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IMPACT OF SOCIO-ECONOMIC FACTORS AND ENERGY MIX ON PM2.5 CONCENTRATION: AN EMPIRICAL ANALYSIS OF NEXT-11 COUNTRIES

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ABSTRACT

The intensified contradiction of economic growth and environmental protection has gained a lot of attention from multidisciplinary scholars. The relationship between socio-economic factors and deadly concentration of PM2.5 remained poorly understood specifically for the developing countries. The study has selected Next-11 countries for the analysis to gauge the influencing factors of PM2.5 concentrations by collecting data from 1995-2017. The cross-sectional dependence test shows mixed results therefore, the study has employed both the first generation and second generation econometric techniques. The results of the panel unit root test indicate that all the variables are stationary at first difference. In Auto-Regressive Distributive Lag (ARDL) estimation, the long-run co-integration vectors show that renewable as well as non-renewable energy have significant long-run co-integration. Gross domestic product is the main influencing factor of PM2.5 concentrations while its quadratic form has a negative association that verifies the existence of the Environmental Kuznets Curve (EKC) in sampled countries. The Westerlund co-integration test also verifies the long-run integration among variables. The results of Fully Modified Least Square (FMOLS) and Dynamic Least Square (DOLS) indicate significant negative relation of industry value-added, trade openness and urbanization. On the other hand, the results of the Dynamic Common Correlated Effect (DCCE) indicate the positive impact of urbanization on PM2.5 concentration. This is the first study that is showing the key contributing factors of PM2.5 concentrations for N-11 countries. Authors have suggested the rational formulation and careful implementation of policies.

1. INTRODUCTION

In recent years, fine particulate matter with aerodynamic diameter of 2.5 μm or less has gained a lot of public attention due to its catastrophic economic and health losses. The Primary factor of air pollution is the concentration of $PM_{2.5}$ that reduces visibility and generates further pollution through chemical reactions as it can suspend in the air (W. Zhu, Wang, and Zhang 2019). Studies show that long-term exposure to the air contaminated by $PM_{2.5}$ can cause serious illness, respiratory problems, cardiovascular disease, damage immune system, and increased risk of premature death (Hui Wang, Ji, and Xia 2019). The concentration of $PM_{2.5}$ is being considered as the main factor for increased mortality, reducing the life expectancy and greater mortality contributor than AIDs and HIV (Diao et al., 2020; Fang et al., 2020; Sarkodie et al., 2019). Air pollutants dominated by $PM_{2.5}$ causing economic losses equal to 1% of the world's GDP and 7 million premature deaths annually have posed a serious concern to human wellbeing (Diao et al., 2020; Fang et al., 2020; Nansai et al., 2020). Given these detrimental statistics, it is indeed the need time to understand the leading factors of its concentration and generation so that appropriate policies can be formed and implemented to obtain ecologically friendly economic development (Chen et al. 2018; J. Yang et al. 2019)

The increasing upward trend in $PM_{2.5}$ concentration and hazy weather persistency has been the notion of debate in multidisciplinary sciences. In recent years many scholars have conducted studies on $PM_{2.5}$ emissions. The main focus of the researchers is the health effects of $PM_{2.5}$ (Lu et al. 2019; S. Yang, Fang, and Chen 2019; Z. Zhang et al. 2019) transboundary diffusion (Haikun Wang et al. 2017) spatiotemporal changes (Li et al. 2019) etc. Empirical studies exhibited the main driving factors of this deadly concentration are urbanization (Fang et al. 2020; Tao et al. 2020; Z. Zhu, Fu, and Liu 2020), income level and economic growth (Ouyang et al. 2019; Sarkodie et al. 2019; Hui

