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# Macroeconomic Factors Determining CO<sub>2</sub> Emission in Bangladesh: Through the Lens of VECM Approach

Md. Tanvir Ahmed\*, Refat Ferdous

Department of Economics, University of Barishal, Barishal, Bangladesh

## Email address:

mtahmed@bu.ac.bd (Md. Tanvir Ahmed), rferdous@bu.ac.bd (Refat Ferdous)

\*Corresponding author

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**Abstract:** Never before has this planet encountered this kind of environmental crisis. Overall macroeconomic activities are inarguably linked to the worsening environmental quality. As a result, designing economic policies inevitably requires the knowledge of the factors that hurt the environment and lead to serious climatic conditions. Using secondary data from the year 1990 to 2021 and employing vector error correction model (VECM), this study attempts to determine the factors impacting carbon dioxide (CO<sub>2</sub>) emission in Bangladesh. The findings of this study show that GDP, total trade volume (TT) and energy consumption (EN) raise the level of CO<sub>2</sub> emission in the short run and the effect of population (PO) is not statistically significant. The long-run model also substantiates that GDP, TT, EN and PO have positive impact on the CO<sub>2</sub> emission. Though the use of renewable energy (RE) reduces emissions both in the short and long run, this effect is not statistically significant. These findings can help recognize the unintended losses incurred and formulate effectual policies for withstanding the pernicious effects of CO<sub>2</sub> emission from a developing country perspective. Thus, this study significantly contributes to the appropriate policymaking activities that help developing nations around the world to sustainably achieve economic growth without hurting the environment.

**Keywords:** CO<sub>2</sub> Emission, GDP, Energy Use, Trade Volume, Population, Environmental Quality, VECM, Bangladesh

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## 1. Introduction

Globally, an unprecedented surge of Carbon Dioxide (CO<sub>2</sub>) emission has gradually led the planet towards the greatest climate challenge that humanity has ever confronted. The National Oceanic and Atmospheric Administration (NOAA) asserts that CO<sub>2</sub> emission and global warming show similar behavior and have a positive correlation between them. As a result, controlling the growing aggregation of CO<sub>2</sub> in the atmosphere turns out to be an insurmountable task especially for the developing nations of the world when most of the developed economies do not fully comply with the Climate Convention [1]. For addressing this issue, many countries around the world have taken a wide variety of measures to ensure that the world becomes a better living place and continues to remain inhabitable for the generations to come [2]. Despite having a sluggish growth rate in carbon dioxide emission, lack of bureaucratic efficiency and inadequacy of

specialized expertise pose serious climatic threats before us thus dilapidating the strength of our promises to work in a collaborative fashion for reaching climate targets. Besides, the current trend of CO<sub>2</sub> emission seems to be precariously alarming and if it goes on uncontrolled and follows the same pathways then achieving 1.5° C goal remains an impossibility and facing environmental consequences is an inevitability [3]. Therefore, it is undeniably very crucial for the governments around the globe to take this issue into consideration and identify the factors determining CO<sub>2</sub> emission before designing efficacious and relevant macroeconomic policies.

Economic growth and environmental quality are inextricably correlated to each other as one cannot be thought of without another. A number of studies use GDP per capita as a measure of economic growth while a few utilize either the log value of the GDP or GDP growth rate to indicate economic development in their studies [4-8]. Globally, economic activities are unavoidably contingent on releasing CO<sub>2</sub> in the atmosphere as using different types of energies is

an indispensable part of this massive production process. Vidyarthi found a unidirectional causal relationship between energy use and carbon emission. Exploiting a wide range of energies for developmental activities like coal, gas and oil from natural sources degrades the environmental quality by generating CO<sub>2</sub> to the environment [9]. The rate of growth of population, especially the increase in population in urban areas, is deemed to be an influential factor for escalating CO<sub>2</sub> emissions. Additionally, growing economic and developmental activities in city areas have negative impacts on environmental quality through different forms of pollution [6]. Furthermore, trade openness appears to be a critical element for economic wellbeing thus intertwined with environmental quality. Gazi et al. finds a bidirectional relationship between CO<sub>2</sub> emission and proportion of international trade [10]. However, another study by Ali et al. reveals that there exists a negative and statistically insignificant association between them where they use the percentage of export and import of GDP to represent trade openness [11]. There are some other factors that are also found to be significantly connected to CO<sub>2</sub> emission such as inflation, unemployment, average rainfall and temperature, rural and urban population rate, forest area ratio, agricultural land ratio, labour force participation rate and foreign direct investment.

Bangladesh, a recently graduated lower-middle income country, experiences serious challenges before ensuring environmental sustainability while at the same time tailoring nature-friendly macroeconomic policies for the overall development of the country. Formulation of relevant policies that help accelerate sustainable economic growth necessitates proper knowledge of the factors that affect environmental quality. Unfortunately, although extremely crucial, there has been a dearth of research on this issue especially in Bangladesh. A few studies have explored the relationship between macroeconomic determinants and the environmental degradation of Bangladesh thus leaving a huge gap for further investigations, particularly in this time of global climate changes. This study, using Vector Error Correction Model (VECM) approach, attempts to fill this research gap and contribute toward harnessing the country's capacity to achieve sustainable development goals and tackle impending climatic challenges.

