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Environmental Kuznets Curve and Income Inequality: Pooled Mean Group Estimation for Asian Developing Countries

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Abstract

Current study explores the association between environmental quality and economic growth along with role of income inequality within Environmental Kuznet Curve (EKC) framework by using three environmental quality variables (CO2, SO2 emission and PM2.5 concentration). The panel data of developing Asian countries have been employed for the investigation. Empirical analysis has been carried out by using PMG estimation technique. Results confirmed the presence of EKC for all environmental quality indicators for developing Asian economies in the long run. However, it does not hold in case of any environment quality indicator in the short run. Moreover, the findings reveal that income inequality is positively related to CO2, SO2 emission and PM2.5 concentrations. It indicates that rise in income inequality leads to increase CO2, SO2 emission and PM2.5 concentrations in the atmosphere. Furthermore, population density, urban population, foreign direct investment and trade openness are also positively related with all environmental quality variables.

Keywords: Environmental Quality, Income Inequality, EKC, PMG

JEL Classification: I3, Q53, O1, F31

1. Introduction

Last few decades have witnessed the evolution of term sustainable development and it gained more popularity among researchers. This term was first time explained by Brundtland commission report in 1987 as "Development that meets the needs of current generations without compromising the ability of future generations to meet their own needs" (WCED, 1987, p. 45). During the discussion of this term that will turn out in future it is important to consider the current and previous circumstances about environment and economy relationship. Sustainable Development is an all-inclusive approach which is surely the rightful successor of growth and development doctrine and key balancing lever, which may ensure

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equity across generations and various groups, is the environmental quality with its all allied linkages that proclaim the efficacy of sustainable development.

Ironically, recent past decades have observed that poor nations have experienced terrible obstacles in the way to get higher pace of economic development and industrialization without damaging the environmental assets and ecosystem. Research endeavors of the early 1990s produced empirical evidences which analyzed the environmental implications of different phases of economic growth. The Environmental Kuznets Curve (EKC) notion came into surface on the same analogy from ground-breaking research work of Simon Kuznets (1955) upon the correlative association of income inequality and per capita income known as Kuznets curve. Grossman and Krueger (1991) work provided the basis for the idea of EKC then it became agenda topic of researchers during 1990s. EKC theory narrates that during early stage of growth, that is, in the pre-industrial phase and/or in some time of industrial phase that needs more utilization of resources, there would have been an experience of increased level of environmental degradation leading to worsening environmental quality. However, in the later stages, that is, the remaining time frame of industrial phase and post-industrial phase, there would be successive improvement in environmental quality. Therefore, there hasn't been the situation of compromise on environment for all times and we do experience win-win situation in the later stages of economic growth.

There are two opinions regarding the explanation of EKC shape i.e. demand-side argument and supply-side argument in the literature. Regarding demand side strand, it is believed that with growth of income people would be more conscious about the environmental issues. On this pretext, we can say that after a certain benchmark in terms of income, people are more eager to pay for improved environment due to increase in income. Due to environmental issues, concerned people would pressurize firms and industries to use low emission production technologies and induce policy makers for inflexible environmental protection laws.

The supply-side argument was put forward by Grossman and Krueger (1995) at earliest place. He explained the idea by arguing in three ways. First is scale effect which is related to impact of expansion of economic activity on environment quality. It narrates that more natural resource consumption is needed for higher level of output which certainly correlates with higher emissions of gases leading to more environmental damage. Second argument known as composition or structural effect is associated with structural changes from agrarian to industrial based economy & rural to urban within the economy. Technique effect posits advancement in technology and scientific progress. It is established that environment-friendly technologies are rooted in technique effect. Overall, the EKC proposition can be summarized into negative and positive effects of economic outcome on environment deterioration. Either it will be 'negative' in the earlier stages of growth during scale effect or 'positive' in later stages of growth as structural and technique effects became dominant over the scale effect.

Sustainable Development Goals (SDGs) also promoted the fight against inequality as one of its key messages because it hampers poverty reduction and growth. Kuznets (1955) affirmed urbanization and rural urban gap as major reasons of rising inequality and these are also reasons of deterioration of environment. It has also been established that environmental degradation and income inequality are interlinked strongly. Boyce (1994) addressed this issue at first place that rise in income inequality affects environment by the rich and poor people. The researchers have developed two different arguments about the influence of unequal income distribution on environment quality. Some are of the view that rise in income inequality improves environment quality while others conceive negative association between higher income inequality and environment degradation.

Many researchers have studied the incidence of EKC but only few have analyzed the role of unequal income distribution in EKC framework but for developed countries. These studies have used CO_2 emission as pollution indicator using conventional panel data analysis methods which ignore the issue of heterogeneity. This study aims to remove the econometric drawbacks by adopting latest econometrics techniques of panel data analysis. The other studies related to EKC and role of inequality have been carried out at county level by employing time series data. These have limitations as time series data do not contain enough information and their findings may lead to incorrect policy implications. The current work also contributes in the existing literature by considering more environmental quality variables.