Wang, Ji, and Xia 2019), trade openness (Haikun Wang et al. 2017), industrialization and energy consumption (Liu et al. 2019; Reddington et al. 2019; Hui Wang, Ji, and Xia 2019; Zhao, Chen, and Zhao 2019). The structure of energy consumption is the leading cause of PM2.5 concentration (Chen et al. 2018; Okedere et al. 2021). Studies have found that fossils fuel energy consumption is the main source of $PM_{2.5}$ emission while most of the energy needs in developing countries are fulfilled by the conventional energy sources as half of the world population depends on fossils fuel energy consumption (Y. Zhang et al. 2019) that causes the more morbidity and health issues. (S. Yang, Fang, and Chen 2019). On the other hand, the renewable energy that pertains to solar (photovoltaic), wind, tidal, etc., is considered eco-friendly (Mahjabeen et al. 2020). Many researchers have documented the benign effect of non-conventional energy sources on climate changes (Dong, Hochman, et al. 2018; Mert, Bölük, and Çağlar 2019; Paramati, Sinha, and Dogan 2017; Sarkodie and Adams 2018; Sreenath, Sudhakar, and Yusop 2020).Some studies showed no differential effects (Bilgili, Koçak, and Bulut 2016; Farhani and Shahbaz 2014; Mert and Bölük 2016) but the exploration of a differential effect of fossils fuel energy consumption and renewable energy consumption for the notion of $PM_{2.5}$ concentration is quite understudied yet. We argue that the rapid urbanization, industrialization, and trade openness that requires a lot of energy consumption and building of infrastructure results in natural resource depletion, emission of environmental impurities, and excessive environmental degradation.

Air pollution is a global issue but developing countries are suffering the most (Chen et al. 2018). The study has selected the Next 11 countries for the analysis. The Next-11 countries are constituted of Bangladesh, Egypt, Indonesia, Iran, Korea, Mexico, Nigeria, Pakistan, Philippines, Turkey, and Vietnam and were introduced by a group of researchers from Goldman Sachs in 2005 (O'Neill, Wilson, and Stupnytska 2005). This group of countries is created considering the various macroeconomic features e.g. demographic profiles, economic stability, trade openness, political maturity, etc. it is predicted that by 2050, these countries would enjoy the improved political wisdom, economic stability, the majority of the population and sustainable development. The N-11grouping has also got recognition in academics and there is a growing body of research on the different aspects of the N-11 countries (Erdoğan, Yıldırım, and Gedikli 2020; Paramati, Sinha, and Dogan 2017; Shahbaz 2019) but the question remained untouched about the $PM_{2.5}$ concentrations and the socio-economic indicators as well as the contributing role of renewable and non-renewable energy sources in this anthropogenic pollutant emission for N-11 countries.

Most of the studies have used spatial econometric models (Cheng, Li, and Liu 2017; Ding et al. 2019; W. Zhu 2020; W. Zhu, Wang, and Zhang 2019). The empirical findings on this impurity are scant and very recently researchers have shifted toward econometric methods to find the driving factors of its concentration. The study has developed a panel data methodology using the rationale of the Environment Kuznets Curve (EKC) that explains the nonlinear relation between economic growth and environmental quality (Hui Wang, Ji, and Xia 2019; Zafar, Saud, and Hou 2019). EKC hypothesis posits that at an early stage of economic growth, the resources are being extracted more than generated which leads to degrade the environmental quality, but later the environmental quality starts to improve due to the environmental consciousness and increased intention on social wellbeing (Ben Amar 2021; Dinda 2004). The pioneering study was conducted in 1991 by Grossman et al., (1991) to validate the claimed U-shaped curved relation between income and environmental degradation. Later on, it has been analyzed by taking the different proxies of income and environmental quality but considering the $PM_{2.5}$ in the EKC framework with empirical panel data analysis is understudied yet (Hui Wang, Ji, and Xia 2019). The study ought to offer very useful implications. Firstly, the study has focused on $PM_{2.5}$ concentrations as the indicator of air quality and the notion of $PM_{2.5}$ is quite understudied yet. Secondly, the study has selected N-11 countries due to their rapid economic growth and little is known about the air quality of these countries. Thirdly, the panel data methodology constituted on first-generation as well as newly developed second-generation econometric techniques to quantitatively find the empirical linkage with air pollution, economic growth, industrialization, trade openness, urbanization, and energy mix for the period 19955-2017. So, to achieve coordinated economic development and air quality, it is of practical importance to study the impact of economic uplift and air quality along with other externalities for policy formulation and to increase the public understanding of the core issue (W. Zhu, Wang, and Zhang 2019). The next chapters pertain to the literature review, followed by the methodology, result and discussion, and finally the limitations and policy implications.

2. LITERATURE REVIEW

The major cause of air pollution is the concentration of fine particulate matter which has far-reaching health and economic adverse consequences (Ouyang et al. 2019). One of the main causes of haze is $PM_{2.5}$ concentration (J. Yang et al. 2019), which can suspend in the air and can cause respiratory issues along with other deadly diseases. Due to the episodic nature of haze, scholars from multidisciplinary sciences are analyzing the health effects of this deadly emission. So, decoupling economic growth from environmental pollution has become imperative in developing countries where certain measures are needed to decrease the environmental cost of economic growth (X. Zhang et al. 2020).