This article is designed and presented in five sections. To begin with, section 1 prefaces the study and consolidates the foundations of the research question investigated. Section 2 reviews and analyses the existing literature thus justifies the relevance of the research conducted. Thereafter, research methodology is explained and validated in section 3. Next, section 4 interprets and exhibits the results found. Finally, section 5 provides the conclusion by articulating some pragmatic and implementable policy recommendations in line with the findings.

## 2. Literature Review

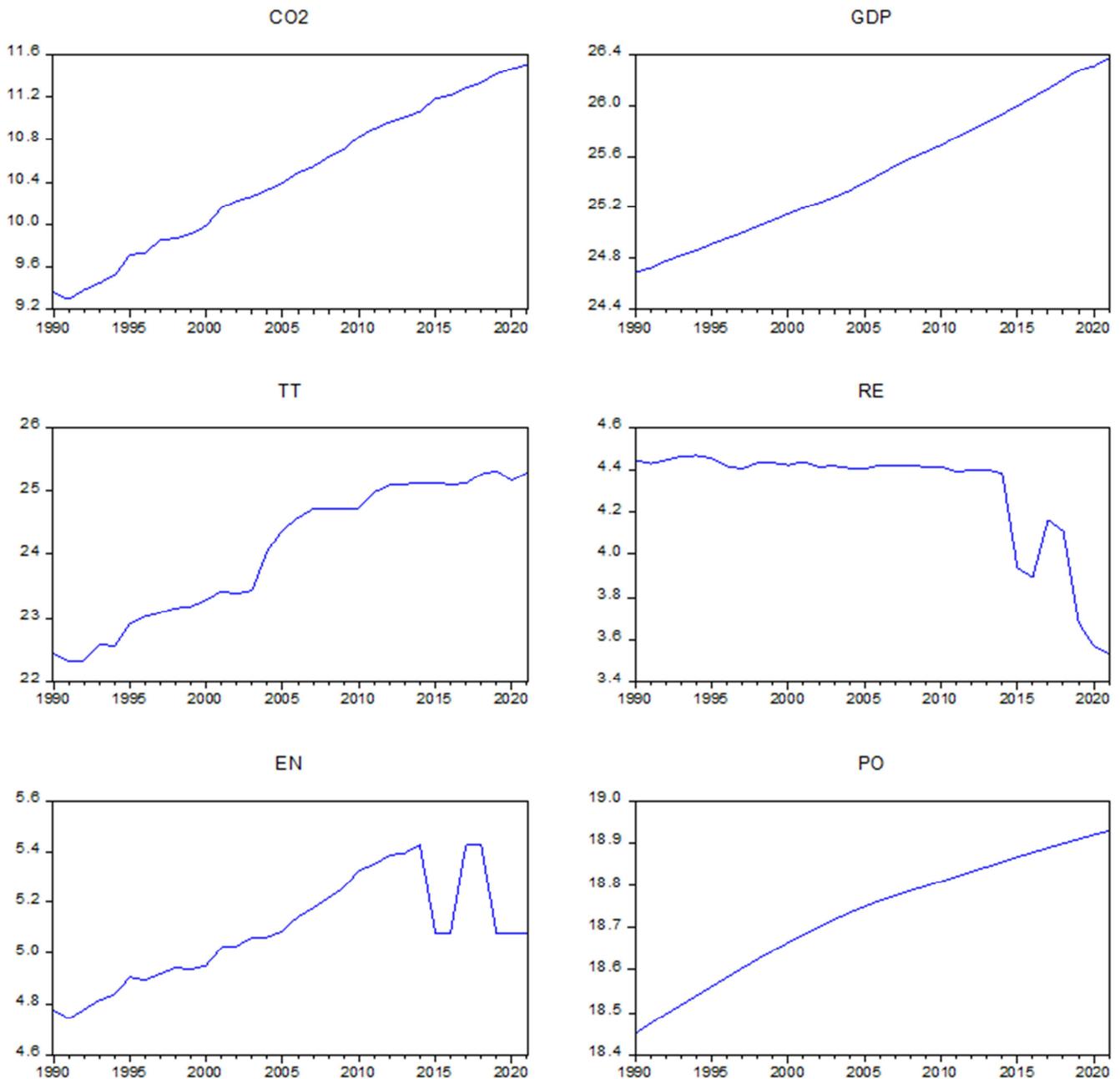
These days, the relationship between economic activities

and environmental quality has been at the very heart of the discourse as people around the world are experiencing serious climatic challenges. Several studies in extant literature attempted to pinpoint the determinants of CO<sub>2</sub> emission in different countries around the world. Resorting to a wide variety of methods, all these studies presented mixed results triggering the exigency for further clarification. That is why researchers around the world have focused on identifying the socioeconomic determinants of environmental degradation. For instance, Ahmad et al., applying autoregressive distributed lag models (ARDL), found a long-run and statistically significant relationship between macroeconomic variables and CO<sub>2</sub> emission [12]. Ali et al. using a panel analysis and employing Ordinary Least Square (OLS) asserted that some of the factors such as trade liberalization and financial advancements actually show negative relationship with CO<sub>2</sub> emission in South Asia [11]. In a similar kind of study conducted in the group of seven countries (G-7) by Anwar et al. showed that increased economic growth and population both pose a serious threat on environmental quality of the countries studied [13]. Growing economic activities to keep abreast with the economically globalized world are inextricably related to worsening environmental conditions [14]. Large scale production inarguably requires extensive use of a wide range of energies and building up proper infrastructural facilities thus wreaking havoc on the environmental quality [15]. Consequently, different types of energy consumption and renewable energy are deemed to be crucial elements affecting CO<sub>2</sub> emission. Besides, while assessing the relationship of economic growth and energy consumption, Saidi and Hammami corroborated that there exists a statistically positive association between increasing economic activity and growing use of energies [16].