The current study has preferred developing Asian countries because of rising environmental deterioration trends in terms of higher CO_2 emission, global warming and inequality since 1990. Asian developing region has witnessed rapid growth rate and often known as growth center of world since last few decades but at same time gap between rich and poor has been rising than before contrast to other developing regions of world (Ota, 2017). So, it is important to encounter rising inequality for appropriate policy implications. On the basis of World Bank Atlas method 2018 these countries are declared as developing countries. Another reason for the selection of this region is that most of the MDGs targets were not fulfilled in these countries. Furthermore, association between environment quality and income inequality is unexplored for this region within the EKC framework. Thus, current study also attempts to fill the gap by including income inequality as an additional channel in explaining the relation between and environment degradation and economic growth. The remaining paper is arranged as; available literature is discussed in section two while section three consists of data and methodological explanation. Section four and five elaborates empirical findings and conclusion respectively.

2. Literature Review

There is bulk of literature available that has assessed the association between environment and per capita income at country level and regional level from many aspects but still few dimensions are not explored. There is some literature which focuses on role of income inequality within EKC framework. This section also presents review about EKC for different environment quality indicators.

Hailemariam et al. (2019) explored the relationship between environment quality and economic growth. The study also analyzed the impact of income inequality on environment quality for 17 OECD countries. It employed data ranging from 1945 to 2010 gathered from Oak Ridge National Laboratory (ORNL) Information Analysis Centre, Maddison Project database and Madsen et al. (2018) Income Database. The study employed CCEMG estimators, FMOLS and DOLS techniques for empirical estimations. The findings indicated positive and significant association between income inequality and CO_2 emission. In addition, study found positive and significant influence of GDP per capita and negative effect of GDP per capita square on CO_2 emission verifying the evidence of EKC for OECD countries.

Hao et al. (2016) used Chinese provincial level data to investigate the influence of income inequality on environment quality. The study used Gini coefficient and per capita growth as measures of income inequality and per capita income respectively. GMM technique has been used for empirical investigations because it deals with the issue of endogeneity. The results concluded that income inequality exerted negative impact on per capita growth in all provinces. The findings also verified the existence of inverted U-shape relationship between per capita growth and CO_2 emission.

Borghesi, (2006) explored the effect of unequal income distribution on environment degradation within the EKC framework for 126 countries during the period 1988-1995. The study estimated two regression equations with and without income inequality by employing different specification. The study employed different functional specification to analyze the correlation by utilizing panel data retrieved from WDI dataset. The study also adopted different estimation tools such as pooled OLS and fixed effect model. Both techniques provided different findings. Income inequality exerted negative impact on CO_2 emission which implied that rise in inequality reduces CO_2 emission while exerted positive effect in fixed effect model. The effect of inequality remained statistically insignificant in case of both techniques. Moreover, analysis was also carried out separately for rich and poor countries to make appropriate suggestions. The finding suggested that income inequality decreases emission in the high-income countries and leads to increase in the low-income countries. The other explanatory variables which includes population density industry value added share were positively associated with CO_2 emission.

Demir *et al.* (2019) analyzed the association between economic growth, income inequality and environment quality for Turkey. The study employed time series data ranging from 1963 to 2011 and carried out empirical analysis by using ARDL approach. The findings depicted that income inequality has negative impact on economic growth meaning that rise in income inequality reduces CO_2 emission in Turkey. Moreover, results indicated that EKC holds for Turkey.

Ravallion *et al*. (2000) estimated regression equation to analyze the income inequality and pollution relationship by using CO_2 emissions as pollution indicator. The study used data for 42 countries during the period 1975 to 1992. Parameters had been estimated first by utilizing fixed effect model and then with pooled OLS. The results concluded negative correlation between carbon emissions and inequality within countries. However, at higher average incomes the effect of income distribution on the environment decreases.

Masud *et al.* (2018) employed panel data from 1985 to 2015 to explore the causality between environmental sustainability and income inequality for five ASEAN countries. The analysis was carried out by employing panel granger causality and generalized least squares (GLS). The results posited that environmental sustainability cause income inequality while there was no evidence of cause from income inequality to environmental sustainability. Moreover, GLS results showed positive and significant correlation between income inequality and CO_2 emission.

Serrano *et al.* (2015) examined the effect of income inequality on environmental degradation for 26 Brazilian states by applying pooled OLS, fixed effect and random effect models to. The study employed panel data from 1990 to 2008 for analysis. Institute of Applied Economic Research data were used for empirical analysis. The empirical estimates have been obtained by using three models and applying different econometrics techniques. The results found that income inequality has no impact on environmental degradation in any model.

Clement and Meunie, (2010) analyzed the relationship between environmental degradation and income inequality by employing panel data from 1988 to 2003 for 67 developing and 16 transition countries. The study used SO2 Emission and BOD for pollution and GINI index to represent inequalities. The data were taken from ASL database and WDI 2007. The random effect model and fixed effect model were employed for econometric analysis and study found that rise in income inequality does not increases SO_2 emission, but water pollution rises for developing and transition economies.

Torras and Boyce, (1998) examined the impact of unequal income distribution on pollution measures except CO_2 emission for high- and low-income countries. The study used seven pollution measures as dependent variable obtained from Global Environment Monitoring System dataset (GEMS) and per capita income, urbanization, literacy rate and political rights as explanatory variables. On the environmental impact of income inequality, they found mixed results with OLS estimation. The effect of income inequality is positive for some water and air pollution measures and negative for some other indicators. The effect of Gini coefficient on SO_2 is positive for low income countries implying that rise in inequality increases SO_2 emission for low income countries and negative for high income group posing income inequality improve environment quality.

