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ABSTRACT

What Matters for Environmental Quality in the Next-11 Countries: Economic Growth or Income Inequality?

This study uses 1971-2013 panel data to explore the implications of growth, wealth disparities and energy consumption on carbon emissions in a sample of Next-Eleven (N-11) countries. It uses modern econometric techniques to highlight a long-run interplay between selected variables in the carbon emissions function for all the N-11 nations and long-run interactions among the series analyzed. Contrastingly, it also shows that economic growth, income inequalities and energy consumption accelerate CO2 emissions. In addition to examining the effects of the wealth disparities square, the study also uses the Environmental Kuznets Curve hypothesis in the context of the N-11 states. Its findings suggest that policymakers should curb rising income inequalities through effective redistributive measures such as tax transfers (cash transfers) and taking up other expenditure programs for the poor. Moreover, the Indian government should emphasize on an energy-reducing strategy policy to reduce income inequalities and achieve sustainable development.

JEL Classification: Q50, O15, C23

Keywords: CO2 emissions, income inequality, panel cointegration, Next-Eleven countries

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1. Introduction

As emerging economies grow at the expense of massive energy consumption (EC) they face several difficult challenges in various areas. Among these, environmental quality is one of the biggest concerns as it impacts climate change and poverty levels via a myriad of effects on agriculture productivity and people's health (Hallegatte and Rozenberg, 2017). Countries require greater volumes of energy to sustain their economic growth and development. Given the inelastic nature of the supply of natural resources such as land, drinking water and clean air, as human activities increase with population the accumulated goods produced in the countries in the form of pollution and greenhouse gas emissions (GHGs) grow disproportionately in relation to the planet's capacity. Increase in economic activities reflects in higher growth rates and per capita GDP which leads to additional environmental concerns as emission levels accumulate along with rising demand for energy. The environmental repercussions of these worry not only domestic economies but also worldwide large states that are interconnected due to globalization; hence, all countries are likely to be affected by GHGs and face the risk of climate change although with different intensities in different regions.[1]

As stated by economic theory poverty alleviation in the developing world needs significant government efforts along with sustainable economic progress otherwise poverty reduction policies will be inefficient. Practical evidence reveals that most industrialized, developing nations are expanding their economic activities and output levels thus seeking to diminish carbon emissions. As production and income differences are profoundly intertwined these in turn lead to large wealth disparities both in the short- and long-run. Thus, the developing world is faced with myriad challenges. Climate change (for example, rising sea levels, storms, droughts, floods) is one of the most severe of these as it drives substantial CO_2 emissions that cause global warming. Environmental degradation generated by rising carbon emissions and climate change is also a pressing problem as it threatens sustainable economic progress in the long-term and also the quality of living standards. It is generally recognized that climate change is a vital issue that needs to be addressed in energy and ecological economics.

Recent available data from the Intergovernmental Panel on Climate Change (IPCC, 2006) shows that carbon emissions were a major determinant of GHG emissions globally, with a 76.7 percent share in the total volume. These represented a mix of fossil fuels, deforestation and other factors at 56.6, 17.3 and 2.8 percent respectively. Hence, rising per capita CO_2 emissions are commonly used as proxy for environmental pollutants often linked with higher per capita incomes. As suggested by various scholars (*inter alia,* Holtz-Eakin and Selden, 1995; Kijima et al., 2010; Ozturk and Acaravci, 2010; Raza et al., 2015), carbon emissions

[1] Climate change is a huge threat to human health, global food security and economic development, as well as to the natural environment. In light of its severe consequences on global well-being, international organizations and governments need to work together to mitigate its risks and cut greenhouse gas emissions that are leading the climate to change.

are a main source of global warming and climate change with an alarming echo for governments worldwide in recent years that they should work to protect environmental health via a number of policy tools such as taxes and reliance on renewable energy. These guidelines proposed by policymakers have generated extensive intergovernmental debates, particularly in developing nations -- the 1997 Kyoto Protocol developed by Japan is a relevant example of efforts to diminish the carbon footprint that leads to global warming. The Protocol entered into force in 2005 and represents a binding agreement to the UN Framework Convention on Climate Change (UNFCCC) (Halicioglu, 2009; Ozturk and Acaravci, 2010).

Given the existing global warming and increasing concerns about scarce energy sources and the concept of sustainable development and environmental quality issues for society as a whole we believe that exploring the interplay between carbon emissions, progress and wealth disparities in the context of N-11 nations[2] is a scientific endeavor worth considering by both scholars and policymakers. It is important to validate empirically the causality, if any, between economic development and income differences on the one hand and environmental degradation on the other in N-11 states. This is essential because understanding the direction of causality will provide valuable insights into the best way to preserve environmental health; such an exercise will also offer examples of best practices to other developing economies. If environmental degradation persists in N-11 countries amid increased production levels and associated massive EC, its impact will transmit like a domino throughout the globe. Hence, N-11 and other developing economies seeking to mitigate climate change will need to strengthen collaboration to address the implications of higher progress and energy consumption domestically. Consequently, powerful nations constantly blaming developing countries for the rising carbon footprint can also be minimized.

Our methodological approach involves examining the interaction between the series. It is based on an innovative model of panel cointegration developed by Pedroni (2004), panel cointegration by Kao (1999), fully modified OLS (FMOLS) proposed by Philips and Hansen (1990) and dynamic OLS (DOLS) created by Stock and Watson (1993). Extant literature does not commonly apply such frameworks. This is a major limitation of these works because scholars elude empirical investigations of the relationships between carbon emissions, growth and wealth disparities which can lead to inaccurate results on the Environmental Kuznets Curve's (EKC) assumptions and misguide policymakers whose aim is to protect environmental health worldwide. The economic rationale behind using these models is that the interplay between selected variables fluctuates as a result of changing economic parameters, natural calamities, energy and environmental strategies and regulatory and technological innovations.

Our study uses annual data series from 1971 to 2013 on a per capita basis for wealth disparities, growth and carbon emissions in the context of N-11 nations selected because of their potential for becoming some of the largest economies in the 21st century based on their contributions to global GDP, share of energy demand and CO_2 emissions to world energy

[2] N-11 nations include Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, Philippines, Turkey, South Korea and Vietnam.

demand and carbon footprint. The N-11 states are increasingly recognized as major influencers in the global open economy and environmental policies next to BRICS (Brazil, Russia, India, China and South Africa) economies, but dissimilar to the latter in terms of economic growth patterns accompanied by a greater degree of trade and financial openness. N-11 countries could surpass their rivals and become major market participants despite being exposed to a larger number of challenges relative to BRICS nations as a result of their strong economic reforms targeted at sustainable economic growth in the long term. For instance, we note Nigeria's efforts to remove corruption, Turkey's struggle to get access to the European Union and Pakistan's success in improving corporate laws, the tax system and its financial system via solid economic and financial schemes.