Several studies in the existing literature identified population as one of the important factors of declining environmental condition as larger population necessitates greater economic activities. For example, Wang et al., with a view to identifying the population-centric factors of CO<sub>2</sub> emission, reported that older population tend to contribute more to the increase in CO<sub>2</sub> emission [17]. This finding has also been substantiated by another study conducted by Yu et al. [18]. In a few other studies, though, trade openness has been reported to have negative correlation with the level of CO<sub>2</sub> emission – trade openness helps lower CO<sub>2</sub> emission remarkably [19], total trade volume has shown a positive relationship. Another study conducted by Ohlan revealed that some socioeconomic indicators such as economic development, population density and trade openness positively and statistically significantly affect CO<sub>2</sub> emission [20]. Since Bangladesh is a densely populated country with the participation in many free trade organizations, it is very crucial to check whether there is any meaningful connection among population, trade volume and CO<sub>2</sub> emission.

The variables discussed above are considered critical macro-indicators for inducing CO<sub>2</sub> emission and thus accelerating environmental degradation. The trends of these

variables are portrayed in Figure 1.



Source: Author's Compilation

Figure 1. Trend of Variables.

Considering the trends of the variables and depending on the analysis and reviews, following hypotheses have been formed:

Hypothesis 1 (H1). GDP positively and significantly impacts the CO<sub>2</sub> emissions in Bangladesh.

Hypothesis 2 (H2). Total Trade Volume positively and significantly impacts the CO<sub>2</sub> emissions in Bangladesh.

Hypothesis 3 (H3). Renewable Energy negatively and significantly impacts the CO<sub>2</sub> emissions in Bangladesh.

Hypothesis 4 (H4). Energy Consumption positively and significantly impacts the CO<sub>2</sub> emissions in Bangladesh.

Hypothesis 5 (H5). Total Population positively and significantly impacts the CO<sub>2</sub> emissions in Bangladesh.

### 3. Materials and Methods

#### 3.1. Data

In this study, the analysis has been embedded on the time series data from the year 1990 to 2021. Carbon dioxide emission (CO<sub>2</sub>) is considered as the dependent variable whereas gross domestic product (GDP), total trade volume (TT), renewable energy consumption (RE), energy

consumption (EN), and total population (PO) are deliberated as independent variables. The explanation of the variables has been elicited on Table 1.

Table 1. General overview of variables.

Name of variables	Denotations	Unit of Measures	Expected Relations	Source of data
Carbon Emission	CO <sub>2</sub>	Kiloton		WDI
Gross Domestic Product	GDP	Constant Price 2015, US\$	+	WDI, BBS
Total Trade Volume	TT	Current Price of Export and Import in US\$	+	WDI
Renewable Energy	RE	kg of oil equivalent per capita	-	WDI
Energy Consumption	EN	kg of oil equivalent per capita	+	WDI
Total Population	PO	Number of Population	+	WDI

WDI: World Development Indicators; BBS: Bangladesh Bureau of Statistics

It is expected that GDP, TT, EN and PO have significant role to influence on environmental degradations which is measured through the volume of CO<sub>2</sub> emitted by a nation. On the flip side, globally it is recognized that the use of renewable energy can reduce the potential threat of environmental pollution by ensuring low or a little carbon emission.

3.2. Unit Root

In the univariate and multivariate econometric model, the presence of unit root is a common and desirable phenomenon. That is why, almost every time-series study starts with checking the existence of the unit root [21]. In data science, the unit root analysis helps us find the internal properties in the time series data which in turn helps us generate some policy-making decisions as well as model selection understanding in the field of applied economics as well as applied econometrics [22-24]. In this study, Augmented Dickey-Fuller test (ADF), Phillips Perron test (PP) and Zivot-Andrew Breakpoints unit root test have been applied to understand the robustness of the presence of unit root in this analysis.

3.2.1. Augmented Dickey-Fuller Test

In the Dickey-Fuller test (DF) shown in equation 1, it has been considered that the consecutive error terms are uncorrelated [25], i.e.  $cov(u_t, u_{t-1}) = 0$ .

$$\Delta X_t = \alpha_1 + \alpha_2 t + \alpha_3 X_{t-1} + \epsilon_t \quad (1)$$

Here,

$\Delta X_t$ : First order difference of X variable.

$\alpha_1$ : Drift Coefficient.

$\alpha_2$ : Deterministic Trend Coefficient.