3. Data and Methodology

3.1. Model Specification

It is obvious from literature that researchers have used linear, log linear and log-log specifications for the analysis of EKC. The studies also differ in case of degree of per capita GDP used in regression equation. However, all the specifications have merits and demerits but use of log-log specification has advantage for the analysis of income environment relationship especially in case of panel data (Perman and Stern, 2003). The selection of functional form and variables has been made after taking into account Drabu (2011), Borghesi (2000) and Masud *et al.* (2018) to examine the relationship among environment quality indicators, per capita income and income inequality.

Model 1

$$Ln\, CO_{2it} = \alpha_0 + \alpha_1 LnGDPPC_{it} + \alpha_2 LnGDPPCS_{it} + \alpha_3 LnINEQ_{it} + \alpha_4 LnPD_{it} + \alpha_5 LnUP_{it} + \alpha_6 LnFDI_{it} + \alpha_7 LnTO_{it} + \varepsilon_{it} \quad (1)$$

Model 2

$$Ln\, SO_{2it} = \beta_0 + \beta_1 LnGDPPC_{it} + \beta_2 LnGDPPCS_{it} + \beta_3 LnINEQ_{it} + \beta_4 LnPD_{it} + \beta_5 LnUP_{it} + \beta_6 LnFDI_{it} + \beta_7 LnTO_{it} + v_{it} \quad (2)$$

Model 3

$$Ln\, PM2.5_{it} = \lambda_0 + \lambda_1 LnGDPPC_{it} + \lambda_2 LnGDPPCS_{it} + \lambda_3 LnINEQ_{it} + \lambda_4 LnPD_{it} + \lambda_5 LnUP_{it} + \lambda_6 LnFDI_{it} + \lambda_7 LnTO_{it} + \mu_{it} \quad (3)$$

Ln depicts natural logarithm whereas i=1,…,16 and t=1973,…….,2016 indicate countries and time periods for model 1 and ε_{it}, v_{it} and μ_{it} are error terms of the models. Model 2 and 3 employs data from 1973 to 2010 based on the availability of data. Carbon Dioxide (CO_2) emission, Sulphur Dioxide (SO_2) emission and Particulate Matter (PM2.5) concentration have been used as environment quality indicators. The Particulate are combination of different liquid droplets and solid matters hanging in the atmosphere. The size of particulate matters varies from 2.5 to 10 micrometers (PM2.5 µm -PM10 µm) and these are categories into Coarse (PM10), Fine (PM2.5) and Ultrafine (PM0.1) particles on the basis of size and composition. The current study focuses on the PM2.5 known as fine particles because these are tiny in size and can stay for longer time in atmosphere. Fine particles affect human health through breathing. It will ultimately reduce economic activity due to fall in labor supply and productivity. The higher value of CO2, SO2 emission and PM2.5 in air indicate more environmental degradation showing poor environmental quality and vice versa. SO_2 emission gigagram (Gg) and PM2.5 gigagram (Gg) data were collected from European Commission, Joint Research Centre (JRC)/PBL Netherlands Environmental Assessment Agency database. GDPPC and GDPPCS represents gross domestic per capita as a proxy of economic growth and square of gross domestic product per capita measured in constant 2010 US dollars are used to analyze the existence of EKC. INEQ denotes income inequality captured by Gini index and its data is retrieved from Standardized World Income Inequality Database (SWIID2016) developed by Solt (2009). The SWIID data is considered better than World Income Inequality Database (WIID) due to greater coverage and more comparability. PD is population density measured per square km of land and UP denotes urban population captured as percentage of urban population. These both variables have been taken into account to measure demographic characteristics of the countries. Economic openness is captured by foreign direct investment (FDI) calculated as percentage of FDI inflows to GDP and trade openness (TO) calculated as exports plus import percentage of GDP. The effect of FDI on environment quality depends upon three effects which are scale effect, technique effect (tech) and composition effect. The data of all economic, demographic variables and CO2 emission metric tons per capita have been obtained from the World Bank World Development Indicator (WDI 2018).

3.2. Levin-Lin-Chu Test (2002)

LLC test is applicable in balanced panel which assumes that autoregressive coefficients to be uniform for entire panel. $H_0 = \rho_i = 0 \quad for\, all\, i$ is null hypothesis of LLC. Levin *et al.* (2002) is basically panel expansion of ADF test and is constructed on following ADF type regression:

$$\Delta P_{it} = \rho_i P_{i,t-1} + \sum_{j=1}^{q_i} \alpha_{ij} \Delta P_{i,t-j} + \phi Z_{it} + \varepsilon_{it} \tag{4}$$

The lag order qi is used for differenced term and it is allowed to differ across individuals. It is used to resolve the issue of residuals correlation. P_{it} represents every variable to be tested for stationary. Z_{it} is deterministic component and may be fixed effect or time trend. The test has 3 steps procedure. In first step above regression equation is estimated for every cross-section in the panel. In second step, the residuals are obtained from the two following auxiliary regressions:

$$\hat{e}_{it} = \Delta P_{it} - \sum_{j=1}^{q_i} \tilde{\pi}_{ij} \alpha_{ij} \Delta P_{i,t-j} - \varphi \hat{Z}_{it} \tag{5}$$

$$\hat{v}_{i,t-1} = P_{i,t-1} - \sum_{j=1}^{q_i} \tilde{\pi}_{ij} \alpha_{ij} \Delta P_{i,t-j} - \varphi \hat{Z}_{it} \tag{6}$$