The soaring demand for all kinds of energies has come from urban infrastructure development, industrialization, public, and private transportation (X. Zhang et al. 2020). Due to the severe consumption and production-related activities, the cities are suffering from severe air pollution. Exposure to $PM_{2.5}$ concentration not only impacts human health but also causes economic loss to individuals and economies (S. Yang, Fang, and Chen 2019). H. Wang, Ji, and Xia (2019) analyzed the energy-related $PM_{2.5}$ in China by using the STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) model for thirty provinces of China. The results show an upward trend over the study period in energy-related $PM_{2.5}$ concentrations. The authors found the positive and heterogeneous influence of energy intensity, energy use, and increase population on energy-related emissions. Further, the author states that energy-related emission varies from area to area and a U-shaped curve was not verified except for eastern China. There is a wide range of literature that has analyzed the health impact of $PM_{2.5}$ emissions. The burning of coal and biomass energy in winter caused more haze and $PM_{2.5}$ concentrations that eventually increase haze, especially in winters as the mortality rate is three times higher in winter in northern cities of China than in summer. Zhang and Wang, (2019) analyzed the impact of $PM_{2.5}$ concentration on subjective wellbeing by constructing longitudinal panel data for Chinese provinces. The dependent variables are happiness and inequality of happiness. The authors reported that high-level concentration decreases subjective well-being by lowering the happiness of individuals especially for those with high income.

There is an increasing interest of the researcher to determine the socioeconomic indicators of $PM_{2.5}$ concentration so that a control action plane can be devised. Xie and Sun (2020) simultaneously investigated the direct and indirect effects of foreign direct investment (FDI) on $PM_{2.5}$ emission for emerging countries for the period from 2010 to 2016. Due to the features of the nonlinear analysis, a generalized panel smooth transition regression(GPSTR) model was introduced for nonlinear analysis. The results reveal that FDI directly contributes to decreasing $PM_{2.5}$ but indirectly increases $PM_{2.5}$ emissions. The total effect of FDI on $PM_{2.5}$ concentrations is proven to be negative, which confirms the pollution halo hypothesis. Ding et al. (2019) analyzed the EKC for $PM_{2.5}$ emission where they found a significant inverted U-shaped relation between income level and $PM_{2.5}$ for China. The concentration of $PM_{2.5}$ is the major reason for haze and residential energy consumption accounts for the major proportion of $PM_{2.5}$ emission. The capital formation and trade embodied in export and imports also have the major share in consumption-based air pollution J. Yang et al., (2019). Cheng et al., (2017) analyzed the impact of key driving factors of $PM_{2.5}$ concentration using the dynamic spatial econometric panel data models using the data from 2001 to 2012 for 285 Chinese cities. Econometric models they used are panel unit root test, error correction based co-integration test, residual integration test, and other tests for correlation and spatial linkage. The results of these tests indicate these Chinese cities have spatial autocorrelation with the globe while cities also get affected by the local agglomeration. Results of the EKC hypothesis confirm the inverted U-shaped relation and the co-integration test also provides significant results for most of the variables.

In another important study by Chen et al., (2019), authors have analyzed the role of technology progress path in $PM_{2.5}$ concertation for 48 cities of China for the period of 2000 to 2015. Where the authors concluded that technological progress can mitigate pollution. Zhu et al., (2019) analyzed the impact of urbanization using the spatial econometric techniques for China's Yangtze River Economic Belt (YREB). Results of various tests indicate no significant U-shaped or inverted U-shaped or N-shaped or inverted N-shaped curve between economic urbanization and $PM_{2.5}$ concentration. Chen et al., (2018) divided the countries into four categories depending on their income level to find the impact of energy consumption, urbanization, energy intensity on $PM_{2.5}$ concentration. The results of the Granger causality test reveals that all the studied variables lead to an increase in the $PM_{2.5}$ concentrations. Importantly they found that the most important factor of $PM_{2.5}$ concentrations in the energy structure in middle-income and low-income countries.

