thus an effort to forecast and analyse the causality and long run trends of the country's carbon emission and industrial production using Vector Error Correction Model (VECM) and Granger causality test.

MATERIALS AND METHODS

Keeping the research hypothesis and objective in mind, this study has gathered relevant time series data and information from several secondary sources. The data for two time series variables covering the period from 1990 to 2007 were collected from the United Nations online database (http://data.un.org/). The variables were coded and entered accordingly into EViews 4.1 data analytical base. For example, the variable of Bangladesh carbon dioxide emissions (Thousands metric tons) was coded as *BDCO2* while Bangladesh industrial production index was coded as *BDIP*. Both series of variables were tested for stationarity or nonstationarity using the widely used augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for a unit root. In fact, the ultimate objective to conduct a unit root test in time series variables is to defend the econometric models against the characteristics of spurious time series regressions.

At the first stage of the models development, simple Ordinary Least Square (OLS) method was employed for the paired time series variables. This was done with the view of observing how and at what extent the results of OLS models will ultimately vary when both series are transformed into numerical log. The log linear regression model was then employed to observe if the paired variables provide any meaningful relationship. Hence, logarithmic dynamic equation was developed and actual fitted residual graph of the model was observed. Other features of the model such as serial correlation LM test, histogram normality test, and white heteroskedasticity (no cross terms) test were also observed here. A non-linear estimation for all the dependent variables was then conducted in their de-trended (1st difference) form. This was actually conducted to estimate the partial adjustment of the model and to find the estimates of the long-run parameters and the speed of adjustment directly. An ARIMA (1,1,1) estimation of all the dependent and independent variables was also conducted to forecast them and view their divergence or convergence graphically.

At the next and final stage, a Vector Error Correction (VEC) estimation of the paired time series was conducted in order to observe the long-run adjustment coefficients on cointregrated equation of the model. Since VEC model is a special type of restricted Vector Autoregression (VAR), which is an econometric model used to capture the evolution and the interdependencies between multiple time series, the unrestricted cointegration test and VEC Pairwise Granger Causality test were also reasonably conducted for the model. Other features of the combined model such as inverse roots of AR characteristics polynomial were checked and VEC lag exclusion Wald test, VEC residual serial correlation LM test, VEC residual normality test, VEC residual heteroskedasticity test, and impulse responses of the variables to Cholesky test were also conducted.

RESULTS AND DISCUSSIONS

Unit Root Test on Six Time Series Variables

This study has used advanced settings for the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests in order to specify how lagged difference terms are to be included in the unit root test equation. In this case, we have chosen to estimate a unit root test that includes level and intercept in the test regression and employs automatic lag length of 7 using a Schwarz Information Criterion for ADF test. For the PP test, however, the default spectral estimation method of Bartlett Kernel with an automatic selection of Newey-West Bandwidth was chosen. The ADF approach controls the higher order correlation by adding lagged difference terms of the dependent time series variable of Y to the right hand side of the regression. The generalized form of the ADF equation can be written as follows:

$DY_t = \mu + \delta Y_{t-1} + \beta_1 DY_{t-1} + \beta_2 DY_{t-2} + \cdots + \beta_p DY_{t-p} + \varepsilon_t$, where μ is a constant, β is the coefficient on a time trend and p the lag order of the autoregressive process. Imposing the constraints $\mu = 0$ and $\beta = 0$ corresponds to modeling a random walk and using the constraint $\beta = 0$ corresponds to modeling a random walk with a drift. Applying these settings to data on both time series variables for the period from 1991 to 2007, two types of unit root test results are described below in tables 1 and 2.

TABLE 1. AUGMENTED DICKEY-FULLER (ADF) TEST RESULTS FOR A UNIT ROOT IN TWO TIME SERIES VARIABLES

Series	ADF Test Statistic	Test Critical Values (t-statistic)			Probability*	Unit Root Test Decision
		1% Level	5% Level	10% Level		
LBDCO2	0.90	-4.30	-3.21	-2.75	0.98^{NS}	Nonstationary
LBDIP	-0.82	-3.89	-3.05	-2.67	0.79^{NS}	Nonstationary

*MacKinnon (1996) one sided p-values
NSNot significant (P>0.1)

The table 1 above reveals that the ADF test statistics values for both series are above the critical values at all levels (1%, 5%, and 10%) so that we cannot reject the null hypothesis of a unit root. It means that both series are clearly nonstationary in nature with default settings of level and intercept.