The residuals are then weighted by the regression standard error to control for heterogeneity across cross sections, becoming $\tilde{e}_{it}$ and $\tilde{v}_{i,t-1}$.

$$\tilde{e}_{it} = \frac{\hat{e}_{it}}{\hat{\sigma}\varepsilon_i} \tag{7}$$

$$\tilde{v}_{i,t-1} = \frac{\hat{v}_{i,t-1}}{\hat{\sigma}\varepsilon_i} \tag{8}$$

Each ADF regression standard error is computed which is represented by $\hat{\sigma}$. Lastly, pooled OLS regression is run on $\tilde{e}_{it} = \rho \tilde{v}_{i,t-1} + \tilde{\varepsilon}_{it}$ to compute pooled t-statistic. Finally, it is compared with table values for possible acceptance and rejection of null hypothesis.

3.3. Im, Pesaran and Shin (IPS) (2003) tests

LLC test has some drawbacks as it assume cross sectional independence and is not applicable in case of presence of serial correlation among the residuals across cross sectional units. The major improvement of IPS is its alternative hypothesis that allows autoregressive coefficient to be different for different cross sections. The basic equation of IPS can be written as:

$$\Delta P_{it} = \alpha_i + \rho_i P_{i,t-1} + \sum_{j=1}^{q_i} \delta_{ij} \Delta P_{i,t-j} + \varepsilon_{it} \tag{9}$$

P_{it} represents every variable under consideration, individual or fixed effect is denoted by α_i and q_i is lagged term used to solve overtime residuals correlation issue. The null hypothesis is $H_0 = \rho_i = 0 \quad for\, all\, i$ Against the alternatives $\rho_i < 0 \quad for\, i = 1, 2, 3....., N_1$ and $\rho_i = 0 \quad for\, i = N_1 + 1, N_1 + 2....., N$. It allows for some (but not all) of individual series to have unit roots. They formulated a *t*-bar statistic, which is computed by taking average of the individual ADF test statistics. Its formula is written as:

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{n} t_{iT} \tag{10}$$

t-statistics for each country i is denoted by t_{iT} computed from ADF regression for testing $\rho_i = 0$. If this statistic is properly standardized, it is asymptotically N (0, 1) distributed**.** The standardized IPS t-bar statistic is given by:

$$t_{IPS} = \frac{\sqrt{N}(\bar{t} - 1/N \sum_{i=1}^{N} E[t_{it} / \rho_i = 0])}{\sqrt{N^{-1} \sum_{i=1}^{N} \operatorname{var}[t_{it} / \rho_i = 0]}} \tag{11}$$

3.4. Pedroni Tests (2004)

Pedroni (1995) introduced the first residual-based panel cointegration test. Pedroni (1999) and (2004) are panel expansion of Engle and Granger (1987) test with more than one explanatory variable in the regression equation. The test allows slope coefficients to be different across cross sectional units and allows heterogeneity in the cointegration vector. Pedroni introduced seven cointegration tests on the basis of residuals with null hypothesis of no cointegration. First four tests cover within dimension effect of panel and are known as panel statistic while three tests cover between dimension effects of panel and recognized as group statistics. The most important characteristic of these statistics is that they are based on common process and also known as within dimension tests. On other hand remaining three tests are based on individual process and known as group panel statistics or between dimension tests. Pedroni defines the seven following statistics:

$$Panel\, v-statistics: Z_v = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} \hat{e}_{it-1}^{2} \right)^{-1} \tag{12}$$

$$Panel\, \rho-statistics: Z_\rho = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} \hat{e}_{it-1}^{2} \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} (\hat{e}_{it-1} \Delta \hat{e}_{it} - \lambda_i) \tag{13}$$

$$Panel\, PP-statistics(Non\, Parametric): Z_t = \left(\sigma^2 \sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} \hat{e}_{it-1}^{2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} (\hat{e}_{it-1} \Delta \hat{e}_{it} - \lambda_i) \tag{14}$$

$$Panel\, ADF-statistics(Parametric): Z^{*}{}_{t} = \left(s^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} \hat{e}_{it-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} R_{11i}^{-2} (\hat{e}_{it-1}^{*} \Delta \hat{e}_{it}^{*}) \tag{15}$$

Group ρ , group *PP* and group *ADF* are three Group Pedroni (1999) statistics;

$$Group\, \rho\, statistics: \tilde{Z}_\rho = \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{e}_{it-1}^{2} \right)^{-1} \sum_{t=1}^{T} (\hat{e}_{it-1} \Delta \hat{e}_{it} - \lambda_i) \tag{16}$$

$$Group\, PP\, statistics(Non\, Parametric): \tilde{Z}_t = \sum_{i=1}^{N} \left(\sigma^2 \sum_{t=1}^{T} \hat{e}_{it-1}^{2} \right)^{-1/2} \sum_{t=1}^{T} (\hat{e}_{it-1} \Delta \hat{e}_{it} - \lambda_i) \tag{17}$$

$$Group\, ADF\, statistics(Parametric): \tilde{Z}_t^{*} = \sum_{i=1}^{N} \left(s_i^{*2} \sum_{t=1}^{T} \hat{e}_{it-1}^{*2} \right)^{-1/2} \sum_{t=1}^{T} (\hat{e}_{it-1}^{*} \Delta \hat{e}_{it}^{*}) \tag{18}$$

