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**Article**

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## Research paper

# Investigation of key contributors of CO<sub>2</sub> emissions in extended STIRPAT model for newly industrialized countries: A dynamic common correlated estimator (DCCE) approach

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## ABSTRACT

The study examined the impact of different forces on carbon dioxide emissions for ten newly industrialized countries (NIC's) by applying the extended STIRPAT model for the period 1991–2013. Moreover, study utilizes the regression of group mean dynamic common correlated estimator (DCCE) to analyze the relationship between carbon dioxide emissions (CO<sub>2</sub>), population, affluence, technology and extended factors such as labor productivity, urban employment level, population carrying intensity of real economy, energy mix, trade openness and energy intensity. The results from DCCE approach are compared with fully modified ordinary least square and dynamic ordinary least square techniques for robustness. Results of the study suggest that population, GDP per capita and CO<sub>2</sub> emission intensity along with energy intensity are main contributors for CO<sub>2</sub> emissions for NIC's, while population carrying capacity of real economy have no significant impact on CO<sub>2</sub> emission level. Furthermore, energy mix and trade openness have marginal contribution in CO<sub>2</sub> emissions. The policymakers can use these results to develop appropriate policies for economic growth through industrial development by curtailing the level of CO<sub>2</sub> emissions.

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## 1. Introduction

The 21st century biggest challenge for humanity is global climatic change that is persistently degrading environments. During the last few decades, it is observed through global consensus that carbon dioxide emissions (CO<sub>2</sub>) are one of the main sources of global warming because of an upsurge in energy consumption (Wang et al., 2017; Soytas et al., 2007; Roy et al., 2017). Since the industrial revolution, CO<sub>2</sub> emissions growth rate is 2.0 ppm per year and it has crossed the total figure of 410 ppm in 2017. During few short decades, this record will reach up to 450 ppm at present pace (Kahn, 2017). To achieve high economic growth rate through industrial output and technical development is at the top priority of newly industrialized countries that are reciprocally increasing urban population, international trade, and financial development. The newly industrialized countries (NIC) contributing 42 percent to total global CO<sub>2</sub> emissions due to acceleration in their economic growth (IPCC, 2013). Therefore, sustainable economic growth with the least environment pollution is a great challenge for today's world. Researchers and policymakers are interested

to find out those factors that are responsible for environmental degradation through CO<sub>2</sub> emissions (Pata, 2017).

In 1997, the Kyoto Protocol was signed by developed countries under the Nations Framework Convention on Climate Change (UNFCCC) to reduce CO<sub>2</sub> emissions to control rapid growth in global warming. In 2015, 195 countries that are emitting 95 percent of global emissions adopted the Paris Agreement of UNFCCC. However, major emission emitting countries include NICs who have signed the agreement. The primary objective of this agreement is to attain back the level of global warming as it was before industrialization (Ozatac et al., 2017). The present study selected the group of ten NICs namely Brazil, India, China, South Africa, Mexico, Indonesia, Philippines, Malaysia, Thailand, and Turkey. A sample of this group of countries has a key role in upsurging of CO<sub>2</sub> emissions as their level of industrialization is higher as compared to other developing countries (Zhang et al., 2017).

Many studies use different models to trace out the key contributor of emission level (Ehrlich and Holdren, 1971; Xu et al., 2005; Dietz and Rosa, 1994; Waggoner and Ausubel, 2002). One of the significant model is STIRPAT model which investigate the impact of population, affluence, and technology on the level of CO<sub>2</sub> emissions (Shi, 2003; Tian and Da Costa, 2014; Li and Lin, 2015). Different researchers extended the STIRPAT model and tested it with different important actors (Yang et al., 2018; Roy

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et al., 2017; Lin et al., 2017) and for newly industrialized countries (Sharif Hossain, 2011) with different techniques. Still, there is a need to investigate, what is the role of energy intensity, labor productivity, trade openness and urban employment in extended STIRPAT model for NIC's using some dynamic modeling approach. The present study used panel data of NICs to investigate the impact of population, affluence, productivity, urban employment, labor productivity, population carrying intensity of the real economy, energy intensity, and trade openness on CO<sub>2</sub> emissions through Dynamic Common Correlated Effects Estimators (DCCE). The study extended the extant body of knowledge using data of NICs through extended STIRPAT model considering the dynamic element of data for robustness of estimates as this aspect cannot get the attention of former studies such as Sharif Hossain (2011) and Zhang et al. (2017).