TABLE 2. PHILLIPS-PERRON (PP) TEST RESULTS FOR A UNIT ROOT IN TWO TIME SERIES VARIABLES.

Series	PP Test Statistic	Test Critical Values (t-statistic)			Probability*	Unit Root Test Decision
		1% Level	5% Level	10% Level		
LBDCO2	-0.37	-3.89	-3.05	-2.67	0.89^{NS}	Nonstationary
LBDIP	-0.83	-3.89	-3.05	-2.67	0.79^{NS}	Nonstationary

*MacKinnon (1996) one sided p-values
NSNot significant (P>0.1)

We also have used PP test in both time series variables to test the null hypothesis that a time series is integrated of order 1. It builds on the Dickey–Fuller test of the null hypothesis δ = 0 in $DY_t = \mu + \beta Y_{t-1} + \varepsilon_t$, where D is the first difference operator, μ is a constant, and β is the coefficient on a time trend. The table 2 above depicts that the PP test statistics values for both series are above the critical values at all levels (1%, 5%, and 10%). So we cannot reject the null hypothesis of a unit root. It further confirms that both series are clearly nonstationary in nature with default settings of level and intercept. Since the above two types of unit root tests clearly reveal that both time series variables are nonstationary, so our conclusions on the nature of data can be taken with confidence.

The presence of a unit root in both series suggests that we need to adopt more sophisticated econometric model. Hence we have chosen the Vector Error Correction Model (VECM) which is widely used for explaining the long-run relationships among the nonstationary time series variables. A VECM can lead to a better understanding of the nature of any nonstationarity time series variables and can also improve longer term forecasting over an unconstrained model. The basic building block of an ECM is an autoregressive distributed lag (ADL) specification for two or more variables with provisions for the possible long-run relationships among the variables (Patrick & Williams, 2007).

Nonlinear Least Square Estimation

Before developing a VECM with two time series variables of CO2 emissions and industrial production for Bangladesh, a simple nonlinear least squares (NLS) model was developed and this NLS model can be presented as: $BDCO2_t = f(BDIP_t, t, \theta) + u_t$, where $BDCO2_t$ is an endogenous variable and $BDIP_t$ is a vector exogenous variable, t is the time variable, θ is a vector or finite set of nonlinear parameters and u_t is a vector of the error terms. This conventional NLS estimation has produced a positive and highly significant (P<0.01) coefficient for *BDIP*, which simply indicates that Bangladesh as an economy tends to generate a higher amount of CO2 emissions with an increasing trend in its industrial production. We are not yet considering this finding as we are now going to estimate a logarithmic dynamic equation with the same variables and to conduct some diagnostic tests for the new model. The estimated logarithmic dynamic equation can be presented in a simple form as: $\log(BDCO2) = C + \log(BDIP) + \log(BDIP)_{t-1} + \log(BDCO2)_{t-1} + @TREND$, where $@TREND$ is a variable that goes 1, 2, 3, etc. and we then find the following estimates:

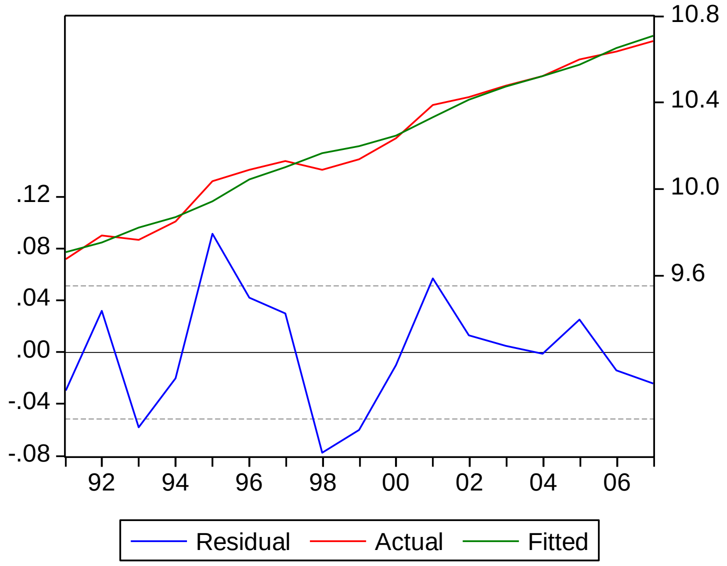
$$\begin{aligned}\log(BDCO2) = C(1) + C(2)\log(BDIP) + C(3)\log(BDIP)_{t-1} \\ + C(4)\log(BDCO2)_{t-1} + C(5)@TREND\end{aligned}$$