$\alpha_3$ : Coefficient of Lag value of X.

$$x_t = \hat{\alpha}_1^a + \hat{\alpha}_2^a DU_t(\hat{\gamma}) + \hat{\alpha}_3^a t + \hat{\alpha}_4^a t x_{t-1} + \sum_{i=1}^k \hat{\alpha}_i^a \Delta x_{t-i} + \epsilon_t \quad (4)$$

$$x_t = \hat{\alpha}_1^b + \hat{\alpha}_2^b DT_t(\hat{\gamma}) + \hat{\alpha}_3^b t + \hat{\alpha}_4^b t x_{t-1} + \sum_{i=1}^k \hat{\alpha}_i^b \Delta x_{t-i} + \epsilon_t \quad (5)$$

$$x_t = \hat{\alpha}_1^c + \hat{\alpha}_2^c DU_t(\hat{\gamma}) + \hat{\alpha}_3^c t + \hat{\alpha}_4^c t x_{t-1} + \hat{\alpha}_5^c DT^*(\hat{\gamma}) + \sum_{i=1}^k \hat{\alpha}_i^c \Delta x_{t-i} + \epsilon_t \quad (6)$$

Here,  $DU_t(\hat{\gamma})=1$  if  $t > T\hat{\gamma}$  and 0 otherwise, and  $DT^*(\hat{\gamma}) = t - \hat{\gamma}T$  for  $t > T\hat{\gamma}$  and 0 otherwise. The null hypothesis is that the series has unit root with structural break.

3.3. Lag Selection Criteria

The optimal number of Lag selection is one of the most

$t$ : Trend variable.

But, in practice, it is very frequent that the error terms are correlated. To address such a phenomenon, Dicky and Fuller develop a new procedure to identify the problem of unit root, which is known as Augmented Dicky-Fuller (ADF) test [26]. The ADF expression is denoted by equation 2.

$$\Delta X_t = \alpha_1 + \alpha_2 t + \alpha_3 X_{t-1} + \sum_{i=1}^m \alpha_4 \Delta Y_{t-i} + \epsilon_t \quad (2)$$

If,  $\alpha_3$  is statistically not different from 0, then the variable is non-stationary. In contrasts, if the value of  $\alpha_3$  is less than 0, then the time-series variable is stationary.

3.2.2. Phillips-Perron Test

Phillips-Perron test (PP) is a non-parametric test in which the asymmetric distribution of the time series variable has been considered [27]. Despite the central limit theory, due to the heterogeneity of the series, in this approach, non-central distribution has been deployed. For the variable X, the test formation can be noted by equation 3.

$$x_t = \vartheta + \mu \left( t - \frac{T}{2} \right) + \pi x_{t-1} + \epsilon_t \quad (3)$$

3.2.3. Zivot-Andrew Breakpoints Unit-Root Test

To allow the structural break of the model, Zivot-Andrew Breakpoints unit root test is applied in this study. In macroeconomics, the data are usually affected by different types of external shocks. In this context, we can recall the financial crisis in the year 1997 or the economic recession in the US economy in the year 1998. In such cases, the PP unit root test or ADF test have been unable to address the structural break in the time series data [28]. The basic models of this test are denoted by equation 4, equation 5 and equation 6.

important pre-requirements to perform the Co-integration test as well as VAR estimation. There are different criteria to select the optimal order of lag and the minimum value has been used to select the optimum number of lags. These criteria have been represented in Table 2.

Table 2. Lag Selection Criteria.

Name of Criteria	Statistics	Developer(s)
a. Likelihood Ratio (LR) =	$(T - c)   \log  \Omega_1  - \log  \Omega_2   $	[29]
b. Final Prediction Error (FPE)=	$\left[ \frac{T+kp+1}{T-kp-1} \right]^k  \sum \hat{u} \hat{u}(p) $	[30]
c. Akaike Criterion (AIC)=	$\ln  \sum \hat{u} \hat{u}(p)  + \frac{(k+pk^2)2}{T}$	[31]
d. Schwarz Criterion (SC)=	$ \sum \hat{u} \hat{u}(p)  + (k + pk^2) \frac{2 \ln(\ln(T))}{T}$	[32]
e. Hannan-Quinn (HQ)=	$\ln  \sum \hat{u} \hat{u}(p)  + \frac{(k+pk^2)2}{T}$	[33]

From the estimators,  $p$  is the length of the model,  $\hat{u}$  is the estimated residual,  $T$  is the number of observation and  $k$  is the number of dependent variables [34-35].

3.4. Johansen Test of Co-Integration

If the time series variables are non-stationary at level 1, i.e. integrated order 1 ( $I \sim (1)$ ), then it is usual that the variables may be compound as long-run co-integrated relationship. If there is long-run or equilibrium relationship exists among the variables, then it is called as cointegrated relationship [25]. In this paper we used the Johansen test of Co-integration which is developed by Soren Johansen in year 1991 and it is unlike the Engle and Granger [36] which is based on Dicky-Fuller or Augmented Dicky-Fuller approach and only considers single cointegration equation on the contrast to Johansen [37], in where several cointegrated equations have been considered. If the model has  $n$  variables and all are non-stationary at level 1, then there is a possibility that the model has maximum  $n-1$  long-run equilibrium vectors [38]. By using the maximum likelihood method on the traditional VAR equation, we can track down the number of co-integrated equations using Trace Test and Maximum Eigenvalue. The general form of VAR (with ECM) co-integration model is demonstrated by equation 7.

$$\Delta Y_t = \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \Pi Y_{t-k} + \phi D_t + \mu + \omega_t \quad (7)$$

Here,

$\Delta$ : Difference Operator.