Rest of paper consists of following sections. Section 2 includes a concise review of previous studies; Section 3 explains model and data description; Section 4 describes estimated results and interpretation; Section 5 check the robustness of estimated results; Section 6 presents conclusions and implications of the study.

## 2. Review of extant literature

The study to explore drivers of carbon dioxide emissions is not a new topic of research. As the era of industrialization has restructured world economies from organic to inorganic that pushed the consumption of fossil fuels for industrial production to correspond to the demands of the population (Stern et al., 1996). This structural change upsurge fossil fuel consumption that results in global warming and unprecedented change in climate (Ahmed et al., 2017). Presently, environmental degradation and global warming is a great worry of policymakers to redress cleaner environment through choking CO<sub>2</sub> emissions. It is the time to investigate and establish the analytical framework to avert environmental degradation through policy measures.

A large of studies investigated the controlling actors of CO<sub>2</sub> emissions on different dimensions like impact of population on CO<sub>2</sub> (Cramer, 2002; Zaba and Clarke, 1994; Zhu et al., 2012; Martínez-Zarzoso et al., 2007; Sadorsky, 2014), the influence of urbanization on CO<sub>2</sub> (York et al., 2003; Jones, 1991; Fan et al., 2006; Jorgenson and Clark, 2010; Knight et al., 2013), impact of technology on CO<sub>2</sub> (Liddle and Lung, 2010; Sadorsky, 2014; Poumanyvong and Kaneko, 2010; Martínez-Zarzoso et al., 2007). Different models such as IPAT, STIRPAT, ImPACT, ICE-STIRPAT, ImPACTS, IPBAT, and extended STIRPAT model were used as a tool to investigate the driving forces that impact on the environments. Among these models, STIRPAT model was developed by Dietz and Rosa (1994), and considered as an extension of the IPAT model which attained high popularity due to its usefulness.

IPAT model investigates the influence of three actors, population (P), affluence (A) and technology (T) on the environment (I).<sup>1</sup> The IPAT identity was introduced by Ehrlich and Holdren (1971) that describes that, the total CO<sub>2</sub> emissions (I) are explained by product of population (P), gross domestic product per capita (A) and CO<sub>2</sub> emissions per unit of GDP (T). Some studies add more factors in IPAT model to develop more understanding of environment. Schulze (2002) develops IPBAT model by incorporating behavior in IPAT identity. Similarly, Waggoner and Ausubel (2002) extended IPAT model using consumption as C and emissions for each energy unit consumed as T by developing ImPACT model, which was further extended by Xu et al.

(2005) by developing ImPACTS model. If the driving forces have a nonproportional effect, then IPAT and ImPACT models are out of the scope. To avoid the nonproportional problem, Dietz and Rosa (1994) proposed STIRPAT as stochastic approach that allows hypothesis testing. The STIRPAT model is widely used for empirical investigation and policy suggestions to avoid environmental degradation (Li and Lin, 2015; Shi, 2003; Tian and Da Costa, 2014).

A large body of researchers extended the STIRPAT model by adding and dropping some variables to analyze the impact of different actors on environmental degradation as indicated by York et al. (2003). A brief summary of literature on extended STIRPAT model is described in Table 1. Yang et al. (2018) extended the model by adding trade openness, urbanization, temperature and found that development of economy, urbanization, and trade are key contributors in promoting CO<sub>2</sub> emissions for China. Roy et al. (2017) used energy intensity, demand of energy and energy mix in the STIRPAT model to extend its scope for India, and concluded that all forces included in the study significantly contributed to environmental degradation, but economic growth share is largest. Lin et al. (2017) level of urban employment, employed urbanization, level of industrialization, and labor productivity to extend the model for 53 countries with different income groups and suggested that economic development has small influence on environmental degradation for low-income economies, while population, affluence along with energy intensity play a major role in emissions in respect of these countries.

Ma et al. (2017) extended STIRPAT model through including urbanization and an index of GDP while studying Chinese tertiary industry and result indicated that all factors have a significant contribution towards CO<sub>2</sub> emissions. Wang et al. (2017) investigated the influence of fixed assets investment in addition to industrialization, tertiary industry proportion, trade openness, and energy consumption. The variation in results was found at different stages of development. However, investment in fixed assets and growth in the economy are leading actors for CO<sub>2</sub> emissions while investigating data of western developing countries since 2001. Abou-Ali et al. (2016) examined the extended STIRPAT model for Arab region by investigating fertility, industrialization, urbanization, government effectiveness, and energy production and consumption and results indicated that government efficiency must be enhanced in addition with production and consumption of energy.