Ding et al., (2019) investigated the existence of the EKC hypothesis for selected cities in China. After finding the spatial effects, the authors have also applied the Spatial Durbin Model (SDM) for EKC analysis where the authors found the significant inverted U-shaped relation between economic growth and $PM_{2.5}$ pollution. The authors further concluded that the region still has an upward trend and the postindustrial stage is still having to come. Another study by Q. Wang et al., (2019) investigated the impact of urbanization and traffic-related emission on countries around the globe by making three sets of countries underdeveloped, developing, and developed countries. Authors found that both the urbanization and traffic-related emission has a strong impact on $PM_{2.5}$ concentration though, the impact is different for the different group of countries

Given the above discussion, the influence of socio-economic indicators and $PM_{2.5}$ concentration was revealed to be complex. The EKC hypothesis offers different results for different countries and sometimes different results for the same country mainly due to the selection of different times, different statistical analyses, and grouping of different regions in a study. The study has selected N-11 countries for analysis for the period of 1995-2017 as this era has witnessed rapid economic growth.

3. METHOD AND MATERIAL

The main objective of the present study is to gauge the influence of socio-economic and energy factors on $PM_{2.5}$ concentrations. The socioeconomic variables include industry value-added, trade openness, economic growth, and urbanization while energy structure includes renewable and non-renewable energy consumption. The study has selected the sample of the Next-11 countries that constitute Bangladesh, Egypt, Indonesia, Iran, Korea, Mexico, Nigeria, Pakistan, Philippines, Turkey, and Vietnam. Panel data set is constructed by collecting the data from 1995-2017. The missing values are treated using the imputation technique. Table 1 contains the details of the data series along with the measurement units and data sources. Following the empirical methodological pattern of Chen et al. (2019) different panel data methodology is developed. The initial function is

PM2.5 = *f (FFEN REN TO URB IVA GDP)*

After adding parameters in the initial function, the equation form is

$$PM2.5 = \alpha + \beta_1(FFEN_{it}) + B_2(REN_{it}) + \beta_3(TO) + \beta_4(URB_{it}) + B_5(IVA_{it}) + B_6(GDP) + \varepsilon \ldots\ldots (1)$$

All variables are transformed into a natural logarithm to treat the distributional properties of data series. Further, the study is using the EKC rationale so, we have added the quadratic form of GDP to measure economic growth. The log-linear form of the equation for the study is

$$PM2.5 = \alpha + \beta_1(lnFFEN_{it}) + B_2(lnREN_{it}) + \beta_3(lnTO) + \beta_4(lnURB_{it}) + B_5(lnIVA_{it}) + B_6(lnGDP) + B_7(lnGDP2) + \varepsilon \ldots\ldots (2)$$

3.1 Econometric Methodology

To estimate the association and co-integration between variables, panel co-integration methodology is adopted because the data set has large T and small N. The panel data co-integration methodology is best suited when the number of crosses sections is less than the time period (Ahmed et al. 2020)

3.2 Cross-Sectional Dependence Test

The study aims to explore the association and co-integration of variables for the Next-11 countries. The cross-sectional(CD) test is applied to analyze whether the cross-sectional units have a dependence on each other due to the contingent events and common shocks. The general equation of the CD test is displayed as

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{I=i}^{N-1} \sum_{J=i+1}^{N} \hat{\imath\jmath} \ldots\ldots\ldots (3)$$

The results indicate the mixed results some variables are showing the cross-sectional dependence and the industry value added and trade openness are showing insignificant results. Therefore, we have developed both the first-generation and second-generation data estimation.

3.3 Panel Unit Root Analysis

Before applying econometric tools, panel unit root tests are applied as the selection of the econometric model is based on the results of the unit root test. Series can be stationary at a level "I (0)", at the first difference" I (1)", or at the second difference "I(2)". To estimate the distributional properties of the series, five different panel unit root tests are applied. The common unit root test is measured by Lavin-Lin-Chu (LLC) test and the individual unit-roots are measured by the Augmented Dicky-Fuller (ADF), Philips-Perron (PP), and Im-Pesaran-Shin (IPS) test. Besides it, the second-generation unit root test is also employed for concrete analysis as the second-generation unit root test accounts for the cross-sectional dependence and heterogeneity in the panel data set. The general equation for the panel CIPS test is