By substituting the model generated coefficient values, we can write the above equation as follows:

$$\begin{aligned}\log(BDCO2) = \underset{(2.29)}{6.64} - \underset{(-0.39)}{0.19\log(BDIP)} + \underset{(0.44)}{0.20\log(BDIP)_{t-1}} \\ + \underset{(1.22)}{0.31\log(BDCO2)_{t-1}} + \underset{(1.44)}{0.04(@TREND)}\end{aligned}$$

The results produced by the above logarithmic dynamic model show that the logarithmic form of Bangladesh industrial production is now negatively and insignificantly (P>0.1) affecting its CO2 emissions while the logarithmic form of $BDIP_{(t-1)}$ is still negatively and insignificantly (P>0.1) affecting the same with an adjusted R-squared of 0.98 for the model. The fitted residual graph (Figure 1) looks better now compared to the one we obtained in the previous NLS model. The Breusch-Godfrey serial correlation LM test for the model reveals that none of the lagged residuals is individually significant (t value is less than 2 and probability value is greater than 0.1) nor are they jointly significant as F-statistic probability value is 0.28. Therefore it is very clear that there is no serial correlation problem with the above equation. Under the residual tests, we also conducted the histogram-normality test and found that Jarque-Bera test statistic of 0.17 and a probability value of 0.92. That just means the model has passed the normality test. We then tested the model for heteroskedasticity problem and found that white heteroskedasticity (no cross terms) probability value is greater than 0.05. So there is no indication of heteroskedasticity, i.e., there is no significant difference among the sizes of the observations.

FIGURE 1. RESIDUAL GRAPHS OF THE LOGARITHMIC DYNAMIC MODEL FOR *BDCO₂* AND *BDIP*



The next stage of analysis deals with the estimation of a nonlinear version of the above model, which can primarily be presented in the following form:
$D(\log BDCO2) = C(1)*(C(2)+C(3)*\log BDIP - \log BDCO2_{t-1})$, where D is the first difference in data. This estimates the partial adjustment model giving estimates of the long-run parameters and speed of adjustment. However, the results obtained from the estimated model are approximately identical to the following equation: $\Delta d_t = \lambda(\theta_0 + \theta_1 e_t - d_{t-1}) + u_t$, and after substituting the coefficient values we can write the above equation as follows:

$$D(\log BDCO2) = \underset{(1.88)}{0.43}*(\underset{(17.18)}{6.51}+\underset{(10.36)}{0.91}*\log BDIP - \log BDCO2_{t-1})$$

The results reveal the fact that the adjusted R-squared of 0.09 is now considerably lower because the model is explaining the change in log *BDCO2*, not the level of log *BDCO2*. The estimated model further reveals that the long-run elasticity of *BDCO2* to *BDIP* is 0.91, which is significantly (P<0.01) different from convergence and the speed of adjustment is 43% a year. The finding from the estimation of an ARIMA (1,1,1) process in relation to this model reveals that *(logBDCO2)* series neither converge nor diverge (Figure 2) as it just tends to remain stable in the long-run. On the other hand, *(logBDIP)* series also shows a trend similar to the one we have observed for *(logBDCO2)* (Figure 3). The forecasting of *(logBDCO2)* reveals that both the AR (t = -0.37) and MA (t = 0.50) terms are not statistically significant (P>0.05) while for *(logBDIP)* the both terms of AR (t = -0.06) and MA (t = 0.21) are also not statistically significant (P>0.05). So this is clearly an inconclusive forecast, outcome of which has prompted us to estimate the both series using the approach of VECM.