Furthermore, Rafiq et al. (2016) used data from 53 countries and extended STIRPAT model considering service sector and agriculture sector besides with industrialization and trade openness and postulated that improving the service sector and agriculture sector can reduce environmental degradation but same is not the case with the industrial sector. Moreover, a sharp increase in economic activities in emerging markets is a leading factor that detrimental to clean environments.

Sadorsky (2014) examined the data of 16 emerging economies to investigate the model with population, affluence, and urbanization, most of the results about urbanization were observed insignificant. However, Liddle (2015) applied the STIRPAT model, and non-fossil fuels demonstrated the negative impact of non-fossil fuels in primary energy on CO<sub>2</sub>.

Another comprehensive investigation was conducted by Martínez-Zarzoso and Maruotti (2011) using extended STIRPAT approach for group of 88 developing economies with different income levels and urbanization demonstrated dissimilar results in respect of three different income group of economies. Nevertheless, Sharif Hossain (2011) concluded that openness of trade and urban population have a strong influence in enhancing CO<sub>2</sub> emissions. Recently, Salim et al. (2017) concluded that nonrenewable energy is the main contributor of carbon emissions in Asian countries while expending the STIRPAT model with nonrenewable

<sup>1</sup> Commoner (1971) introduced the impact of different driving forces on environment algebraically, which made this concept more understandable with the help of data analysis.

**Table 1**Brief Summary of previous studies on Extended STIRPAT models with CO<sub>2</sub> as Dependent Variable.

Authors	Number of Objects	Time Period	Variables and Results			
			IPAT Model (P) & (A)	Technology (T)	Extended Variables	Estimation Tools
Yang et al. (2018)	China	1995–2014	(+) & (+)	Energy Intensity (-)	Trade Openness (+) Urbanization (+) Mean Temperature Anomaly (+) Cooling degree days (+)	Principal Component Analysis
Roy et al. (2017)	India	1990–2016	(+) & (+)	Carbon Intensity of GDP growth (-)	Energy demand (-) Energy mix (+) Fossil fuel energy intensity (+)	Ridge Regression
Lin et al. (2017)	53 Countries <sup>a</sup> GDP > \$100 M Population >1 million	1991–2013	(+) & (+)	Energy intensity (+)	Urbanization level (+) Urban employment level (-) Industrialization level (+) Population carrying intensity of real economy (-) CO <sub>2</sub> intensity (+) Labor Productivity (-)	Fixed Effect Random Effect
Ma et al. (2017)	China	2000–2015	(+) & Floor area per capita (+)	Carbon emission intensity (+)	Urbanization (+) GDP index in the Chinese tertiary industry (+)	OLS Ridge regression K-fold cross-validation
Wang et al. (2017)	China (Xinjiang)	1952–2012 In three stages <sup>b</sup>	(+) & (+)	Carbon emissions per unit gross GDP (-)	Industrialization (+) Tertiary industry proportion (-) Fixed assets investment (+) Trade openness (+) Energy consumption structure (+)	OLS Ridge regression
Salim et al. (2017)	13 Asian Countries	1980–2010	(+) & (+) & AFL <sup>2</sup> (-)	Non-renewable Energy Consumption (+)	Urbanization (-) Renewable energy (-) Trade liberalization (-)	Mean Group estimator (MG) Common Correlated Effects Mean Group estimator (CCEMG) Augmented Mean Group estimator (AMG)
Abou-Ali et al. (2016)	21 Arab Countries 6 GCC 5 Non GCC 9 Low middle Income 1 Low Income	1990–2012	GCC(-);Non GCC (+) & (+)	Energy intensity (+)	(GDP Per Capita) <sup>2</sup> (-) Population <sup>2</sup> (-) Fertility (+) Industrialization (+) Urbanization (+) Government Effectiveness (-) Energy Production (+) Services output (+) Energy Consumption (+)	Fixed Effect Random Effect
Rafiq et al. (2016)	53 countries	1980–2010	(-) & (+)	Energy intensity (+)	Industrialization (-) Service sector contributions to GDP (-) Agricultural sector contribution to GDP (+) Trade openness (+)	MG CMG AMG
Sadowsky (2014)	16 Emerging Countries	1971–2009	(+) & (+) & lagged AFL (-)	Energy intensity (+) Lagged Energy intensity (-)	Urbanization (-)	MG estimator CCEMG AMG
Liddle (2015)	80 Countries: OECD countries(26) Non-OECD countries(54)	1971–2011 12 different time spans	(+) & (+)	Industry energy intensity (+)	Share of non-fossil fuels in primary energy (-)	MG CMG AMG FMOLS
Martínez-Zarzoso and Maruotti (2011)	88 Developing	1975–2003	(+) & (+) & AFL <sup>2</sup> (-)	Energy Efficiency (-)	Lagged CO <sub>2</sub> (+) Urbanization (+) Urbanization <sup>2</sup> (-) Population between (15–64) (+) Population > 64 (+) Industrial Activity (+)	LSDVC Fixed-effects Instrumental variable GMM
Sharif Hossain (2011)	9 Industrialized countries	1971–2007	(#) <sup>c</sup> & (+)	Per capita energy consumption (+)	Trade openness (+) Urbanization (-)	GMM