N-11 countries are enjoying rapid growth and are participating in global trade and investment projects (except for Iran which is a closed economy affected by EU and US imposed sanctions). They are faced with rising energy demand triggered by investment and industrialization activities that use less energy-efficient technologies to boost economic progress; this is a major cause of environmental degradation. To limit their carbon footprint, Mexico and Nigeria introduced incentives for businesses to enhance national production via more efficient energy technology. In 2007, N-11's contributions to global GDP stood at 7 percent with EC at 9 percent of worldwide demand and 9 percent of total GHG emissions (Sachs, 2007). The upward trend in economic progress increased EC's share to 11 percent of global consumption which further aggravated environmental degradation (Yildirim et al., 2014). According to Sachs' (2007) projections, in 2050 the N-11 nations' total GDP could be two-third that of the Group of Seven (G7) countries, meaning that N-11 nations could have a major impact on the political, economic, energy and environmental global landscape. CO_2 emissions measured in kg per capita and income inequality measure as the GINI coefficient for the N-11 nations from 1971 to 2013 is presented in Figures 1 and 2 respectively. The pattern differs among the nations more in case of income inequalities than in the case of CO_2 emissions.

The rest of this study is organized as follows: Section 2 reviews major scholarly works in this field. Section 3 details the methodology and the data used for our analysis. Section 4 gives the results of our study and discusses their significance. Section 5 provides concluding remarks, policy implications and indicates future research avenues.

2. Review of Related Studies

Kuznets' (1955) landmark study linking the inverted U-shaped interplay between wealth disparities and progress[3] prompted many researchers to investigate the role of growth in income inequalities empirically leading to many cross and individual country studies.

[3] The inverted U-shaped hypothesis shows the non-linear relationship between the series indicating that economic growth initially increases income inequalities and narrows them after reaching a particular level.

Dollar and Kraay (2002) argue that growth is good for the poor as there is evidence of a trickled down effect from the production process that not only creates employment opportunities and increases agriculture productivity but it also reduces income inequalities by improving income distribution to the poorest. However, Kashwan's (2017) findings contradict this. Kashwan is of the view that development does not favor the poor because it does not benefit the entire population (haves and have-nots) equally. As a consequence, preference for environmental quality declines over time. In contrast, Sachs (2014) postulates that rising concerns about the impact of economic growth on environmental quality are driven by higher income inequalities. This implies that economies in the globalized world may be good at achieving higher progress, but they fail to maintain an equitable distribution of income with sustainable environmental quality. Therefore, some scholars (for example, Torras and Boyce, 1998; Boyce, 1994, 2008; Magnani, 2000; Ravallion et al., 2000; Newton, 2009; Drabo, 2011; Cushing et al., 2015; Jorgenson, 2015; Islam, 2015; Laurent, 2016) underline that challenges of environmental quality are caused by social issues mainly generated by wealth disparities and power inequalities. Given ecological crises (loss of environmental quality), which could be triggered by wealth inequalities, the nexus between income disparities and environmental quality has become the most pressing problem of our time adding to the debatable complexity of environmental and developmental economics (Hao et al., 2016 June et al., 2011; Zhang and Zhao, 2014; IPCC, 2014; Berthe and Elie, 2015; Jorgenson et al., 2016; Wolde-Rufael and Idown, 2017). Hence, it is essential to explore major academic achievements on the effects of income inequalities, EC, progress and urbanization on CO_2 emissions.

2.1. CO_2 Emissions and the income inequality nexus

Using a panel analysis, Torras and Boyce (1998) found that income levels enhanced environmental quality in low income nations and deteriorated it in high income states. Eriksson and Persson (2003) report that the reduction of income inequality via greater democracy is beneficial for environmental quality as it lowers pollution levels. Similarly, Drabo (2011) observes that income inequalities were detrimental to environmental quality for 90 developed and emerging states. Baek and Gweisah (2013) highlight that wealth differences and economic growth increase environmental quality, whereas energy consumption harms the US economy. Berthe and Elie (2015) argue that individuals' economic behavior is detrimental to environmental quality. Baloch et al., (2017) document the positive effects of income inequalities and income per capita on environmental health in the context of Pakistan. Kasuga and Takaya (2017) point out the harmful impact of wealth disparities on air quality in commercial zones but they do not identify any significant consequences of income inequalities in the industrial areas of Japan.

2.2. The interplay between CO_2 Emissions and Energy Consumption

Acaravci and Ozturk (2010) observed a long-run positive association among selected variables for a panel of 19 European states along with evidence of an inverted U-shaped EKC hypothesis. Al Mulali et al., (2012) identified a similar nexus for seven regions. Saboori and Sulaiman (2013a) found long-term interaction between CO_2 emissions and energy consumption in the context of Malaysia. Saboori and Sulaiman (2013b) emphasized a long-run positive nexus among CO_2 emissions and energy consumption for a number of ASEAN countries. Shahbaz et al., (2014) confirmed this relationship in the case of United Arab Emirates and indicated that the deterioration in environmental quality was driven by energy consumption. Begum et al., (2015) documented a range of positive effects of EC on CO_2 emissions within the Malaysian economy. Mercan and Karakaya (2015) also detailed a long-term positive impact of EC on CO_2 emissions in selected OECD countries. Bilgili et al.'s (2016) study also has similar findings.

2.3. The nexus between CO_2 Emissions and Economic Growth

Nnaji et al., (2013) report a positive impact of fossil fuel consumption and development on CO_2 emissions in Nigeria. Wang (2013) notes the reducing effect of differentiated output growth on CO_2 emissions in the US and China. Salahuddin and Gow (2014) claim that progress has no long-term implications on environmental degradation in the Gulf Cooperation Council countries. Kivyiro and Arminen (2014) emphasize the long-run economic growth-CO_2 emissions nexus for six sub-Saharan African states. Lau et al., (2014) found that CO_2 emissions stimulated economic growth in Malaysia. Allali et al., (2015) reveal a positive impact of development on CO_2 emissions in Algeria. Similarly, Abid (2015) observed both a short-run and a long-run interplay between growth and the carbon footprint in Tunisia, in addition to unidirectional causality running from progress to CO2 emissions. In a similar vein, Begum et al., (2015) underline that in Malaysia, CO_2 emissions are negatively linked with economic growth. Esso and Keho (2016) also identified a positive long-term relationship among CO_2 emissions and progress and a bi-directional causal link between variables within the Nigerian economy.