$$Cips(N,T) = N^{-1} \sum_{i=1}^{N} ti\,(N,T) \ldots\ldots\ldots (4)$$

where $ti\,(N,T)$ denotes the ith cross-section of CIPS test

3.4 Panel Co-integration Analysis

The study has employed autoregressive distributive lag (ARDL) for estimating the co-integration among variables. The ARDL approach of co-integration is developed by Pesaran, Shin, and Smith (2001) and used by many researchers (Dong, Sun, et al. 2018; Paramati, Sinha, and Dogan 2017; Shahbaz et al. 2015) as it has many advantages over other co-integration tests e.g. Johansen and Juselius. To establish long-run parameters, ARDL uses one equation while other techniques use more than one equation. ARDL can also be used whether the series is stationary at the level or first difference. Most importantly, it avoids serial correlation and endogeneity problems and allows predictors to have different lag orders and finally, it works well even for the small sample (Sarkodie and Adams 2018). After examining the ARDL, Wald statistics is applied to determine the robustness of the parameters. The null hypothesis assumes no co-integration among estimates ($\beta1 = \beta2 = \beta3 = \beta4 = \beta5 = \beta6 = \beta7 = 0$) while alternative hypothesis assumes co-integration among parameters ($\beta1 \neq \beta2 \neq \beta3 \neq \beta4 \neq \beta5 \neq \beta6 \neq \beta7 \neq 0$).

The empirical specification based on the ARDL estimation is

$$\Delta \ln PM2.5_t = \alpha_0 + \delta_1 PM2.5_{t-1} + \delta_2 lnFFEN_{t-1} + \delta_3 lnREN_{t-1} + \delta_4 lnTO_{t-1} + \delta_5 lnURB_{t-1} + \delta_6 lnIVA_{t-1} + \delta_7 lnGDP_{t-1} + \delta_8 lnGDP2_{t-1} + \sum_{i=1}^{p} \beta 1j \Delta PM2.5t - i + \sum_{i=0}^{p} \beta 2j \Delta lnFFENt - 1 + \sum_{i=0}^{p} \beta 3j \Delta lnRENt - 1 + \sum_{i=0}^{p} \beta 4j \Delta lnTOt - 1 + \sum_{i=0}^{p} \beta 5j \Delta lnURBt - 1 + \sum_{i=0}^{p} \beta 6j \Delta lnIVAt - 1 + \sum_{i=0}^{p} \beta 7j \Delta lnGDPt - 1 + \sum_{i=0}^{p} \beta 8j \Delta lnGDP2t - 1 + \varepsilon t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where $PM_{2.5}$, lnFFEN, lnREN, lnTO,lnURB, lnIVA lnGDP,lnGDP2 indicates the natural log of particulate matter ($PM_{2.5}$) as the measure of air quality, fossils fuel energy consumption or nonrenewable energy consumption, renewable energy consumption, trade openness, urbanization, industry value-added, gross domestic product per capita and the square of gross domestic product per capita respectively. The intercept is denoted by α, Δ represent the first difference operator, δ and β denote the slope coefficient, p is the lag order ε is a stochastic term. To inculcate the cross-sectional dependence, the study has also estimated the newly developed Westerlund error correction co-integration test that accounts for the cross-sectional dependence in the panel data set. The equation for Westerlund co-integration test is

$$\Delta yit = \acute{\delta} d_t + ai(y_{it-1} - \beta \acute{i}\, x_{i,t-1}) + \sum_{j=-qi}^{q=i} aij \Delta y_{i,t-1} + \sum_{j=-qi}^{q=i} \gamma_{ij} \Delta x_{i,t-1} + ei, t \ldots\ldots (6)$$

3.5 Panel long run Elasticities

The study has employed DOLS and FMOLS to find the co-integrated vectors. DOLS is a parametric approach that accounts for serial correlation in errors by using the generalized least square procedures and leads and lags to correct the endogeneity in independent variables. On the other hand, FMOLS is the semi-parametric approach which accounts for the first differences of the regressors and possible correlation with error term but both of the techniques have normal limiting properties (Kao and Chiang 2000; Pedroni 2000; Pradhan et al. 2017). The study has employed both the DOLS and FMOLS techniques for robustness. the biggest disadvantage of these techniques is that they don't inculcate the cross-sectional dependence and heterogeneity of the panel. Therefore the study has also employed the dynamic common correlated effect (DCCE) that accounts for cross-sectional dependence in economies (Chudik and Pesaran 2013, 2015; Pesaran 2006). The general equation for the DCCE test is

$$PM_{2.5} = \alpha i PM_{2.5_{it-1}} + \delta X_{it} + \sum_{p=0}^{PT} \gamma xip\, \bar{\boldsymbol{X}}_{t-p} \sum_{p=0}^{PT} \gamma yip\, \bar{Y} t - p + \mu_{it} \ldots\ldots.. (7)$$