<sup>a</sup>Non-high income countries, Upper middle-income countries, Lower middle-income countries.<sup>b</sup>Stage 1: Before Reform and Opening up (1952–1978); Stage 2: After Reform and Opening up (1978–2000); Stage 3: Western Development (2000–2012).<sup>c</sup>Variable not analyzed in the study.

energy and renewable energy consumption, urbanization, and trade liberalization. Contrarily, [Zhang et al. \(2017\)](#) linked trade

openness with environment Kuznet curve (EKC) model comprising CO<sub>2</sub> emissions and energy consumptions for ten emerging

economies and concluded that advancement in trade openness would curtail carbon emissions.

A recent review of previous studies indicates that current policies on international climate change and environmental degradation may influence future decision making. Hence, it is urgent to investigate main actors causing environmental degradation in different regions. Therefore, the current study has extended the STIRPAT model, including new environmental degradation factor for newly industrialized countries because countries are contributing a large share in elevating environmental degradation. The study intended to examine the impact of energy intensity, energy mix, labor productivity, level of urban employment, population carrying the intensity of the real economy, and trade openness in addition with population, affluence and technology factors on CO<sub>2</sub> emission.

### 3. Empirical methodology for testing extended STIRPAT model

**Ehrlich and Holdren (1971)** study on IPAT identity provides the base for many investigations related to identifying environment degradation factors. The famous identity showing that CO<sub>2</sub> emissions are the product of population (P), affluence (A) and technology (T) and can be described as follows.

$$I = P.A.T \quad (1)$$

**Dietz and Rosa (1994)** extended the IPAT model and develop the STIRPAT model, Eq. (2) can give some idea about standard STIRPAT model.

$$I = \delta.P^\alpha.A^\beta.T^\gamma \quad (2)$$

After taking the logarithm, Eq. (2) is transformed into Eq. (3) as follows.

$$\ln I = \ln \delta + \alpha \ln P + \beta \ln A + \gamma \ln T + \ln e \quad (3)$$

where  $\delta$  is the coefficient of the model,  $\alpha, \beta, \gamma$  are exponentials of independent variables and STIRPAT model random error term is represented by  $e$ .

In this study, the effects of the population (P), affluence (A), technology (T) and other actors on CO<sub>2</sub> emissions are empirically analyzed with the help of dynamic panel common correlated effects (DCCE) approach developed by **Chudik and Pesaran (2015)** which estimates an error correction (EC) model. The original approach by **Pesaran (2006)** assumes that there is exogeneity in variables and allow feedback effect among observables, which can cause serious consistency issues.