$Y_t$ : Target Variable.

$Y_{t-i}$ : Lag Value of Target Variable.

$D_t$ : Seasonal Dummy Variable.

$\Gamma_i$ : Parameter without Restrictions.

$\Pi$ : Eigenvalue.

The Track Test and Maximum Eigenvalue Formula with null and alternative hypothesis are expressed by equation 8 and equation 9.

Track Test

$$Tr(r) = -T \sum_{i=r+1}^k \ln(1 - \hat{\lambda}_t) \quad (8)$$

$H_0: (\Pi) = r_0$

$H_a: r_0 < rank(\Pi) \leq n$

Max Eigen Value

$$\lambda_{\max(r,r+1)} = -T \ln(1 - \hat{\lambda}_t) \quad (9)$$

$H_0: (\Pi) = 0$

$H_a: (\Pi) = 1$

Here,

$r_0$ : Number of Cointegrated Equation.

$\hat{\lambda}_t$ : Estimated Values of Eigen Matrix.

$T$ : Number of Observation.

$k$ : Number of Endogenous Variables

3.5. VECM

Vector Error Correction model (VECM) model is the extended expression of Vector Autoregressive Model (VAR), which is developed by Christopher Sims in the year 1980 [39]. It is a stochastic model which evokes the inherent dependency of multiple variables regardless of the exogeneity of the variables. In the simultaneous equation models, we consider some variables to be exogenous and others remain endogenous, which is fiercely criticized by Sims. According to his view, this argument is subjective, especially in macroeconomics, when long-run fluctuation is the subject of interest, in that case, all concerned variables are highly likely to interact with each other. In this model, we assume all variables are stationary at level,  $I \sim (0)$  [38]. The basic VAR model,  $AR(p)$  is displayed by equation 10.

$$y_t = \eta y_{t-1} + u_t \quad (10)$$

Here:

$y_t$ : Vector of Variables at time  $t$

$\eta$ :  $nk \times nk$ , order coefficient matrix of vector  $y_{t-1}$

$u_t$ : Vector of stochastic error term.

In the time series data, the problem of unit root is a common phenomenon. That is why, differencing process is necessary to remove this problem. But, if the series is cointegrated then this process leads towards over-differencing of the variables, so that there has some probability to lose some information in long-run prediction. As the remedy, VAR model is extended to be a VECM with order  $p - 1$  [40]. VECM model also helps explain the short-run fluctuation to the path of long-run equilibrium. The standard VECM model can be written by the equation 11.

$$\Delta x_t = \psi \phi' x_{t-1} + \sum_{i=1}^{p-1} \Theta_i \Delta x_{t-1} + v_t \quad (11)$$

Here:

$\Delta$ : Difference operator.

$x_t$ : Vector of Dependent Variables.

$\psi$ : Adjustment Vector, matrix order  $(k \times r)$

$\phi'$ : Cointegration vector, long-run adjustment

$x_{t-1}$ : Endogenous variable Vector with lag 1.

$\Theta_i$ : K x K coefficient matrix of  $i^{th}$  endogenous variable.  
 $v_t$ : White Noise disturbance term vector.

## 4. Result and Discussion

### 4.1. Common Statistics

In Table 3, we demonstrated the basic statistical properties such as mean, maximum value and minimum value as well as the results of the normality test (Jarque-Bera). The average carbon emission in the year 1990 to 2021 is 10.44 whereas, in this period, the lag value of GDP is 25.47 and the mean value of total trade volume (TT), renewable energy consumption (RE), energy consumption (EC) and total population (PO) are 24.06, 4.30, 5.08 and 18.73 respectively.

Table 3. Basic Statistical Profile of the Variables.

Statistics \ Variables	CO <sub>2</sub>	GDP	TT	RE	EN	PO
Mean	10.44	25.47	24.06	4.30	5.08	18.73
Median	10.44	25.43	24.48	4.41	5.07	18.75
Maximum	11.51	26.37	25.32	4.47	5.43	18.92
Minimum	9.29	24.69	22.32	3.53	4.74	18.45
Jarque-Bera	2.12	2.08	3.50	25.21	1.52	2.28
Probability	0.36	0.35	0.17	0.00	0.47	0.32

Source: Author’s Computation

The maximum level of CO<sub>2</sub> is 11.51 compared to minimum value of 9.29 whereas for GDP maximum value is 26.37 and the minimum value is 24.69. For TT, RE, EN and PO the maximum value is 25.32, 4.47, 5.43 and 18.92 respectively. On the other hand, the minimum value of variables is 22.32, 3.53, 4.74 and 18.45 individually. The Jarque-Bera (JB) test shows whether the series is normally distributed or not which is one of the important preconditions to estimate best, linear and unbiased estimation of a regression model [41]. The test statistics is represented by equation 12.

$$JB = n \left[ \frac{s^2}{6} + \frac{(k-3)^2}{24} \right] \tag{12}$$

Here

$n$ : Number of Sample size.

$s$ : The Skewness of the series.

$k$ : Kurtosis of the series.

The test hypothesis is:

$H_0$ : Series is normally distributed.

$H_a$ : Series is not normally distributed.

From Table 2, all variables except RE are normally distributed because corresponding p-values are greater than 10% but for RE the value is less than 5%.