3. Model Building and Data Description

3.1. Model

Given our research objective and the context of theoretical and empirical literature discussed earlier we specified the basic CO_2 emissions function as noted below to understand the nature of interaction and the effects of the key variables on the CO_2 function (CO_2 emissions). Because of the limited number of annual time series available (the use of a larger number of variables in the same model would result in over parameterization, that is, consumption of freedom on the one hand and the inclusion of related variables that would trigger multicollinearity issues on the other) we estimate different versions of our basic models to avoid estimation problems:

$$CO_2 = f(ENERGY, GINI, GDP) \qquad (1)$$

The functional form of Eqn. 1 can be represented as:

$$LNCO_{2t} = \alpha_0 + \beta_1 ENERGY_t + \beta_2 LNGINI_t + \beta_3 LNGDP_t + \mu_t \qquad (2)$$

where, $LNCO_2$ emissions represent CO_2 emissions per capita -- proxy of environmental quality; LNENERGY denotes EC per capita; LNGINI is the net GINI coefficient -- proxy of income inequality; $LNGINI^2$ is the GINI coefficient squared, used to understand whether it has an inverted U-shape or not; LNGDP is GDP per capita -- proxy of economic development and μ_t is the error term; all series are in natural logarithmic form to confirm their smoothening. α_0 is the fixed effect and β_1, β_2 and β_3 are slope coefficients.

According to the EKC hypothesis, the long-term interplay between EC, wealth disparities and economic growth on CO_2 emissions can be captured by Equation 3. The EKC hypothesis describes an inverted U-shaped link among environmental degradation and economic growth. We are interested in identifying an inverted U-shaped connection between environmental degradation and income inequalities which can be obtained mathematically by embedding the squared value of the GINI coefficient in the array of regressors:

$$LNCO_{2t} = \alpha_0 + \beta_1 ENERGY_t + \beta_2 LNGINI_t + \beta_3 LNGINI^2{}_t + \beta_4 LNGDP_t + \mu_t \qquad (3)$$

3.2. Methodological approach

We seek to explore the causal interactions among carbon CO_2 emissions, EC, income inequalities and economic development via modern econometric techniques. This analysis involves a three-step scientific approach. First, we determine the integration order of the series based on panel unit root tests. Second, we apply panel cointegration tests to verify the existence of any long-term relationships. Finally, we examine the size and direction of any potential causal interactions among our series.

3.2.1. Panel unit root tests

We apply standard time series unit root tests on the determinants of CO_2 emissions, total energy consumption, income inequalities and GDP per capita. Narayan and Smyth (2009) argue that the Augmented Dickey-Fuller (ADF) test has a low power to reject the null hypothesis of stationarity, particularly for short periods. Hence, recent academic works claim that panel stationarity tests are more powerful compared to individual time series ones (for example, Al-Iriani, 2006). We use the panel unit root tests suggested by Levin et al., (2002), IPS, Im et al., (2003), Hadri (2000) and Beitung (2000). These are generally more robust than the first generation of panel tests (Narayan and Smyth, 2009).

Moreover, the first generation panel unit root tests are applied to panel data which neglects both structural breaks and cross-sectional dependence. These are commonly used in the carbon emission-energy consumption literature. These are similar to the ADF-based IPS test which assumes a heterogeneous unit root (Im et al., 2003). In contrast, Breitung (2000) and Levin et al., (2002) point out a homogenous unit autoregressive root. LLC and IPS test the null hypothesis of time series integration. Hadri (2000) suggests a residual-based Lagrange Multiplier test for the null of level or trend stationarity that includes heterogeneous disturbance terms.

3.2.2. Panel Cointegration tests

3.2.2.1. *Pedroni Residual Panel Cointegration test (2004)*

Pedroni (2004) detailed seven statistics for panel data cointegration tests in a heterogeneous sample. Out of these seven, four capture the effect of *within* dimensions whereas three calibrate the *between* dimensions. The former statistics are referred to as panel cointegration statistics while the latter are known as group mean panel cointegration statistics. Pedroni's statistics are obtained via the extension of the two-step residual-based strategy developed by Engle and Granger (1987). We apply the parametric ADF statistics and non-parametric PP statistics for panel as well as for group dimensions. Both these tests are focused on a null hypothesis (no cointegration) and an alternative hypothesis of cointegration ($\rho_i \angle 0$ for all i). The first step in estimating the seven test statistics is to model the following panel regression and store the residuals:

$$y_{i,t} = \alpha_i + \rho_i t + \beta_{1,i}\, x_{1i,t} + \beta_{2,i}\, x_{2i,t} + \beta_{3,i}\, x_{3i,t} + \beta_{\mathrm{m},i}\, x_{mi,t} + \varepsilon_{t,i} \qquad (4)$$

t=1, 2, …, T; i=1, 2, …, N; and m = 1, 2, …, M

where, T refers to the time observation, N refers to cross-section observation and M explains the number of regression variables. Pedroni noted that partial slope coefficients $\boldsymbol{\beta_{1i}}, \boldsymbol{\beta_{2i}}, \ldots, \boldsymbol{\beta_{mi}}$ are varied across the individual members of the panel. $\boldsymbol{\alpha_i}$ is the member specific intercept or the fixed effect parameters. Deterministic time trends, specific to the individual numbers of the panel, are captured by the parameter $\boldsymbol{\rho_i}$.