FIGURE 2. FORECASTING GRAPHS OF THE ARIMA (1,1,1) PROCESS FOR (*logBDCO*$_2$)

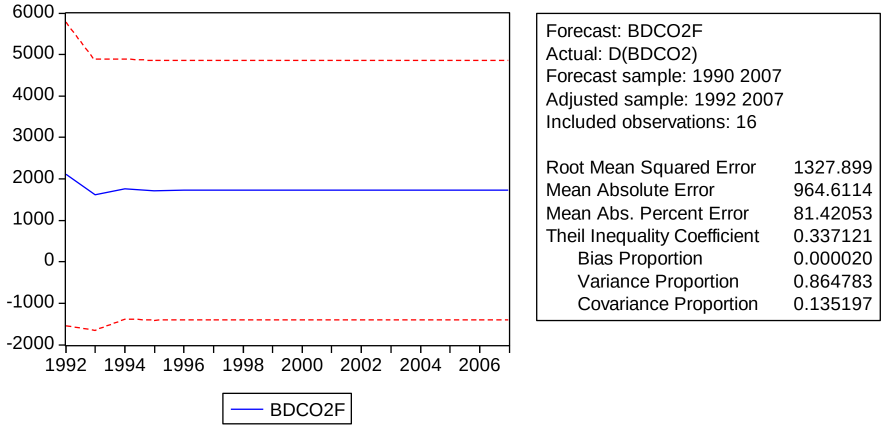
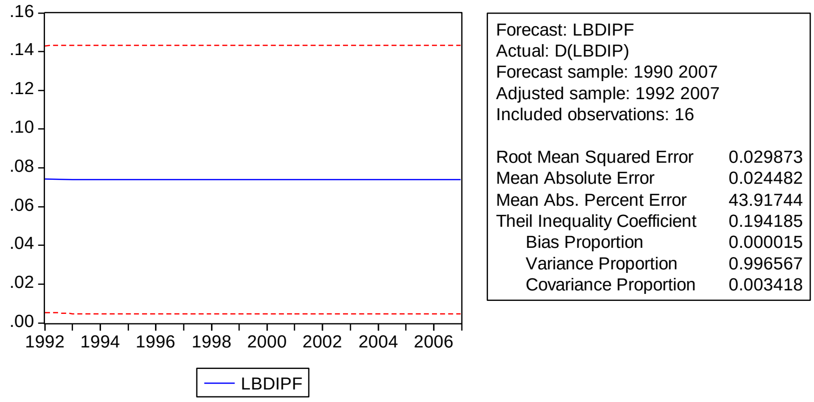


FIGURE 3. FORECASTING GRAPHS OF THE ARIMA (1,1,1) PROCESS FOR (*logBDIP*)



Estimated VECM for Bangladesh's CO2 Emissions and Industrial Production

As mentioned earlier a vector error correction model (VECM) is a special type of restricted Vector Autoregression (VAR). Therefore, the general equation of a VECM with two dependent variables {hence, *(logBDCO2)* and *(logBDIP)}* using the best '*Lag Interval for Endogenous*,' option of '1 3' can be presented in the following form:

$$D(Y_{g,t}) = A(g,1) * Co\mathrm{int} + \sum_{k=1}^{G} C(g,3k-1) * D(Y_{g,t-1})$$
$$+ \sum_{k=1}^{G} C(g,3k-2) * D(Y_{g,t-2}) + \sum_{k=1}^{G} C(g,3k) D(Y_{g,t-3}) + C(g,3G+1) + \mu_{g,t}$$

In the above equation, $Y_{g,t}$ is the g^{th} endogenous variable at the time t, for g = 1, 2, …, G. The estimated results based on the above VECM of *logBDCO2* and *logBDIP* with lag specification '1 3' reveal that the cointegrating equation has a significant effect on each of the endogenous variables. The coefficient of $logBDIP_{(t-1)}$ in the cointegrating vector is almost 1, i.e., 0.95 as it should be and we cannot reject the hypothesis that the coefficient is 1. Hence the critical value for t with 12 degrees of freedom is -1.67 {(0.95-1.0)/0.03}. Using the above VECM we actually estimate the changes in Bangladesh industrial production on Bangladesh CO_2 emissions and the changes in Bangladesh CO_2 emissions on Bangladesh industrial production. The cointegrating system within the VECM includes the variables of Bangladesh CO_2 emissions and Bangladesh industrial production. Outside the cointegrating system, variables include differences in lags of all endogenous variables to the first, second and third orders. The cointegrating vectors represent the coefficients of the linear combination of nonstationary variables, which are now stationary in nature. The estimated cointegrating equation can be presented as: $\log BDCO2_{(t-1)} = -6.25 - \underset{[-29.83]}{0.95}\log BDIP_{(t-1)}$