### 4.2. Correlation Matrix

Gross domestic product, total trade volume, energy consumption and population have positive impact on the carbon emission in contrast to renewable energy, because it has negative impact on carbon emission.

Table 4. Outcome of Correlation Matrix.

Statistics \ Variables	CO <sub>2</sub>	GDP	TT	RE	EN	PO
CO <sub>2</sub>	1	0.99	0.97	-0.69	0.79	0.99
GDP	0.99	1	0.95	-0.74	0.75	0.97
TT	0.974	0.95	1	-0.57	0.85	0.97
RE	-0.69	-0.74	-0.57	1	-0.14	-0.63
EN	0.79	0.75	0.85	-0.14	1	0.81
PO	0.99	0.97	0.97	-0.63	0.81	1

Source: Author’s Computation

On Table 4, the correlation between CO<sub>2</sub> and GDP is 99 %, whereas the impact of TT on CO<sub>2</sub> is 97 %; for EN it is 79 %, and the impact of PO on CO<sub>2</sub> is 99 % but the impact of RE on CO<sub>2</sub> is negative and the value of coefficient of correlation is 69 %.

### 4.3. Unit Root

#### 4.3.1. Augmented Dicky-Fuller Test

Table 5 represents the outcome of ADF test. At level with intercept, all variables are non-stationary which implies that the time series has time varying mean and variance. Besides, at level considering trend and intercept, all variables are submersible into the problem of unit root because the estimated unit root coefficients do not belong to critical values. Taking the first order difference turned all variables into stationary with 1% level of significance.

Table 5. ADF Unit Root.

Name of Variables	Level		1 <sup>st</sup> Difference		Decision
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	
CO <sub>2</sub>	-0.28	-3.43	-7.85***	-7.88***	I (1)
GDP	4.35	-1.41	-3.84***	-5.44***	I (1)
TT	-1.02	-1.39	-4.58***	-4.74***	I (1)
RE	3.39	1.68	-6.33***	-7.90***	I (1)
EN	-1.70	0.28	-7.03***	-7.66***	I (1)
PO	-2.69	-3.42	-3.15***	-3.65***	I (1)

Source: Author’s Computation; \*, \*\*, \*\*\* are defined as 10%, 5% and 1% level of significance respectively.

#### 4.3.2. Phillips-Perron Test

In the Phillips-Perron test the result is analogues with ADF

findings. At level, the series with intercept, the unit root coefficient value for CO<sub>2</sub>, GDP, TT, RE, EN and PO is -0.25, 5.21, -1.01, 1.79, -1.77 and -8.43 respectively and corresponding

p-value is more than 10%, which reckon that the variables have the problem of unit root (in Table 6). The series with trend and intercept at integrated order 0, has evidence of presence of unit root because the estimated coefficient does not statistically reject null hypothesis. By taking the first order difference on variables,

both presences of intercept as well as intercept and trend do statistically reject the null hypothesis at 1% level of significance which expounds that the variables are stationary at integrated order 1.

Table 6. PP Unit Root.

Name of Variables	Level		1 <sup>st</sup> Difference		Decision
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	
CO2	-0.25	-3.55	-10.82***	-15.75***	I (1)
GDP	5.21	-1.45	-3.90***	-5.51***	I (1)
TT	-1.01	-1.24	-4.58***	-4.74***	I (1)
RE	1.79	0.68	-4.78***	-6.01***	I (1)
EN	-1.77	-2.04	-6.09***	-7.33***	I (1)
PO	-8.43	-1.89	-3.47***	-1.18	I (1)

Source: Author's Computation; \*, \*\*, \*\*\* are defined as 10%, 5% and 1% level of significance respectively.

#### 4.3.3. Zivot-Andrew Breakpoints Unit-Root Test

Structural breaks with the presence of unit root considering the variables have the intercept and trend has been rejected in this study. The data for the given period from the year 1990 to 2021 do not reveal any evidence on structural breaks. The

t-value on Table 7 for variables CO2, GDP, TT, RE, EN and PO is -5.89, -4.25, -5.82, -7.01, -3.79 and -5.99 respectively and corresponding p-value for all variables is less than 5%. This statistically ensures that the model does not encounter any policy adjustment issues.

Table 7. Zivot-Andrew Breakpoints Unit-Root.

Name of Variables	Break Point Year	Level		Decision
		t-value	p-value	
CO2	2010	-5.89	0.002	I (0)
GDP	2002	-4.25	0.033	I (0)
TT	2004	-5.82	0.00	I (0)
RE	2015	-7.01	0.00	I (0)
EN	2015	-3.79	0.018	I (0)
PO	2001	-5.99	0.00	I (0)

Source: Author's Computation

#### 4.4. Lag Selection Criteria

The optimal number of lags in this study is 3. In the lag selection process, we consider the LR, FPE, AIC, SC, and HQ to select the optimum number of lag order. The

minimum value of the different lag order is the criteria to select the optimum lag for VECM model. In Table 8, at lag 3 the value of LR, FPE, AIC, SC and HQ is minimum, and this is the accepted lag order in this study.