We obtain the residual $\hat{\varepsilon}_{it}$ by running the cointegration regression. The estimated residual requires the following structure. For non-parametric statistics, we estimate:

$$\hat{\varepsilon}_{i,t} = \psi_i \hat{\varepsilon}_{i,t-1} + \hat{\kappa}_{i,t}$$

For parametric statistics, we estimate:

$$\hat{\varepsilon}_{it} = \psi_i \hat{\varepsilon}_{it-1} + \sum_{k=1}^{K} \psi_{i,k} \Delta\hat{\varepsilon}_{i,t-k} + \hat{\mu}^*_{i,t}$$

Second, we take the first difference of the original data series of each country and compute the residual of the differenced regression:

$$y_{it} = \theta_{1i}\Delta x_{1i,t} + \theta_{2i}\Delta x_{2i,t} + \ldots + \theta_{mi}\Delta x_{mi,t} + \omega_{it} \quad (5)$$

Third, we estimate the long-run variance ($\widehat{K}_{11,i}^{-2}$) from the residual (ω_{it}) of the differenced regression. Fourth, we estimate the appropriate autoregressive model based on the residual ($\hat{\varepsilon}_{it}$) of the original cointegration equation. The seven statistics are obtained by working with the mean and variance adjustment terms detailed by Pedroni (2004) as:

The panel v-statistics is:

$$Z_v \equiv T^2 N^{\frac{3}{2}} (\sum_{i=1}^{N} \sum_{i=1}^{N} \widehat{K}_{11,i}^{-2} \, \hat{\varepsilon}_{it-1}^{2})^{-1} \tag{6}$$

The panel ρ -statistics is:

$$Z_\rho \equiv T\sqrt{N} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{K}_{11,i}^{-2} \, \hat{\varepsilon}_{it-1}^{2} \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{K}_{11,i}^{-2} (\hat{\varepsilon}_{it-1} \Delta \hat{\varepsilon}_{it} - \hat{\gamma}_i) \tag{7}$$

The panel t-statistics (non-parametric) is:

$$Z_t \equiv \left(\tilde{\sigma}^2 \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{K}_{11,i}^{-2} \, \hat{\varepsilon}_{it-1}^{2} \right)^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{K}_{11,i}^{-2} (\hat{\varepsilon}_{it-1} \Delta \hat{\varepsilon}_{it} - \hat{\gamma}_i) \tag{8}$$

The panel t-statistics (parametric) is:

$$Z_t^* \equiv \left(\tilde{s}_{N,T}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{K}_{11,i}^{-2} \, \hat{\varepsilon}_{it-1}^{2} \right)^{-\frac{1}{2}} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{K}_{11,i}^{-2} \hat{\varepsilon}_{it-1}^{*} \Delta \hat{\varepsilon}_{it}^{*} \tag{9}$$

The group ρ-statistics is:

$$\tilde{Z}_\rho \equiv T N^{-\frac{1}{2}} \sum_{i=1}^{N} (\sum_{t=1}^{T} \hat{\varepsilon}_{it-1}^{2})^{-1} \; \sum_{t=1}^{T} (\hat{\varepsilon}_{it-1} \Delta \hat{\varepsilon}_{it} - \hat{\gamma}_i) \tag{10}$$

The group t-statistics (non-parametric) is:

$$\tilde{Z}_t \equiv N^{-\frac{1}{2}} \sum_{i=1}^{N} (\hat{\sigma}_i^2 \sum_{t=1}^{T} \hat{\varepsilon}_{it-1}^{2})^{-\frac{1}{2}} \sum_{t=1}^{T} (\hat{\varepsilon}_{it-1} \Delta \hat{\varepsilon}_{it} - \hat{\gamma}_i) \tag{11}$$

The group t-statistics (parametric) is:

$$\tilde{Z}_t^* \equiv N^{-\frac{1}{2}} \sum_{i=1}^{N} (\sum_{t=1}^{T} \tilde{s}^{*2} \hat{\varepsilon}_{it-1}^{2*})^{-\frac{1}{2}} \sum_{i=1}^{N} \hat{\varepsilon}_{it-1} \Delta \hat{\varepsilon}_{it}^{*} \tag{12}$$

where, $\hat{\gamma}_i = \frac{1}{2} (\hat{\sigma}_i^2 - \hat{s}_i^2)$ and $\tilde{s}^{*2} = \frac{1}{N} \sum_{i=1}^{N} \hat{s}^{*2}$

The null hypothesis of no cointegration is:

H_0: $\rho_i = 1$ for all i=1, 2, …, N

The alternative hypothesis can be written as:

H_1: $\rho_i < 1$ for all i=1, 2, …, N

where a common value for $\rho_i = \rho$ is not required. The alternative hypothesis for within dimension-based statistics is represented as:

H_0: $\rho_i = \rho < 1$ for all i=1, 2, …, N

assuming a common value for $\rho_i = \rho$. Under this hypothesis, all statistics diverge to negative infinity. Hence, we need the left tail of the standard normal distribution to reject the null hypothesis.

3.2.2.2. ***Kao's Residual Panel Cointegration test (1999)***

Consider the model:

$$y_{it} = \alpha_i + x_{it}\beta + e_{it}, \qquad (13)$$

$i = 1, 2, \ldots, N, \qquad t = 1, 2, \ldots, T$

in which e_{it}, is I (1), the slope coefficient β is cross-section invariant (the cointegrating vector is homogeneous) and the intercept α_i is heterogeneous.

$y_{it} = \sum_{s=1}^{t} u_{is}$ *and* $x_{it} = \sum_{s=1}^{t} \epsilon_{is}$ are restricted to be most I(1) with $u_{it} \sim (0, \sigma^2{}_u)\ i.i.d,$ and $\epsilon_{it} \sim (0, \sigma^2{}_u)\ i.i.d,$ the error process $w_{it} = (u_{it}, \epsilon_{it})^!$ is independent across i and it seems to fulfil the invariant principle.

Chihwa Kao suggested the DF tests by using AR(1) which denotes LSDV (Least Square Dummy Variables) residuals$\hat{e}_{it} = \rho\hat{e}_{i,t-1} + v_{it}$, where AR(1) parameter ρ is homogeneous. This shows that e_{it}, is I(1), is a unit root. Based on the OLS residuals ρ is:

$$\widehat{\rho} = \frac{\sum_{i=1}^{N}\sum_{t-2}^{T} \hat{e}_{it}\, \hat{e}_{i,t-1}}{\sum_{i=1}^{N}\sum_{t-2}^{T} \hat{e}^2{}_{i,t-1}} \qquad (14)$$

$$y_{it}{}^* = y_{it} - \sigma_{ou\epsilon}\, \sigma_{o\epsilon}{}^{-2} x_{it} \qquad (15)$$

$$x_{it}{}^* = \sigma_{o\epsilon}{}^{-1} x_{it} \qquad (16)$$

in which $\sigma_{o\epsilon}$ is the long-run variance of ϵ_{it} conditional of u_{it} and $\sigma_{ou\epsilon}$ is the long-run covariance of ϵ_{it} and u_{it} :

$$s_e{}^2 = \frac{\sum_{i=1}^{N}\sum_{t-2}^{T}(\widehat{e},{}^*{}_{it}\, \widehat{\rho} e^*{}_{i,t-1})^2}{NT} \qquad (17)$$

where, $\widehat{e},{}^*{}_{it} = y_{it}{}^* - \widehat{\alpha},{}^*{}_{it} - x_{it}{}^*\widehat{\beta},{}^* \quad \widehat{\alpha},{}^*{}_i = \hat{\alpha}_{i,}\ \widehat{\beta}^* = \sigma_{o\epsilon}\widehat{\beta}, - \sigma_{o\epsilon}{}^{-1}\sigma_{ou\epsilon}$.