We begin with by examining the coefficient estimates within the cointegrating relationship. The above equation presents the estimated cointegrating vectors with normalization on the variable of the *log* Bangladesh CO_2 emissions. Since we intend to know the movements of Bangladesh CO_2 emissions to Bangladesh industrial production, normalizing on the *log* Bangladesh CO_2 emissions will serve this purpose. The only cointegrating coefficient estimate for *log* Bangladesh industrial production suggests the degrees of influence that Bangladesh industrial production can have on the Bangladesh CO_2 emissions in the long-run. The estimated coefficient for Bangladesh industrial production is -0.95. Assuming all other factors remain constant, when the industrial production in Bangladesh decreases by 1%, the CO_2 emissions in the country is expected to increase by 95%. In fact, this finding goes against the widely assertion that there is a positive connection between industrial production and CO_2 emissions. This clearly suggests Bangladesh's industrial production does not have any meaningful influence on the country's CO_2 emissions. However, the representation of the VECM with the two dependent variables is presented below:

$$\begin{aligned} D(\log BDCO2) = {} & A(1,1)*(B(1,1)*\log BDCO2_{t-1} + B(1,2)*\log BDIP_{t-1} + B(1,3) \\ & + C(1,1)*D(\log BDCO2_{t-1}) + C(1,2)*D(\log BDCO2_{t-2}) \\ & + C(1,3)*D(\log BDCO2_{t-3}) + C(1,4)*D(\log BDIP_{t-1}) \\ & + C(1,5)*D(\log BDIP_{t-2}) + C(1,6)*D(\log BDIP_{t-3}) + C(1,7) \end{aligned}$$

$$\begin{aligned} D(\log BDIP) = {} & A(2,1)*(B(1,1)*\log BDCO2_{t-1} + B(1,2)*\log BDIP_{t-1} + B(1,3) \\ & + C(2,1)*D(\log BDCO2_{t-1}) + C(2,2)*D(\log BDCO2_{t-2}) \\ & + C(2,3)*D(\log BDCO2_{t-3}) + C(2,4)*D(\log BDIP_{t-1}) \\ & + C(2,5)*D(\log BDIP_{t-2}) + C(2,6)*D(\log BDIP_{t-3}) + C(2,7) \end{aligned}$$

After substituting the coefficient values we can write the above equations as follows:

$$\begin{aligned} D(\log BDCO2) = {} & -\underset{[-0.69]}{0.54}(\log BDCO2_{t-1} - \underset{[-29.83]}{0.95}\log BDIP_{t-1} - 6.25) \\ & + \underset{[0.53]}{0.31}D(\log BDCO2_{t-1}) - \underset{[-0.20]}{0.10}D(\log BDCO2_{t-2}) - \underset{[-0.48]}{0.20}D(\log BDCO2_{t-3}) \\ & - \underset{[-0.22]}{0.14}D(\log BDIP_{t-1}) - \underset{[-0.18]}{0.12}D(\log BDIP_{t-2}) - \underset{[-0.06]}{0.04}D(\log BDIP_{t-3}) + \underset{[1.15]}{0.09} \end{aligned}$$
$$R-squared = 0.43, F-statistic = 0.65$$

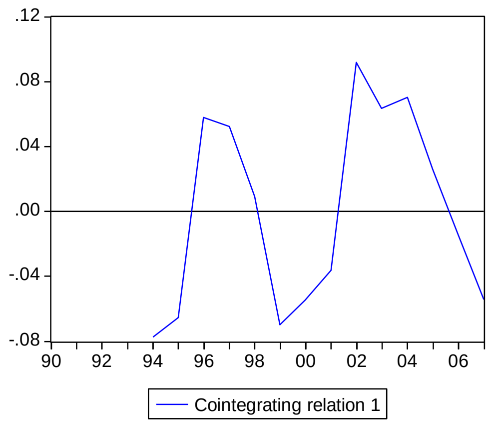
$$\begin{aligned} D(\log BDIP) = {} & \underset{[2.24]}{0.83}(\log BDCO2_{t-1} - \underset{[-29.83]}{0.95}\log BDIP_{t-1} - 6.25) \\ & - \underset{[-1.78]}{0.50}D(\log BDCO2_{t-1}) - \underset{[-1.88]}{0.43}D(\log BDCO2_{t-2}) - \underset{[-1.34]}{0.27}D(\log BDCO2_{t-3}) \\ & + \underset{[1.29]}{0.39}D(\log BDIP_{t-1}) + \underset{[1.13]}{0.36}D(\log BDIP_{t-2}) + \underset{[0.75]}{0.23}D(\log BDIP_{t-3}) + \underset{[1.96]}{0.07} \end{aligned}$$
$$R-squared = 0.47, F-statistic = 0.76$$