$PM_{2.5}$ denotes the particulate matter, $\alpha i PM_{2.5_{it-1}}$ denotes the lag value of particulate matter. δ_{it} indicates the number of proposed independent variables while the number of lags is denoted by PT

Table 1: Data Sources and Description

Code	Variable name	source
$PM_{2.5}$	Particulate matter = mean annual exposure (micrograms per cubic meter)	WDI
FFEN	Fossils fuel energy consumption = Fossils fuel energy consumption as % of total	WDI
REN	Renewable energy consumption = renewable energy consumption as % of total	WDI
TO	Trade openness = export +imports as % GDP	WDI
URB	Urbanization = urban population as % of total population	WDI
IVA	Industry value added as % of GDP	WDI
GDP	Gross Domestic Product Per Capita	WDI
Note:	*WDI= World Development Indicator*	

4. RESULTS AND DISCUSSION

Empirical testing of the data started with descriptive statistics and a correlation matrix of the panel data. Results are presented in Table 2 where the values indicate little dispersion in data series and no outlier showing the stability of the data. The correlation matrix indicates that the highest correlation is **"**-0.6623" between renewable energy consumption and GDP per capita that means these variables move in the opposite direction. conventional energy consumption has a "-0.206" coefficient of correlation while renewable energy has a "0.14228" coefficient of correlation that means positive co-movement of variables. Urbanization Gross domestic product, trade openness, industry value added and nonrenewable energy consumption has negative co-movement with air quality having the coefficient -0.3792, -0.3761, -0.5051, -0.581, -0.206 respectively. Renewable energy consumption has positive co-movement (0.14228) with $PM_{2.5}$ concentrations.

Table 2: Descriptive Statistics and Correlation Matrix of N-11 Countries

	Mean	SD	LNFFEN	LNGDP	LNIVA	LN $PM_{2.5}$	LNREN	LNTO	LNURB
LNFFEN	4.18092	0.44883	1						
LNGDP	7.72373	1.16057	0.45089	1					
LNIVA	3.43999	0.24155	0.31057	0.26093	1				
LN $PM_{2.5}$	3.66604	0.47288	-0.206	-0.3761	-0.581	1			
LNREN	2.73927	1.50586	-0.6582	-0.6623	-0.441	0.14228	1		
LNTO	3.96713	0.43949	0.1321	0.16718	0.49839	-0.5051	-0.0791	1	
LNURB	17.6795	0.43879	-0.032	0.33101	0.0802	-0.3792	0.07991	-0.3232	1

Table 3 presented the results of the cross-sectional dependence test that indicates that trade openness is significant at a 10% level of confidence while industry value added is insignificant showing cross-sectional independence. Therefore, the study's methodology contains both the first generation as well as second-generation econometric techniques.

Table 3: Results of Cross-Sectional Dependence Test

variables	CD test	P-value
LNREN	10.52	0.000*
LNFFEN	9.65	0.000*
LNTO	1.72	0.085 ***
LNURB	35.45	0.000*
LNIVA	0.43	0.667
LNGDP	32.03	0.000*

*asterisks symbol *,**.*** refer to the rejection of null hypothesis at 1%, 5% and 10% level of significance, respectively*

Results of the first-generation unit root test are presented in Table 4 while results of the second-generation unit root test are presented in Table 5. Results indicate that all the series are stationary at first difference which means that these series as a group might have long-run co-integration. The decision about stationery of first-generation unit root tests is made considering the majority results i.e. the variable is considered stationary at the level if three out of four tests indicate stationary at level. It is important to note that none of the series is stationary at the second difference which leads to examine the long-run co-integration.