3.5. Panel Autoregressive Distributed Lag Model (ARDL)

After analyzing the existence of long run relationship next step is to estimate long run parameters. The typical methodology to establish long run relationship in panel analysis is panel Autoregressive Distributed Lag Model. It has several advantages over DOLS, FMOLS and GMM. This technique estimates long run and short time estimates simultaneously. Secondly, it resolves the issue of endogeneity by introducing lagged terms of dependent and independent variables. Thirdly, it is applicable either variables are integrated at level, first difference or mixed order. Autoregressive Distributed Lag Model is based on three different estimators for analysis of panel data. These estimators are:

i) Mean group estimator (MG)

ii) Pooled mean group estimators (PMG)

iii) Dynamic fixed effects estimators (DFE)

3.6. The Pooled Mean Group

Pooled Mean Group (PMG) within ARDL framework was devised by Pesaran *et al.* (1999) to investigate the short run and long run parameters. The basic prerequisites for PMG estimator to be consistent ad efficient are as:

i) Error terms should not be serially correlated and this issue is resolved by introducing lag of dependent variable (p) and lag of explanatory variables (q) in error correction representation. All the explanatory variables are supposed to be truly exogenous.

ii) Long run relationship is present between dependent variables and regressors.

iii) It assumes long run estimates to be same for all countries.

The main feature of PMG estimator is that it assumes long run parameters to be same for all the countries but short run coefficients, ECM coefficient, intercepts and error variance to be different for each country.

The ARDL specification in PMG formulation is given below:

$$y_{it} = \sum_{j=1}^{p} \gamma_{ij} y_{t-j} + \sum_{j=0}^{q} \beta_{ij} x_{t-j} + \mu_i + \varepsilon_{it} \quad (19)$$

y_{it} is dependent variable such as CO2, SO2 emission and PM2.5 in the current study. x_{it-j} denotes explanatory variables including GDP per capita, GDP per capita square, income inequality, population density, urban population, trade openness and FDI. μ_i depicts fixed effect and ε_{it} is error component. The above model can be written in VECM representation as:

$$\Delta y_{it} = \theta_i (y_{it-1} - \beta_i x_{it-1}) + \sum_{j=1}^{p-1} \lambda_{ij} \Delta y_{it-j} + \sum_{j=0}^{q-1} \delta_{ij} \Delta x_{it-j} + \mu_{it} + \varepsilon_{it} \quad (20)$$

β_i are long-run parameters, θ_i shows convergence of variables towards long run equilibrium. λ_i and δ_i denote short-run coefficients of dependent and independent variables respectively. The selection of suitable lag length for each country is made using SBC and AIC for both MG and PMG estimations. The sign of ECM term should be negative that will represent stable long run relationship. PMG require large T and N for consistent and efficient results. Hausman's test distinguishes between appropriateness of MG and PMG. The null hypothesis of Hausman's test is that MG is appropriate meaning that long run slopes are homogenous against the alternative that PMG is appropriate which depicts that long run slopes are heterogeneous. If the alternative hypothesis is accepted the PMG estimator would yield efficient results and vice versa. All the three estimators are computed by maximum likelihood estimations. PMG estimator lies in between MG and DFE as it is based on pooling and averages of estimated coefficients.

4. Results and Discussion

To avoid spurious results and moving towards econometric analysis, it is essential to analyze the stationary properties of data. Thus study applies Levin, Lin & Chi (LLC) and Im Pesaran & Shin (IPS) panel unit root test to do so. The results of both tests with intercept and trend are presented in the Table 1 and 2.

Table 1: Model 1 Panel Unit Root Tests Results

	LLC		IPS	
Variables	**At Level**	**1st Difference**	**At Level**	**1st Difference**
LnCO2	-10.7960*	-13.2375	-6.65607*	-15.4338
LnGDPPC	8.65440	-12.58044**	16.0939	-11.0186*
LnGDPPCS	13.1895	-1.51614**	19.7094	-8.80836**
INEQ	1.35217	-1.13124**	1.94465	-0.33264**
LnPD	5.42870	- 9.24309*	4.87859	-1.07201*
UP	-1.40996*	-2.22364	-1.03413*	-1.95335
FDI	-1.09748*	-11.1048	-3.79698*	-18.6471
TO	1.31658	-11.0733*	0.23015	-14.3080*

Note: *** Shows 10%, ** represents 5% and * indicates 1% level of significance.

Due to different time span LLC and IPS have been performed separately for model 1 and model 2 & 3. Both tests have almost similar findings regarding variables however, none of above variables is stationary at I(2). The findings of both LLC and IPS tests depict that some variables are stationary at I(0) and others are I(1) in both tables. The results further necessitate the application of cointegration test and study employs Pedroni Cointegration test to identify the existence of cointegration among variables. Pedroni test results are reported in the Table 3.