The adjustment coefficient on CointEq1 for Bangladesh CO_2 emissions is negative and the estimated speed of adjustment to disequilibrium is -0.54. It indicates how fast the equilibrium is restored. Taking half-life, a mathematical and scientific description of exponential or gradual decay, it will take approximately 54 years to converge to the long-run equilibrium. In fact, the half-time, $t_{½} = \ln 2/\lambda = 0.69/\lambda$, where λ is the rate of decrease in emissions per year. On the other hand, the adjustment coefficient in the same equation for Bangladesh industrial production is positive and the speed of adjustment is relatively faster at the rate of 83% a year. Therefore, most of the adjustment is being done by Bangladesh industrial production. The results also reveal that two lagged variables of Bangladesh CO_2 emissions such as $D(logBDCO2_{(t-1)})$ and $D(logBDCO2_{(t-2)})$ are both statistically significant in the Bangladesh industrial production equation at the probability values of 0.05 and 0.04 respectively. But all other lagged variables of CO_2 emissions and industrial production for Bangladesh are found to be statistically insignificant in both equations. The results also reveal that the regressions with the dependent variables of *D(logBDCO2)* and *D(logBDIP)* have positive *R*-squared values (0.43 and 0.47 respectively), which indicate that forty-three percent of the variation in *D(logBDCO2)* and forty-seven percent of the variation in *D(logBDIP)* could be explained by the above VEC models. F-statistic supports the models are well specified.

The cointegration tests for the above VEC models were also conducted in order to justify the robustness of the model in the real world situation. In fact, there are two tests, the Trace statistic, which is more reliable and the Max-Eigenvalue statistic. The results show that there is no cointegrating equation at both 0.05 and 0.01 levels based on the Trace test and the Max-Eigenvalue test. This clearly suggests that the variables of *logBDCO2* and *logBDIP* are not cointegrated in the long-run.

The VEC models also reveal that when Bangladesh's CO_2 emission levels deviate from the long-run equilibrium, the error correction will be triggered automatically. Thus the speed of adjustment is expected to have a negative sign. For example, whenever the CO_2 emissions of Bangladesh move higher than the equilibrium level the CO_2 emissions will soon start correcting itself by lowering the emission levels. Figure 4 provides the cointegrating graph and it suggests that with regards to the industrial production of Bangladesh the present CO_2 emissions in the country are well below the equilibrium level.

FIGURE 4. COINTEGRATING RELATION BETWEEN (*logBDCO2*) AND (*logBDIP*).

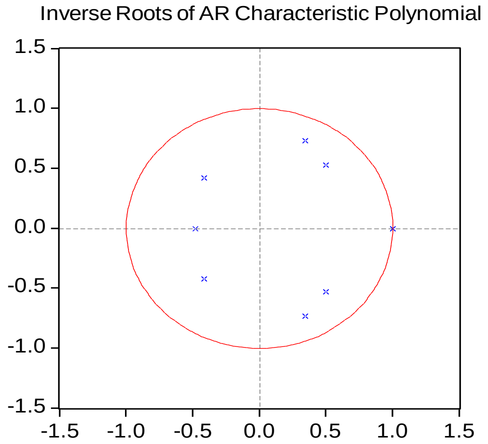


In our effort to check the other characteristics of the above developed model, the VEC Pairwise Granger Causality test was also conducted. The results reveal that facts that the Bangladesh industrial production *D(logBDIP)* is not a Granger causal (P>0.1) for Bangladesh CO2 emission *D(logBDCO2)* and that Bangladesh CO2 emission *D(logBDCO2)* is also not a Granger causal (P>0.1) for Bangladesh industrial production *D(logBDIP)*. Since the null hypothesis is that the coefficients are zero, there is clearly no Granger causality between the variables. The inverse roots graph of the lag polynomial was also generated in order to check the model stability. Figure 5 below shows that one of the eight roots lies on the unit cycle corresponding