Table 4: Panel Unit Root Test

Variables	LLC		IPS		ADF		PP		Decision
	1(0)	1(1)	1(0)	1(1)	1(0)	1(1)	1(0)	1(1)	
LN $PM_{2.5}$	5.1984 (1.000)	-1.688 (0.0486)	3.591 (0.999)	-3.3879 (0.0004)	8.0011 (0.9971)	56.4772 (0.0000)	12.32 (0.9512)	153.484 (0.0000)	1(1)
LNFFEN	-3.09348 (0.0001)	-7.7411 (0.0000)	-0.6608 (0.2543)	-6.4856 (0.0000)	23.5252 (0.3726)	82.910 (0.0000)	30.1213 -0.6705	163.590 (0.0000)	1(1)
LNREN	-7.19375 (0.000)	- 5.44871 (0.0000)	0.3080 (0.6210)	- 7.44837 (0.0000)	17.6843 (0.7245)	95.4653 (0.0000)	23.8353 (0.3559)	167.011 (0.0000)	1(1)
LNTO	-0.4627 (0.3218)	-5.3525 (0.0000)	0.1870 (0.5743)	- 7.33907 (0.0000)	17.9850 (0.7069)	94.6867 (0.0000)	25.0052 (0.2968)	197.529 (0.0000)	1(1)
LNURB	-1.2083 (0.1135)	- 4.88171 (0.0000)	2.74951 (0.9970)	- 2.46056 (0.0069)	12.4345 (0.9477)	49.2918 (0.0007)	129.606 (0.0000)	37.4725 (0.0210)	1(1)
LNIVA	0.32972 (0.6292)	- 5.53959 (0.0000)	0.13811 (0.5549)	- 7.43291 (0.0000)	20.7212 (0.5380)	95.9850 (0.0000)	21.6752 (0.4794)	164.735 (0.0000)	1(1)
LNGDP	1.71289 (0.9566)	- 2.47645 (0.0066)	3.49055 (0.9998)	-3.7309 (0.0001)	11.3517 (0.9694)	54.8754 (0.0001)	17.0197 (0.7629)	93.6847 (0.0000)	1(1)

Table 5: Second Generation Unit Root Test

variables	level	First difference
LN $PM_{2.5}$	-2.003	-3.826***
LNREN	-1.898	-4.445***
LNFFEN	-2.113	-4.470***
LNTO	-1.804	-4.883***
LNURB	-1.971	-2.893***
LNIVA	-1.733	-4.703***
LNGDP	-1.988	-3.666***

A single asterisk (*), double asterisks (**) and (***)refer to levels of significance at 10% and 5% and 1% respectively

The long-term results of panel ARDL are presented in Table 6. Results indicate that both sources of energy have significant positive coefficients that indicate that both kinds of energies are the significant contributor to the $PM_{2.5}$ concentration similar to the findings of Mahjabeen et al.,(2020). We argue that these countries need to maintain a nice blend of both kinds of energies and a gradual transition toward renewable energy sources is required. The fossil fuel energy consumption is the major contributor to air pollution and certain policies are urgently required to control its deadly concentration. Trade openness and industry value added didn't prove significantly co-integrated while urbanization is significant at a 10% level of significance with a negative coefficient. The gross domestic product proves significant with positive co-efficient showing that with economic growth the environmental quality is compromised and air pollution is the necessary cost of economic development for the N-11 countries until the turning point comes in the postindustrial phase. The quadratic form of GDP has a significant but negative coefficient which implies that with higher income level air pollution decreased.

Table 6: Long Run Estimates of Panel ARDL Test

Variables	Coefficient	t-Stat	Sig
LNFFEN	1.8393	6.64472	0.000
LNREN	0.65241	4.73697	0.000
LNTO	-0.0367	-1.2924	0.198
LNURB	-0.1112	-1.7979	0.074
LNIVA	0.01052	0.08459	0.932
LNGDP	0.94971	2.50598	0.013
LNGDP2	-0.0676	-2.6115	0.001

The EKC hypothesis is validated if the coefficient of income has a positive sign and the square of income has a negative coefficient (Alotaish Mohammed Saud et al. 2019). So the result of long-run elasticities verifies the EKC hypothesis in long run.

Table 7: Results of Westerlund ECM Co-integration test

	value	Z value	p-value
Gt	-2.867	-1.432	0.076
Ga	-2.122	4.666	1.000
Pt	-10.797	-3.140	0.001
Pa	-3.915	2.307	0.990

The results of the Westerlund co-integration test are presented in Table 7. This co-integration technique inculcates the cross-sectional dependence and gives two group statistics (Gt, Ga) and two-panel statistics (Pt, Pa). Out of four, two statistics are significant at a 10% level of confidence and one statistic is significant at a 1% level of significance. So, we can say that the variables of the study have long-run co-integration with each other.