Table 2: Model 2 and Model 3 Panel Unit Root Results

	LLC		IPS	
Variables	**At Level**	**1st Difference**	**At Level**	**1st Difference**
LnSO2	1.72498	-6.26306*	2.62796	-8.73883*
LnPM2.5	-20.9040*	-15.5122	-5.87696*	-7.94349
LnGDPPC	1.17171	-10.6654*	1.33628	-10.4682*
LnGDPPCS	2.56254	-9.80749*	1.60556	-9.94236*
INEQ	1.12081	-7.96758*	1.21447	-7.39984*
Ln PD	9.37277	-6.15123*	13.6903	-8.92464*
UP	-17.6046*	-33.1149	-7.75302*	-29.9695
FDI	-2.36718*	-9.61282	-2.08386*	-8.9759
TO	2.02253	-3.30387*	0.91243	-8.17830*

Note: *** Shows 10%, ** represents 5% and * indicates 1% level of significance.

Table 3: Pedroni Cointegration Results

Models	**Model 1**	**Model 2**	**Model 3**
Test Statistics	t-statistic	t-statistic	t-statistic
Panel v-statistic	-1.558544	-1.739901	0.038834
	(0.9404)	(0.9591)	(0.4845)
Panel rho-statistic	1.459375	3.247312	1.143257
	(0.9278)	(0.9994)	(0.8735)
Panel PP-statistic	-3.565545*	-1.155620*	-0.913976*
	(0.0002)	(0.0061)	(0.0014)
Panel ADF-statistic	-4.596395*	- 0.306038**	-0.560959*
	(0.0000)	(0.0202)	(0.0024)
Group rho-statistic	2.968924	4.263798	1.350153
	(0.9985)	(1.0000)	(0.9115)
Group PP- statistic	-3.940041*	-1.434349**	-4.020403*
	(0.0000)	(0.0357)	(0.0000)
Group ADF-statistic	-4.246767*	-1.734753**	-3.468722*
	(0.0000)	(0.0414)	(0.0003)
Kao Residual Cointegration Test Results			
Test	t-Statistic	t-Statistic	t-Statistic
ADF	-14.54847*	-6.138318*	-13.23463*
	(0.0000)	(0.0000)	(0.0000)

Note: *** Shows 10%, ** represents 5% and * indicates 1% level of significance. p value are shown in parentheses.

The findings of Pedroni test illuminates that majority of test statistics have rejected null hypothesis of no cointegration at 1% and 5% level of significance in all models so there is strong evidence of cointegration relationship. Moreover, Kao test also

Table 4: PMG Estimation Results

Variables	**Dependent Variables: Environment Quality**		
Variables	CO2	SO2	PM2.5
LnGDPPC	1.977342*	1.298677*	4.562469**
	(0.750053)	(0.232093)	(2.044403)
LnGDPPCS	-0.087424**	-0.083520*	-0.307415**
	(0.044329)	(0.015395)	(0.151392)
INEQ	0.018937**	0.012978**	0.053081**
	(0.008070)	(0.005991)	(0.025909)
LnPD	0.168645***	0.439800**	0.294724*
	(0.101212)	(0.180445)	(0.110902)
UP	0.047568*	0.030569	0.150679*
	(0.005317)	(0.021252)	(0.014263)
FDI	0.005237	0.095818*	0.084638*
	(0.007386)	(0.019786)	(0.029489)
TO	0.003100*	0.010101*	0.018386*
	(0.000938)	(0.001709)	(0.004079)
	Short Run Results		
ΔLnGDPPC	1.123396***	0.921310**	2.075240**
	(0.596012)	(0.460199)	(1.11150)
ΔLnGDPPCS	0.263629	-0.057965	-0.119823
	(0.376988)	(0.046209)	(0.137902)
ΔINEQ	0.045723**	0.032586	0.014885***
	(0.021142)	(0.052248)	(0.007656)
ΔLnPD	2.673201**	5.506705*	1.413826**
	(1.079724)	(2.077080)	(0.613764)
ΔUP	0.187367*	0.028397	0.116830
	(0.096421)	(0.094027)	(0.075779)
ΔFDI	0.006344	0.002240	-0.003129
	(0.006781)	(0.007717)	(0.003193)
ΔTO	0.000766	0.001175**	0.000600
	(0.000721)	(0.000579)	(0.000553)
ECT(t-1)	-0.241615*	-0.151576*	-0.349079*
	(0.076476)	(0.055868)	(0.097902)

Note: * shows 1% ** and *** represents 5% and 10% significance level respectively. Standard Errors are shown in parentheses.

rejects the null hypothesis of no cointegration as value of t-statistics of ADF test is statistically significant for all models. When long run relationship is identified the study adopts panel ARDL to obtain long run estimates. First of all, Haumans' test is performed whose value is 13.776 with probability 0.01 which is less than 0.05 thus rejects the null hypothesis that MG is preferable over PMG estimator. So PMG estimation technique has been adopted to obtain empirical estimates and it is more appropriate to our analysis because developing countries have similar demographic and economic conditions. The choice of lag ARDL (1, 1, 1, 1, 1, 1, 1, 1) has been made by considering SBC criterion on the basis of smallest value. The results of PMG estimation for all regression models are stated in the Table 4.