ISBN 978-0-9925622-1-2

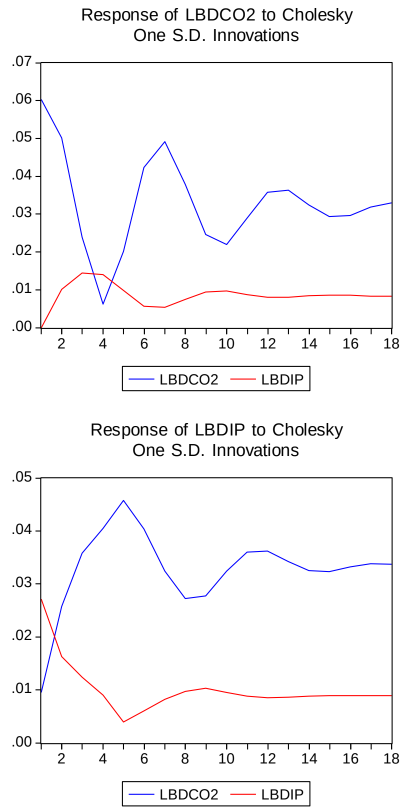
to the stochastic trend while the all other roots lie inside. Since no root lies outside the unit circle the model appears to be stable.

FIGURE 5. THE INVERSE ROOTS GRAPH OF THE LAG POLYNOMIAL FOR *D(logBDCO2)* AND *D(logBDIP*)



The VEC Lag Exclusion Wald Tests were also conducted and the results reveal that the joint effects of the first, second, and third differentiated lags of *(logBDCO2)* and (*logBDIP)* are not statistically significant (P>0.1). The VEC Residual Serial Correlation LM Tests were also conducted to check the serial correlation problem in the model. With the null hypothesis that there is no serial correlation at lag order h (=12), however, the probability values from Chi-square at all 12 lags are not statistically significant (P>0.05), except the lag 3 which is statistically significant (P<0.05). This is clearly an evidence of no major serial correlation problem in the model. Then VEC Residual Normality Tests were also conducted to check the multivariate normality of the residuals. With the null hypothesis that residuals are multivariate normal, Jarque-Bera statistic of 7.48 for the joint component is found to have been statistically insignificant (P>0.1). That means the model residuals are clearly multivariate normal. Finally, the impulse response combined graphs with Cholesky – degrees of freedom adjusted were generated in order to check the effect on the system of shocks to each variable. Figure 6 provides a graphical view of the Cholesky (One S.D. Innovations) impulse response function using the estimated VEC models. It actually provides the dynamic responses of the log Bangladesh CO2 emissions and log Bangladesh industrial production to a shock in the equilibrium.

FIGURE 6. IMPULSE RESPONSE GRAPHS SHOWING THE SYSTEM OF SHOCKS TO (*logBDCO2*) AND (*logBDIP*).



CONCLUSIONS

Based on the findings obtained from above models, this study concludes that Bangladesh industrial production and the related policy do not have any meaningful effects on the country's CO_2 emissions. This study also concludes for Bangladesh that any disequilibrium between CO_2 emissions and industrial production could take approximately 54 years to converge to the long-run equilibrium. The adjustment rate for Bangladesh industrial production is positive as it should be and quite faster at the rate of 83 percent a year. So any disequilibrium will be corrected mostly by the adjustment in Bangladesh industrial production. This implies huge potential for Bangladesh's industrial policy to the country's CO_2 emissions. This study further concludes that the country's CO_2 emissions are currently below the equilibrium level. This is an advantageous situation for the country as it is expected that its industrial sector will not face stricter CO_2 regulations in the near future. This study also concludes that neither the Bangladesh industrial production is a Granger causal for Bangladesh CO_2 emission nor the Bangladesh CO_2 emission is a Granger causal for Bangladesh industrial production. But it is thus worth noting that having observed a cointegrating relation between two variables does not necessarily mean they are causal one to other. This is because two or more time series variables could be found as cointegrated if they share a common stochastic drift, which can be described as the change of the average value of a stochastic (random) process. That being the case, the crucial conclusion of this study should actually be based on the findings obtained from the VEC estimations. While the nexus between CO_2 emission and industrial production is being debated widely, a solid and universal conclusion of what causes what and why and how they are mutually causal does require more in-depth investigation using multidisciplinary approaches at the levels where the primary stakeholders practically face the both phenomenon.

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