Both $\hat{\alpha}_{i,}$ *and* $\widehat{\beta},$ are the LSDV estimatorsα_i *and* β:

$$DF_\rho{}^* = \frac{\sqrt{N}T(\widehat{\rho}-1) + \frac{\sqrt{N}\widehat{e}_{v,}{}^2}{\widehat{e}_{ov,}{}^2}}{\sqrt{3 + \frac{36\widehat{e}_{v,}{}^4}{5\widehat{e}_{ov,}{}^4}}} \qquad (18)$$

$$DF_t{}^* = \frac{\frac{(\widehat{\rho}-1)\sqrt{\sum_{i=1}^{N}\sum_{t-2}^{T}(\widehat{e},{}^*{}_{i,t-1})^2}}{s_e} + \frac{\sqrt{6N}\widehat{e}_{v,}{}^2}{2\widehat{e}_{ov,}{}^2}}{\sqrt{\frac{\widehat{e}_{ov,}{}^4}{2\widehat{e}_{v,}{}^2} + \frac{3\widehat{e}_{v,}{}^2}{10\widehat{e}_{ov,}{}^2}}} \qquad (19)$$

$\hat{e}_{ov,}{}^2$ is a constant coefficient of the long-run conditional variance,$\sigma^2{}_{ov} = \sigma^2{}_{ou} - \sigma^2{}_{ou\epsilon}\, \sigma^{-2}{}_{o\epsilon}$ and $\hat{e}_{v,}{}^2$ is a constant estimator of the contemporaneous variance $\sigma^2{}_v = \sigma^2{}_u - \sigma^2{}_{u\epsilon}\, \sigma^{-2}{}_\epsilon$. The term $\sigma^2{}_{ou}$ reflects the long-run variance of u_{it} , whereas $\sigma_{u\epsilon}$ is the covariance between u_{it} andϵ_{it}. The estimator of contemporaneous variance can be calculated as:

$$\hat{\Omega} = \begin{pmatrix} \hat{\sigma}_{u,}{}^{2} & \hat{\sigma}_{u\epsilon,}{}^{2} \\ \hat{\sigma}_{u\epsilon,}{}^{2} & \hat{\sigma}_{\epsilon,}{}^{2} \end{pmatrix} = \frac{\sum_{i=1}^{N}\sum_{t-2}^{T}\hat{w}_{it}\,\hat{w}`_{i,t-1}}{NT} \tag{20}$$

To estimate the long-run variance and covariance we need to choose an appropriate bandwidth and a kernel estimator. The DF statistics are asymptotically standard normally distributed as $\mathrm{T} \rightarrow \infty$ $and\ N \rightarrow \infty$. The ADF statistics follows AR(1):

$$\hat{e}_{it} = \rho\hat{e}_{i,t-1} + \gamma_1\Delta\hat{e}_{i,t-1} + \cdots + \gamma_\rho\Delta\hat{e}_{i,t-\rho} + v_{it\rho} \tag{21}$$

which notices that $\hat{e}_{it}$ depends on the lagged change of the LSDV residuals. ADF panel t statistics test as:

$$ADF = \frac{\frac{\sum_{i=1}^{N}(e_i`Q_iv_i)}{s_v\sqrt{[\sum_{i=1}^{N}(e_i`Q_ie_i)]}} + \frac{\sqrt{6N}\hat{\sigma}_v}{2\hat{\sigma}_{ov}}}{\sqrt{\frac{\hat{\sigma}_{ov,}{}^{2}}{2\hat{\sigma}_{v,}{}^{2}} + \frac{3\hat{\sigma}_{v,}{}^{2}}{10\hat{\sigma}_{ov,}{}^{2}}}} \tag{22}$$

with $Q_i = I - X_{i\rho}\left(X_{i\rho}{}^{!}X_{i\rho}\right)^{-1}X_{i\rho}{}^{!}$

Here, $X_{i\rho}$ denotes the matrix of the observations on the ρ progressors$(\Delta\hat{e}_{i,t-1} + \cdots + \Delta\hat{e}_{i,t-\rho})$, $e_{i\,,}$is the observations vector on $\hat{e}_{i,t-1}$ and $s_v{}^2 = \frac{\sum_{i=1}^{N}\sum_{t-2}^{T}\hat{v}^2{}_{i,t\rho}}{NT}$, $\hat{v}^2{}_{i,t\rho}$ is the estimate of $v_{it\rho}$. $If\ x_{it}$ regressors are not cointegrated, then the tests can be implemented as a multiple regressor case. To find the finite simple properties of the test, Kao used the Monte Carlo test statistics to the simulation study of:

$$DF_\rho = \frac{\sqrt{N}T(\hat{\rho}-1)+3\sqrt{N}}{\sqrt{51/5}} \tag{23}$$

$$DF_t = \sqrt{\frac{5t_\rho}{4}} + \sqrt{\frac{15N}{8}} \tag{24}$$

in which, $t_\rho = \frac{(\hat{\rho}-1)\sqrt{\sum_{i=1}^{N}\sum_{t-2}^{T}(\hat{e}_{,}^{*}{}_{i,t-1})^2}}{s_e}$, is the t- statistics $\rho = 1$.

3.3. Data Description

We work with annual data covering 1971-2013 for N-11 countries (Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, the Philippines, Turkey, South Korea and Vietnam). Our study includes CO_2 emissions (CO_2) in kg per capita, EC per capita in kg of oil equivalent and per capita real GDP (GDP) in constant 2010 US \$, used as the proxy of economic growth borrowed from the World Development Indicators (WDI, 2014). The GINI coefficient which measures income distribution is collected from SWIID (2015).