The PMG results for model 1 indicate that per capita GDP is positively attached with CO_2 emission and per capita GDP square has negative effect on CO_2 emission. These findings are statistically significant at 1% significant at 5% when CO_2 emission is used as environmental quality indicator. These results confirm the presence of EKC for developing Asian countries in long run. Hailemariam *et al.* (2019) and Drabu (2011) have found identical outcomes. Short run findings reveal no evidence of EKC and same has been found by Audi and Ali (2018). The main interest of the study is effect of income inequality that is positively attached with environmental degradation. Masud *et al.* (2018) and Drabu (2011) have identical results for growing countries. Demographic indicators are positively related with environmental degradation in case of Asian developing economies. The rise in population density and urban population raises CO_2 emission. Similar results have been traced in earlier work of Jun *et al*. (2011) and Omotor (2016). The coefficient of FDI carries positive sign but is insignificant. The effect of trade openness on CO_2 emission is also positive and significant. Mahmood (2018) *et al.* and Tjoek and Wu (2018) also found positive impact of trade openness and FDI on environment quality for Asian countries. In the short run, trade openness and FDI exert positive but statistically insignificant impact on CO_2 emission.

The assessment of PMG results for model 2 depicts the presence of EKC in case of SO_2 emission. These findings are similar with the work of Rawashdeh *et al.* (2014), Hao *et al.* (2016) and Omotor (2016) and Torras and Boyce (1998) for developing countries. However, EKC does not found in the short run for SO_2 emission which is consistent with Asongu *et al.* (2015). The key variable is also positively related with SO_2 emission that indicate higher the income inequality more will be environmental damage. This is somewhat similar with Boyce (1994) and Torras and Boyce (1998). The estimated coefficients of population density, urban population indicates that rise in demographic variables accelerate SO_2 emission significantly. Trade openness and foreign direct investment are positively correlated with SO_2. Tjoek and Wu (2018) and Omotor (2016) found positive association between trade openness and SO_2 emission. *Zhu et al*. (2017) established positive effect of FDI on SO_2 emission. However, the coefficient of FDI is negatively associated with environment quality in short run. The study found direct association between population density and SO_2 emission both in long and short run. This is somewhat similar with Zhu *et al.* (2017). The effect of urban population is positive but insignificant in long run. Similarly, income inequality, urban population and FDI have insignificant impact on SO_2 emission in short run.

There is positive association between per capita growth and exposure to PM2.5 while GDP per capita square is negatively associated with PM2.5. It indicates the incidence of EKC in the long run. These finding are significant at 5% and similar with Orubu et al. (2009) and Stern and Zha (2016). There is no evidence of EKC in the short run in case of PM2.5. The income inequality has positive and significant effect on environmental degradation at 5% significance level showing more deterioration in environment quality is attached with rising differences in income. Marsiliani and Renstrom (2000) have same findings about unequal income distribution effect. There is positive and significant effect of population density, urban population on PM2.5 indicating that demographic variables exacerbate deterioration of environment and Orubu *et al.* (2009) obtained same results. Trade openness and FDI also exert positive impact on environment quality variable. Urban population, trade openness and FDI have no impact on PM2.5 in short run. The coefficient of ECT is negative and statistically significant for all models showing speed of adjustment towards long run equilibrium.

5. Conclusion and Discussion

The study attempts to explore the relationship between environmental quality and economic growth along with role of income inequality within EKC framework by using balanced panel data for developing Asian countries. Three models have been estimated by using CO_2, SO_2 emission and PM2.5 as environmental quality indicators. PMG estimation within ARDL framework recommended by Hausman's test has been employed for empirical analysis. Empirical findings of PMG estimator validate the existence of EKC for CO_2, SO_2 emission and PM2.5 in the long run. However, EKC does not hold in short run for developing Asian countries. The existence of EKC in developing countries demonstrates that economic expansion requires more energy which is mostly obtained from the combustion of fossil fuel for industries and transportation that results in higher CO_2 emission in developing countries. Existence of polluted industries and old technology are also reasons of EKC existence. Moreover, these economies major focus is more on growth rather than environment. The results compel governments of developing economies to focus on the use of clean energy and carbon tax in order to save environment from CO_2 emission. Another reason behind positive effect may be overuse of natural resources by the rich community as well as poor as they have no other source available for their survival. Similarly, the people of developing countries do not afford clean fuel and are dependent on biomass fuel especially for cooking and heating which is also major contributor of CO_2 emission in air.

There are various rationales for the incidence of EKC in case of SO_2 emission. The rising trend of SO_2 emission illustrates that these countries are growing economies and dependent on coal especially in power generation sector to fulfill the energy demand of industrial sector and other sectors of the economy. Industries, vehicular emission, combustion of solid and biomass fuel are also the main sources of SO_2 emission in developing nations. Similarly sources of Particulate matter includes combustion, dust and automobile emission that are rising overtime leading to rise in particulate concentrations. These findings insist governments of developing nations to explore renewable and clean energy resources and efficient coal technology to save the environment. Overall, industrial expansion, advance farming and intensification of agriculture sector are also contributing to degradation of environment.

Furthermore, income inequality exerts positive and significant influence on all environment quality indicators. The reason of positive effect may be overuse of natural resources by the poor as they have no other source of livelihood for their survival. The positive association between rising inequality and pollution indicators indicate that poor people and unequal societies of developing nations do not consider environment as an essential commodity due to lack of awareness and sound regulations about environmental protection. These findings suggest governments to promote equal societies to conserve the environment.