Table 8. Lag Selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	198.45	NA	6.93e-14	-13.27	-12.98	-13.18
1	476.59	422.01	4.11e-21	-29.97	-27.99	-29.35
2	560.73	92.844	2.11e-22	-33.29	-29.61	-32.14
3	708.59	101.97*	2.95e-25*	-41.00*	-35.63*	-39.32*

Source: Author's Computation

#### 4.5. Co-integration Test

Co-integration test shows the long-term, or equilibrium relationship among the variables though there is a short-run disequilibrium among the variables. In this study, by using track statistics and max eigen value, it is detected that the model has two co-integration equations. For the alternative

hypothesis (Table 9), the model has two cointegrated equations, the track statistics value is 90.18 and the value of eigen statistics is 45.37. Their relevance p-value is less than 5 percent, which shows the statistical evidence to reject the null hypothesis and acknowledge the existence of two co-integrated equations in the model.

Table 9. Johansen Test of Cointegration.

Null Hypothesis	Alternative Hypothesis	Trace test		Max-eigenvalue	
		Trace Statistic	P-value	Max-Eigen Statistic	P-value
No Co-integrated Equation	One Co-integrated Equation	165.99	0.00	75.81	0.00
One Co-integrated Equation	Two Co-integrated Equations	90.18	0.00	45.37	0.00
Two Co-integrated Equations	Three Co-integrated Equations	44.81	0.09	25.72	0.08

Source: Author’s Computation

VECM Short-run Model with ECT

The short-run model with two co-integrated equations (error correction term or ECT) is expressed by equation 13.

$$\Delta CO2_t = \beta_1 + \sum_{i=1}^{n-1} \beta_i \Delta CO2_{t-i} + \sum_{j=1}^{n-1} \beta_j \Delta GDP_{t-j} + \sum_{k=1}^{n-1} \beta_k \Delta TT_{t-k} + \sum_{l=1}^{n-1} \beta_l \Delta RE_{t-l} + \sum_{m=1}^{n-1} \beta_m \Delta EN_{t-m} + \sum_{o=1}^{n-1} \beta_o \Delta EN_{t-o} + \sum_{q=1}^{n-1} \beta_q \Delta PO_{t-q} + \delta_1 ECT_{t-1}^1 + \delta_2 ECT_{t-1}^2 \tag{13}$$

On Table 10, in panel A, the value of short-run coefficients and their corresponding t-values have been presented. The GDP at lag 1 and lag 2 is statistically insightful to influence the carbon-emission in the short-run. Notwithstanding their signs are negative, but over the long run, after adjusting the error, these signs have been reversed which has been explained on Table 10. Trade volume has a negative impact (-0.05) in the first period but for the second period its impact is positive (0.09). The fact is that the first period lag value is not statistically significant because t-value is less than 2 but the impact of TT at lag 2 is significant (t-value > 2). Renewable energy consumption has a significant role in reducing the carbon outflow in the short run because the coefficient values

at lag 1 and lag 2 is -1.87 and -2.43 respectively and those values are efficient to explain the change of CO<sub>2</sub> at short run. Energy consumption is a potential factor (at lag<sub>1</sub> 1.44; at lag<sub>2</sub> 2.06) impacting the CO<sub>2</sub> emission in short-run and the population is also another driving factor to induce the environmental pollution in the context of Bangladesh. The first co-integration coefficient (i.e., ECT<sup>1</sup><sub>t-1</sub>) is significant to correct the short-run disequilibrium and converges to long-run equilibrium because its coefficient value is negative (-2.18) and statistically significant (t-value: -5.59). On the flip side, ECT<sup>2</sup><sub>t-1</sub> is statistically significant but not acceptable because the sign of coefficient is positive (2.28), which is not desirable.

Table 10. Short-run Coefficient with ETC.

Panel A			
Variables	Coefficient and t-value	Variables	Coefficient and t-value
intercept	-0.22 [-1.28]	$\Delta RE_{t-1}$	-1.87 [-4.48]
$\Delta CO2_{t-1}$	0.31 [1.21]	$\Delta RE_{t-2}$	-2.43 [-3.23]
$\Delta CO2_{t-2}$	-0.31 [-1.50]	$\Delta EN_{t-1}$	1.44 [3.73]
$\Delta GDP_{t-1}$	-1.46 [-2.02]	$\Delta EN_{t-2}$	2.06 [3.00]
$\Delta GDP_{t-2}$	-3.12 [-3.23]	$\Delta PO_{t-1}$	2.87 [0.20]
$\Delta TT_{t-1}$	-0.05 [-1.15]	$\Delta PO_{t-2}$	21.00 [1.20]
$\Delta TT_{t-2}$	0.09 [2.28]	$ECT_{t-1}^1$	-2.18 [-5.59]
$ECT_{t-1}^2$	2.28 [6.00]		
Panel B			
R-squared		0.83	
Adj. R-squared		0.65	
F-statistic		4.73	
Akaike AIC		-4.26	
Schwarz SC		-3.55	

Source: Author’s Computation; [ ] shows t-statistics

4.6. Long-run Co-Integrating Coefficient

In long run (Table 11), most of the variables has significant positive effect on the carbon dioxide emission in Bangladesh except renewable energy which reduces the emission in long-run. In this study, it has been found that RE has negative impact (-0.10), but it is not statistically significant in long-run which has an in-depth policy implication which has been explained in next section of this paper.