Table 1 gives the mean values and standard deviations of the data series for N-11 countries. The descriptive statistics reveal that the data series is fairly dispersed, but the standard deviations are homogeneous. The table shows that South Korea had the highest means of CO_2 emissions (6677.444) and energy consumption (2670.633), Turkey had the highest GDP mean (6953.612) and Mexico registered the highest mean of the GINI coefficient (47.381). The lowest means of CO_2 emissions (184.668) and energy consumption (131.617) were in Bangladesh and the lowest GINI coefficient (31.088) and GDP (757.444) in Pakistan. Moreover, South Korea had the highest volatility in the case of CO_2 emissions (3273.488), energy use (1617.452) and GDP per capita (7000.265). The highest volatility of the GINI coefficient was in Nigeria (3.788).

Table 1: Descriptive statistics and pairwise correlation of the variables used (before taking logarithm) 1971-2013

Country		CO_2 Emission (kg per capita)	Energy use (kg of oil equivalent per capita)	GINI Coefficient	GDP Per Capita (constant 2010 US $)	Period
Bangladesh	Mean	184.6679	131.6169	35.6024	478.7004	1971-2013
	Std. dev.	111.5216	36.0876	3.6501	153.0717	
Egypt	Mean	1571.8980	565.2152	34.7121	1678.9820	1971-2013
	Std. dev.	591.6827	215.2245	3.1993	567.0324	
Indonesia	Mean	544.1110	570.7360	34.4496	1850.4450	1971-2013
	Std. dev.	63.2482	197.5233	2.4222	811.6094	
Iran	Mean	1003.7160	1601.7570	42.1453	5125.8290	1971-2013
	Std. dev.	265.7120	730.2027	2.3876	1356.7030	
Mexico	Mean	3612.8430	1351.3720	47.3807	7611.2000	1971-2013
	Std. dev.	475.7381	202.9817	2.6974	1091.1430	
Nigeria	Mean	653.8632	690.1914	43.9710	1660.8320	1971-2013
	Std. dev.	182.6912	52.4181	3.7889	390.0648	
Pakistan	Mean	637.2212	402.9434	31.0879	757.4445	1971-2013
	Std. dev.	218.6540	76.2916	1.3293	198.7942	
Philippines	Mean	793.1211	455.8078	42.8155	1651.0720	1971-2013
	Std. dev.	119.4988	25.1957	2.1218	265.2116	
Turkey	Mean	2761.7970	1009.3280	43.3288	6953.6120	1971-2013
	Std. dev.	893.7635	284.4049	3.3541	2028.9190	
South Korea	Mean	6677.4440	2670.6330	31.4508	11037.9000	1971-2013
	Std. dev.	3273.4880	1617.4520	1.3821	7000.2650	
Vietnam	Mean	819.7588	408.2190	36.1794	807.2760	1984-2013
	Std. dev.	523.8860	145.0561	2.3461	361.5859	
Aggregate	Mean	2570.0630	909.9553	38.5304	3680.1670	
	Std. dev.	2510.8410	898.2884	6.0420	4091.1380	
Pairwise correlation matrix						
CO_2 emissions		1.0000				
Energy consumption		0.9968	1.0000			
GINI Coefficient		0.9529	0.9472	1.0000		
GDP		0.9832	0.9855	0.9378	1.00000	

Note: CO_2 emissions are carbon emissions per capita in kg. EC is the energy use per capita in kg of oil equivalent. GINI coefficient is the level of income inequality. GDP per capita is the gross domestic per capita in constant 2010 US $ terms.

4. Results and Discussion

4.1 Cross-sectional dependence test

This study applies the cross-sectional dependence (CD) test developed by Pesaran (2004) to verify the cross-section dependence across the 11 countries under investigation. Table 2 gives the results of the test applied to CO_2 emissions, energy consumption, income inequality and GDP per capita variables. We reject the null hypothesis of cross-sectional independence for all the variables, except for income inequality.

Table 2: Cross-sectional dependence test

Variable	CD-test	p-value	Corr	abs(corr)
$lnco_2$	25.99	0.000	0.558	0.669
Lnenergy	36.88	0.000	0.782	0.791
Lngini	0.34	0.736	0.002	0.455
$(lngini)^2$	0.37	0.714	0.003	0.456
Lngdp	30.29	0.000	0.651	0.701

Note: All variables are taken in their natural logarithm form to give smoothness to the variables.

4.2. Unit root tests' results

We use the unit root tests developed by Levin, Lin and Chu (LLC), Im, Pesaran and Shin (IPS), Hadri (2000), and Breitung (2000) to verify the existence of unit roots. Levin et al., (2002) proposed the panel-based ADF test and assumed homogeneity in the dynamics of the autoregressive coefficients for all panel units. Under the LLC (2002) unit root test, the null hypothesis indicates the presence of a unit root; the alternative hypothesis claims there is no unit root. The IPS (2003) test which solves the serial correlation problem by accepting heterogeneity between units in a dynamic panel framework shows that under the null hypothesis of non-stationarity the statistic follows the standard normal distribution asymptotically.

Table 3. Panel unit root tests

Variable in level	$lnco_2$		Lnenergy		Lngini		$(lngini)^2$		lngdp	
	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Levin, Lin & Chu t*	0.70918	0.7609	0.59461	0.7239	-0.13778	0.4452	-0.22137	0.4124	-1.27480	0.1012
Im, Pesaran and Shin W-stat	-0.17824	0.4293	0.13655	0.5543	0.67573	0.7504	0.63161	0.7362	2.85995	0.9979
Hadri Z-stat	12.60050	0.0000	13.9522	0.0000	7.75064	0.0000	7.69224	0.0000	13.02360	0.0000
Breitung t-stat	-0.13619	0.4458	3.01039	0.9987	0.70121	0.7584	0.78079	0.7825	1.88511	0.9703
Variable in first difference										
Levin, Lin & Chu t*	-8.44605	0.0000	-8.56690	0.0000	-3.15038	0.0008	-3.22668	0.0006	-5.68608	0.0000
Im, Pesaran and Shin W-stat	-11.0753	0.0000	-9.28139	0.0000	-3.93814	0.0000	-3.94892	0.0000	-8.89460	0.0000
Hadri Z-stat	-0.23116	0.5914	3.61663	0.0001	1.30529	0.0959	1.21132	0.1129	1.20651	0.1138
Breitung t-stat	-4.95811	0.0000	-4.79859	0.0000	-3.56289	0.0002	-4.50790	0.0000	-6.24552	0.0000

4.3. Panel cointegration results

After applying panel unit root tests, we proceed to panel cointegration tests. Cointegration can be described as a systematic long-term interplay among two or more economic variables (Yoo, 2006). Based on the Pedroni test findings, Table 4 gives the cointegration between selected variables at the 5 percent level of significance for both the frameworks. Therefore, we have long-run interactions among series. The Kao (1999) residual cointegration results also support cointegration at the 5 percent level of significance. Thus, there is strong evidence of a long-term relationship between the series. This is consistent with Lee (2005) and Sadorsky (2009). We used the Wasteland test cointegration (2007) to establish the long-run relationship among the series. It also confirms cointegration among selected variables.