Table 8: Estimates of long Term Elasticities

	FMOLS Estimation			DOLS Estimation		
Variables	Coefficient	T-Stat	Sig	Coefficient	T-Stat	Sig
LNFFEN	-0.12302	-1.14015	0.2553	-0.10198	-0.84732	0.3977
LNGDP	0.694343	1.527432	0.1279	0.543277	1.042635	0.2983
LNGDP2	-0.04673	-1.6582	0.0986	-0.03676	-1.12946	0.2599
LNREN	-0.04694	-0.87193	0.3841	-0.03337	-0.52374	0.601
LNTO	-0.53341	-3.95332	0.0001	-0.57645	-3.33882	0.001
LNURB	-0.58245	-4.30513	0.0000	-0.60424	-3.83151	0.0002
LNIVA	-0.66099	-2.74142	0.0066	-0.59132	-1.98988	0.0478
	Adjusted R-squared= 0.643362			Adjusted R-squared = 0.636262		

The results of FMOLS and DOLS are presented in Table 5 that shows that trade openness, urbanization and industry value added are the most significant factors but contrary to the assumption, they have a significant negative association with PM2.5. From this finding we can say that to decrease air pollution, these countries need to increase trade openness, urbanization, and industrialization as coordinated urbanization doesn't hinder economic growth (Wu, Zhang, and Ding 2020). GDP has a positive but insignificant association with PM2.5 and GDP^2 has a negative but insignificant association with pm2.5 concentrations alike in FMOLS and DOLS. We can infer that though; the impact is minimal but it is according to the EKC hypothesis's rationale. Results of DCCE are presented in Table 9 that indicates that besides urbanization and lag value of Pm2.5, all other variables are insignificant.

Table 9: Results of Dynamic Common Correlated Effect Estimates

variables	Coefficient	sig
LNPM2.5(_1)	-0.3664025	0.036
LNREN	-0.6146675	0.199
LNFFEN	-0.3403132	0.71
LNTO	-0.0139233	0.841
LNURB	5.761691	0.011
LNIVA	-0.1436904	0.169
LNGDP	0.3425991	0.684
LNGDP2	-0.0373472	0.533

5. CONCLUSION

The primary factor of air pollution is the concentration of $PM_{2.5}$ as it negatively impacts the climate, atmospheric visibility and human health (W. Zhu, Wang, and Zhang 2019). Researchers found that economic activity, industrialization, open biomass burning, residential energy consumption, and urbanization are the leading factors of accelerating $PM_{2.5}$. Deadly haze and $PM_{2.5}$ concentration is the leading challenge of the globe but less is known for the developing countries. This study has focused on the Next-11countries as they are the next emerging economies with a substantial share in the world's GDP as well as suffering from increasing environmental degradation. Data is collected from1995-2017 and panel econometric tools are applied to find the distributional properties of urbanization, trade openness, industry value-added, nonrenewable energy, renewable energy, and income level.

Results of the cross-sectional dependence test show mixed results as some variables show cross-sectional dependence and others independence, therefore both the first generation as well as second-generation data analysis techniques are employed for robust results. The results of both the first generation and second generation panel unit root tests indicate that all the variables are stationary at the first difference. The results of the ARDL approach indicate the long-run association of renewable energy and nonrenewable energy with $PM_{2.5}$ showing that both of the energies are contributing to this anthropogenic concentration. Further, the GDP showed a positive impact and GDP^2 showed a negative impact on $PM_{2.5}$ that indicates the presence of the EKC hypothesis in our sampled countries. Results of the Westerlund co-integration technique indicates that out of four, three statistics are significant that confirm the long-run co-integration among the variables of the study. Contrary to the expectations, the results of DOLS and FMOLS showed an insignificant association of income level and energy mix with $PM_{2.5}$ concentration while negative and significant results for industry value-added, trade openness and urbanization. On the other hand, the results of DCCE show insignificant results except for urbanization that shows a significant positive impact on $PM_{2.5}$ concentrations.

5.1 Policy Implications

Though all the Next-11 countries are not clustered geographically they have shared economic challenges and environmental issues. Based on findings, we can state that these countries require to maintain a nice blend of both kinds of energy resources and then gradual transition towards renewable energy resources with technological advancements. To decrease the environmental cost of economic growth, persistent economic policies should be devised and the government of these countries should involve in green activities. According to [1]IQAir the two member countries of the N-11 group, Bangladesh and Pakistan have the first and 2nd position on the ranking of most polluted countries and worst air quality. So, for green industrialization, the government of these countries needs to panelized the unclean industrial activities by the proper imposition of environmental taxes while subsidies and tax relief can be provided on eco-friendly industrial activities. Most importantly, public awareness through the proper campaign at the national level is required to communicate the importance of a clean environment.

[1] *https://www.iqair.com/us/world-most-polluted-countries retrieved on 4/12/2020*

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