Table 11. Co-integrating Coefficient (Long-run).

Variables	Coefficient and t-value
$GDP_t$	0.73 [4.29]
$TT_t$	0.03 [1.03]
$RE_t$	-0.10 [0.59]
$EN_t$	0.84 [4.42]
$PO_t$	1.43 [7.53]

Source: Author’s Computation; [ ] shows t-statistics

**4.7. VECM Granger Causality**

Granger causality outcome on VECM environment on Table 12 explains that the selected variables for this study are capable to explain the change of CO<sub>2</sub>. None of the variables has been excluded from the model as per  $\chi^2$  value under p-value approach.

*Table 12. Granger Causality.*

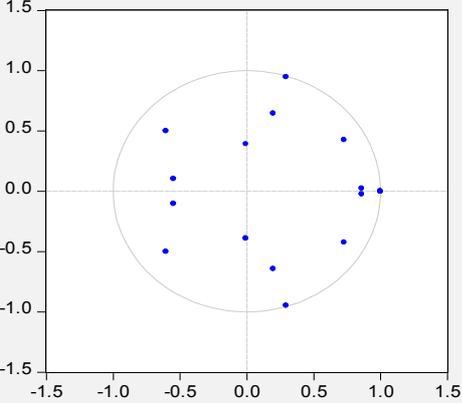
Dependent Variable: $\Delta CO2_t$			
Null Hypothesis	$\chi^2$	DF	P-value
Excluded variable $\Delta GDP_t$	13.73	2	0.00
Excluded variable $\Delta TT_t$	5.98	2	0.05
Excluded variable $\Delta RE_t$	24.03	2	0.00
Excluded variable $\Delta EN_t$	21.30	2	0.00
Excluded variable $\Delta PO_t$	9.02	2	0.01
Excluded All Variables	35.41	10	0.00

Source: Author's Computation

**4.8. Diagnostic Tests**

The acceptance of empirical research is not only based on the selection of perfect model but also it depends on different types of diagnostic test. To detect the serial correlation, we pursued LM test developed by Breusch-Godfrey. The null hypothesis shows that the residual of VECM outcome is serially uncorrelated as it has been on Table 13. The p-value at lag 1, lag 2 and lag 3 are 0.69, 0.18 and 0.48 respectively which is more than 5% critical level and emphasize on not rejecting the null hypothesis. The second test of diagnostics shows that the residual is normally distributed because the p-values at lag1, 2 and 3 are highly significant to accept the null hypothesis. On the other hand, the model is stable also. Besides, the AR root characteristic values are within the stability region. The variance of the disturbance term is homoscedastic because the p-value is 0.22 which is more than 5% critical range.

*Table 13. Diagnostic Tests Findings.*

Name of Test	Hypothesis	Test Result	Remark
Serial Correlation LM Tests	<i>Null hypothesis:</i> No serial correlation	P-value: 0.69 (lag 1) P-value: 0.18 (lag 2) P-value: 0.48 (lag 3)	The VECM is serially uncorrelated.
Normality Tests	<i>Null hypothesis:</i> Residuals are multivariate normal	P-value: 0.56 (joint at lag 1) P-value: 0.45 (joint at lag 2) P-value: 0.59 (joint at lag 1)	Residuals are normally distributed.
Inverse Root of AR Characteristic Polynomial	<i>Null Hypothesis:</i> Model is Stable	Inverse Roots of AR Characteristic Polynomial 	AR roots within the circle. So, the model is stable in long-run.
Heteroskedasticity Test	<i>Null Hypothesis:</i> No Heteroskedasticity	P-value: 0.22	The variance of the error term is distributed equally.

Source: Author's Computation

**5. Conclusion and Policy Implications**

This study aims at examining the socio-economic determinants of CO<sub>2</sub> emission in Bangladesh both in short and long run using secondary data from 1990 to 2021. The VECM method has been applied to find the existence of meaningful correlations among different macroeconomic indicators and CO<sub>2</sub> emission. Short-run results are slightly different from that of long run. In the short run, GDP, total trade volume (TT), population (PO) and energy consumption (EN) showed a statistically significantly positive association with CO<sub>2</sub> emission, though the effect of population is

statistically insignificant. On the other hand, the long-run results supported the short-run relationship, and the outcome is statistically significant. Additionally, the expected effect of renewable energy (RE) has been validated both in the short and long run, though this relationship is statistically insignificant. For making noticeable strides towards achieving sustainable development goals (SDGs), Bangladesh requires to design policies that incentivize conducting economic activities without compromising environmental quality. Encouraging firms to adopt the use of nature friendly technologies to curb the level of pollution is a meaningful way forward for preserving the environment. Furthermore, imposing carbon tax and inspiring the use of

renewable energy can help improve environmental quality. Finally, controlling the growth of population, nature-friendly terms and conditions of trade and improved waste management system can also harness country's ability to reach the sustainability goals. This study is not beyond any limitations. This study only considers a single country to find the macroeconomic factors that affect CO<sub>2</sub> emission, a cross-country or cross-continent analysis might provide us with even stronger outcome. Furthermore, comparing countries in different development stages can shed light from different perspectives. Future research might be directed towards addressing these limitations.

## Data Availability

The data of this study will be made available upon request.

## Conflicts of Interests

The authors declare that they have no competing interests.

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