Table 4: Panel cointegration test results

	Series: $lnco_2$, lnenergy, lngini lngini2, lngdp	Statistics	P – value
Padroni Cointegration test	Panel v weighted statistic	-0.577556	0.7182
	Panel σ weighted statistic	-1.887474	0.0295
	Panel ρρ weighted statistic	-4.260884	0.0000
	Panel adf weighted statistic	-2.234407	0.0127
	group σ statistic	-1.682348	0.0463
	group ρρ statistic	-5.530865	0.0000
	group adf statistic	-2.483712	0.0065
Westeland cointegration test	Gt	-2.755	0.006
	Ga	-14.062	0.026
	Pt	-8.596	0.005
	Pa	-11.521	0.007
KAO Cointegration test	ADF test	-2.768727	0.0028

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4.4. Long-run Elasticity

We first present the outcomes of the empirical interplay between EC, economic growth, income inequalities and CO_2 emissions. Pedroni (2004) recommended a superior test relative to single equation methods that can be used to explore the cointegration vector. This assumes that the null hypothesis is in a natural form. We seek to identify a strong interaction between total EC, economic development, income inequalities and CO_2 emissions for all panel countries. Equation (7) points out the regression between these four factors. The dependent variables include carbon emissions, a function of total energy consumption, GDP per capita and income inequalities.

Table 5: Panel long-run results

CO_2 EMISSION : Dependent variable						
	FMOLS		DOLS		Random effect	
	Model1	Model2	Model1	Model2	Model1	Model2

	Without EKC	With EKC	Without EKC	With EKC	Without EKC	With EKC
Lnenergy	0.589455*	0.592152*	0.626768*	0.586308*	0.584288*	0.570516*
Lngini	0.862505*	21.26711*	0.437516	16.94047**	0.780637*	20.00548*
$lngini^2$		-2.798858*		-2.27681**		-2.63679*
Lndgdp	0.456898*	0.449064*	0.401824*	0.381898*	0.453617*	0.453848*
Adj R^2	0.9737	0.9754	0.9835	0.9859	0.7227	0.7266
Threshold level		44.66		41.27		44.41

Note: Optimum lag obtained from SIC criteria; *and ** indicate rejection of the null hypothesis at the 1% and 5% levels of significance respectively.

Table 5 presents the findings of the FMOLS, DOLS and Random effect estimation methods which highlight whether EC, wealth disparities and level of income per capita stimulate CO_2 emissions in the N-11 countries. The Hausman test confirms the random effects model as a preferred model over the fixed effects model which helps avoid the cross-sectional effects and also allows us to cross-examine our long-run outcomes returned by FMOLS and DOLS. Both FMOLS and DOLS tests show consistent results that demonstrate a positive interplay running from EC, income inequalities and level of income to CO_2 emissions at the 1 percent level of significance.

The long-run elasticities of CO_2 emissions with respect to total energy consumption are estimated at 0.589, 0.626 and 0.584 in Model 1 (without EKC) and 0.594, 0.586 and 0.57 in Model 2 (with EKC). This means that a 1 percent increase in energy consumption leads to a 0.58 to 0.59 percent rise in CO_2 emissions. These findings indicate a monotonic relationship between CO_2 emissions and energy consumption for all N-11 countries. There is no doubt that CO_2 emissions are driven by unsustainable energy consumption patterns.

Our results confirm the presence of an inverted U-shaped relationship between income inequalities and carbon emissions for N-11 countries. Initially, CO_2 emissions increase; they start declining after a threshold level of income inequality. We identified an environmental EKC interplay among income inequalities and CO_2 emissions. The threshold level of wealth disparity for all N-11 nations varied from 41 to 45. If a country has a level of inequality below 40, reducing the gap will trigger a decrease in carbon emissions. If inequality is higher than 45, reducing inequality will have no beneficiary effects on environmental quality.

Regarding the long run elasticity of CO_2 emissions with respect to wealth disparity, we found inelasticity coefficients in Model 1 (without EKC), but elasticity in Model 2 (with EKC) when including the GINI coefficient squared. The coefficient of income inequality is 0.862, 0.437 (insignificant) and 0.78 in Model 1. A 1 percent increase in income inequality drives a 0.78 to 0.86 percent growth in carbon emissions. Our results illustrate that rising income inequalities force poor people to use low cost fuels which release more carbon emissions. By contrast, falling income inequalities improve environmental quality. The coefficients for wealth disparity and income inequality square in Model 2 are 21.267, 16.94 and 20.00, and -2.798, -2.276 and -2.636 respectively. Further, the estimated threshold levels are 44.66, 41.27 and 44.41. Our study found an inverted 'U' shape relation between the level of income inequality and CO_2 emissions. This result shows that wealth disparities decreased CO_2 emissions when the level of income inequalities was more than 45 percent and increased CO_2 emissions when income inequality was less than 40 percent. In countries with more equal distribution of income, a rise in inequality has a bad effect on the environment. Similarly, countries with more unequal income distribution policies towards lowering inequalities will causes environment degradation. So in both the cases, level of wealth distribution plays a critical role in environment quality. This indicates that the rich people are more responsible for the degradation in environmental quality as compared to poor people because when the rich become richer, they try to invest their wealth in leading industries to get higher returns without caring about their impact on environmental quality. But in the case of poor people where environment forms a part of their livelihood strategy they try and protect their environment.

The estimated long-run elasticity of CO_2 emissions with respect to GDP per capita is 0.456, 0.401 and 0.453 for Model 1 (without EKC) and 0.449, 0.381 and 0.453 for Model 2. This implies that a 1 percent increase in GDP per capita induces CO_2 emissions of 0.38 to 0.44 percent. We found a positive long-run interaction among CO_2 emissions and GDP per capita. This shows that a rise in disposable incomes motivates households to consume pollution free fuel (renewable energy) for their activities.