Industrial expansion and FDI development are associated with intensive use of energy obtained from oil, gas, fossil fuels and other natural resources which are considered basic inputs of industrial sector therefore positive association holds between FDI and environment quality measures. Trade openness has also not favourable impact on environment. No doubt trade is driver of any economy but results show that trade expansion is attached with pollution through production process. The positive effect of trade openness and FDI implies that clean production technology is not being adopted in developing economies. Results suggest that developing countries should adopt environment friendly production technologies. Less developed economies should improve economic structure through modernization and ensure environmental regulation for sustainable growth. The findings suggest that tree plantation campaign and restoring the forests are most appropriate tool to control greenhouse gas emission. Moreover government should construct industrial zones outside the city areas. It will also be easy for the enforcement of polices about reducing pollution. Government should promote environment friendly transport like electric vehicles and lead battery techniques

Population growth is supportive for economic upturn but it becomes danger when increases from threshold limit. On the same lines, lack of employment opportunities, inadequate infrastructure, recreational facilities and other social privileged benefits are pushing people towards urban areas and this tendency has risen since few decades. The growing population and unplanned expansion of cities require more environmental resources that will put pressure on resources through the overuse of resources. It also creates mismatch between demand and supply of natural and environmental resources resulting in deterioration of environment in the form of air, water and land pollution. Therefore, coefficients of population density and urbanization carry positive sign in case of all pollutants meaning that rising population escalate more degradation. The issue of urbanization should be resolved through proper planning & local community involvement. Government should focus on creation of jobs and poverty reduction strategies in rural areas to control rising population in urban areas.

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Appendix A

List of Countries:

Bangladesh, Egypt, India, Iran, Indonesia, Malaysia, Pakistan, Sri Lanka, Nepal, Jordon, Cambodia, Nepal, Philippines, Thailand, Maldives, Vietnam

Appendix B

Descriptive Statistics for Model 1

	CO2	GDPPC	GDPPCS	INEQ	PD	UP	FDI	TO
Mean	1.572365	2494.985	12393783	39.94200	221.2274	36.49206	1.955026	72.42180
Median	0.964500	1656.283	2743300.	39.75000	111.8281	31.91450	0.988664	57.68444
Maximum	8.492000	12592.67	1.59E+08	50.30000	1391.640	90.50600	23.53737	220.4074
Minimum	0.000000	315.9296	99811.53	30.40000	18.97411	4.399000	-6.0080	8.320137
Std. Dev.	1.734070	2485.479	24315406	4.871768	278.4962	19.35239	2.677938	46.13145
Skewness	1.877924	1.694114	3.210719	0.255603	2.327467	0.586204	2.527049	1.084872
Kurtosis	6.573733	5.670976	14.22568	2.376532	7.839312	2.522899	13.04811	3.318771
Sum Sq. Dev.	2113.920	4.34E+09	4.16E+17	16685.09	54524759	263284.2	5041.462	1496062.
Observations	704	704	704	704	704	704	704	704

Descriptive Statistics for Model 2

	SO2	GDPPC	GDPPCS	INEQ	PD	UP	FDI	TO
Mean	575.6558	5943.754	65255546	39.938	207.2509	35.0657	1.78883	70.8913
Median	195.0866	4084.000	16679105	39.700	106.1323	29.9200	0.84331	57.7927
Maximum	9452.590	29546.00	8.73E+08	50.300	1223.333	86.0880	23.5373	220.407
Minimum	0.200255	737.0000	543169.0	30.400	18.97411	4.39900	6.008030	8.32013
Std. Dev.	1165.848	5475.093	1.25E+08	4.8784	256.4924	18.6481	2.60085	46.0135
Skewness	4.124628	1.724775	3.716666	0.2023	2.249314	0.57570	2.76667	1.16067
Kurtosis	22.62872	6.333038	19.21081	2.3840	7.408483	2.46580	15.4092	3.58629
S. Sq. Dev.	8.22E+08	1.82E+10	9.56E+18	14446.	3993353	211086.	4106.00	1285166
Obs.	608	608	608	608	608	608	608	608

Descriptive Statistics for Model 3

	PM2.5	GDPPC	GDPPCS	INEQ	PD	UP	FDI	TO
Mean	739.0680	5943.754	6525554	39.9383	207.2509	35.0657	1.78883	70.8913
Median	168.4956	4084.000	16679105	39.70000	106.1323	29.92000	0.843317	57.79279
Maximum	8870.921	29546.00	8.73E+08	50.30000	1223.333	86.08800	23.53737	220.4074
Minimum	0.032026	737.0000	543169.0	30.40000	18.97411	4.399000	6.008030	8.320137
Std. Dev.	1498.282	5475.093	1.25E+08	4.878424	256.4924	18.64816	2.600850	46.01350
Skewness	3.264461	1.724775	3.716666	0.202336	2.249314	0.575701	2.766679	1.160673
Kurtosis	13.51206	6.333038	19.21081	2.384029	7.408483	2.465802	15.40925	3.586294
S. Sq. Dev.	1.36E+09	1.82E+10	9.56E+18	14446.01	39933536	211086.7	4106.003	1285166.
Obs.	608	608	608	608	608	608	608	608

Appendix C

Limitations and Future Perspective

The study can be further extended by separated analysis of indoor and outdoor air pollutants. Moreover, other pollutants which are harmful for human health like PM10 can be considered for better analysis.