5. Concluding remarks, policy implications and Future research directions

This research explained the nexus between CO_2 emissions, energy consumption, income inequalities and GDP per capital for N-11 countries over the period 1971-2013. It explored this topic because scholars have paid little attention to the interplay between CO_2 emissions and wealth disparities in an era of globalization. To the best of our knowledge there is no study that explores the interactions between income disparities and carbon emissions in the context of N-11 nations. Hence, this leads to questions like whether income levels or income inequalities matter in CO_2 emissions. We considered two models. In each model, the dependent variable was *CO_2 emissions* and the independent variables were *energy consumption, income inequality and GDP per capita.* Model 1 used all variables in linear form as in extant literature. In Model 2, we added income inequality square as an independent variable to verify the environmental Kuznets curve hypothesis for the N-11 countries.

Our results show that all coefficients were positive and statistically significant. Income inequalities, economic development and energy consumption stimulated CO_2 emissions in selected countries. Therefore, in the long-run an increase in energy consumption, income inequalities and income levels will increase CO_2 emissions. This is happening in the N-11 states because for the sake of economic growth and poverty reduction the governments' policies enable growth without paying much attention to the health of the environment.

Our findings also highlight an inverted U-shaped interaction between wealth inequality and environment pollutants (CO_2 emissions). Wealth disparity had both positive and negative effects in the countries that we studied. In countries with equal income distribution, a rise in inequality had a bad effect on the environment. Similarly, in countries with more unequal income distribution policies towards lowering inequality can lead to environment degradation. So, in both the cases the level of wealth distribution played a critical role in environment quality. This indicates that the rich people are more responsible for deterioration in environmental quality as compared to poor people because when the rich becomes richer they invest their wealth in leading industries to get higher returns without caring about their impact on environmental quality. But in the case of poor people where the environment forms a part of their livelihood strategy, they try and protect their environment.

Therefore, policymakers and governments in N-11 nations can increase environmental protection by applying carbon taxes and trading schemes. Moreover, governments can also encourage both national and foreign investors to work with energy efficient technologies when increasing production levels. In addition, N-11 governments should adopt energy reduction policies not only to preserve environmental quality but also to distribute already scarce resources to sectors with high growth potential and use resource-saving technologies.

Future analyses are warranted in terms of applying the Quantile-on-Quantile Regression (Q-Q-R) approach developed by Sim and Jhou (2015), or the Non-Linear Autoregressive Distributed Lag framework detailed by Pesaran et al., (2001) who postulate the possibility of an empirical examination of non-linear cointegration and asymmetric dynamic relationships. Based on these methodologies, academics can examine which groups are the main influencers of environmental quality (the lower section or the upper section). Our study also provides reliable and consistent empirical findings that can be valuable for policymakers when implementing comprehensive environmental strategies for sustainable economic development and growth.

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Figure 1: CO_2 Emissions (kg per capita)

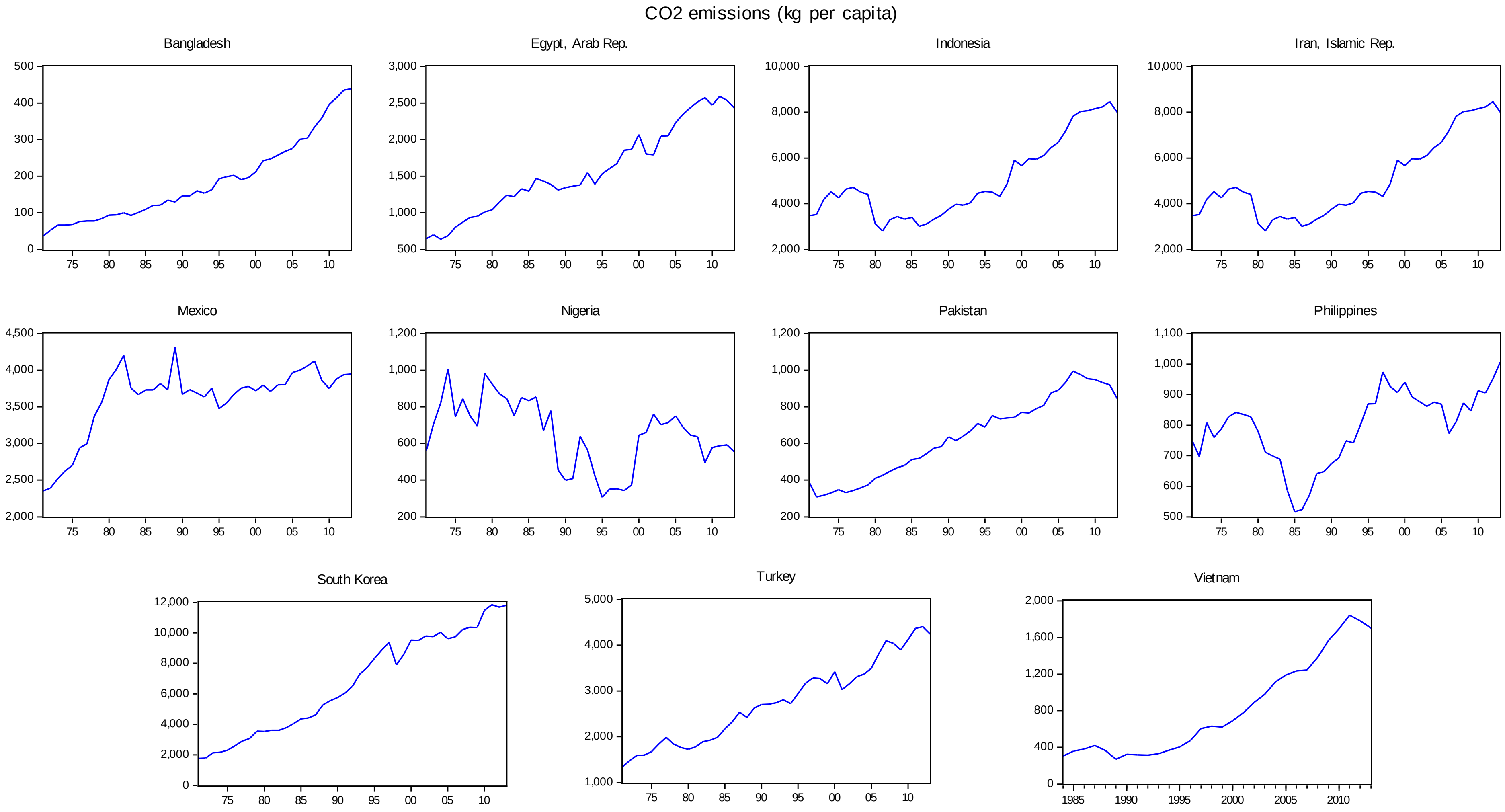

Figure 2: Income inequality (GINI coefficient)