The latest approach by **Chudik and Pesaran (2015)** takes into account three main issues, the first issue is cross-sectional dependencies, which are solved by taking the cross-sectional averages and lagged cross-sectional averages of dependent variables on right side of model with independent variables. The second issue is heterogeneity in the parameters, which can be resolved with the help of mean group method proposed by **Eberhardt and Presbitero (2015)**. The third issue is dynamics which can be resolved by incorporating lag of dependent variable in the model as the independent variable. The dynamic panel common correlated effects (DCCE) approach solve all the problems discussed above and provide more reliable estimates for the extended STIRPAT model. The concerned model is composed of the following equations:

$$I_{it} = g_i + \sum_i I_{i,t-1} + q_1 P_{it} + q_2 A_{it} + q_3 T_{it} + \gamma'_0 EV_{it} + w_{it} \quad (4)$$

$$w_{it} = \varphi'_i r_t + \epsilon_{it} \quad (5)$$

$$\epsilon_{it} = \begin{pmatrix} EV_{it} \\ k_{it} \end{pmatrix} = g_{\epsilon_i} + \vartheta_i I_{i,t-1} + \omega'_i r_t + v_{it} \quad (6)$$

where  $i = 1$  to  $N$ ;  $t = 1$  to  $T$ ;  $I_{it}$  is dependent variable that represent CO<sub>2</sub> emission;  $P_{it}$  is measure of population;  $A_{it}$  is measure of affluence;  $T_{it}$  is measure of technology and  $EV_{it}$  denotes different explanatory variables for extended STIRPAT model which includes, energy intensity, labor productivity, urban employment level, population carrying intensity, energy mix and trade openness.

Also  $g_i$  represents effects specification to the country which are unobserved;  $k_{it}$  consist variables that are dependent on some factors which are common but they do not depend on dependent variable.  $r_t$  is the country specific effects of time varying factors which are unobserved and also represents shocks which are on global level that affect all newly industrialized countries with same degree.  $\epsilon_{it}$  represent errors which are not correlated with regressors. Also  $\epsilon_{it}$  exhibit shocks which are common and unobserved as well, furthermore these errors are also weakly independent across countries and are also serially correlated.  $\omega_i$  denotes matrix for factor loadings,  $\vartheta_i$  represents vector of coefficients and  $v_{it}$  is a covariance stationary process regardless of error  $v_{it}$ . Further it is assumed that vector consisting of factor loadings ( $\varphi_i, \omega_i$ ) and coefficients such as  $\Omega_i = (w_i, q_1, q_2, q_3, \gamma'_0)'$  follow below models with random coefficients.

$$\varphi_i = \bar{w} + \eta_{0,i}, \mu_{0,i} \sim IID(0, \Theta_0) \quad (7)$$

$$vec(\omega_i) = vec(\omega) + \eta_{\omega,i}, \mu_{\omega,i} \sim IID(0, \Theta_{\omega}) \quad (8)$$

$$\Omega_i = \Omega + \eta_{\Omega,i}, \eta_{\Omega,i} \sim IID(0, \Theta_{\Omega}) \quad (9)$$

To estimate asymptotic variance of the mean group estimator following equation will be used:

$$\bar{\Sigma}_{MG} = \frac{1}{N-1} \sum_{i=1}^N (\hat{\Omega}_i - \hat{\Omega}_{MG})(\hat{\Omega}_i - \hat{\Omega}_{MG})' \quad (10)$$

For the estimation equation we adopted the technique dynamic common related effect estimation by **Chudik and Pesaran (2015)** and dependent variable CO<sub>2</sub> emissions is used as cross-sectional averages. The model in Eq. (11) also includes lag of dependent variable as a proxy for common factors effect along with P, A and T and extended variables.

$$I_{it} = g_i + \sum_i I_{i,t-1} + q_1 P_{it} + q_2 A_{it} + q_3 T_{it} + \gamma'_0 EV_{it} \\ + \sum_{x=0}^y \gamma_{1ix} \bar{I}_{t-x} + \sum_{x=0}^y \gamma_{2ix} \bar{P}_{t-x} + \sum_{x=0}^y \gamma_{3ix} \bar{A}_{t-x} \\ + \sum_{x=0}^y \gamma_{4ix} \bar{T}_{t-x} + \sum_{x=0}^y \gamma_{5ix} \bar{EV}_{t-x} + \epsilon_{it} \quad (11)$$

where  $\bar{I}_{t-x}$ ,  $\bar{P}_{t-x}$ ,  $\bar{A}_{t-x}$ ,  $\bar{T}_{t-x}$  and  $\bar{EV}_{t-x}$  represents dependent variable cross sectional average and  $y$  represents cross sections averages lags. Dependent variable ( $I_{i,t-1}$ ) included as explanatory variable because models with dynamic properties such as Dynamic Common Correlated Estimator (DCCE) uses lag of independent variable **Chudik and Pesaran (2015)**.

### 4. Variables, data and variations

Panel data<sup>2</sup> for ten newly industrialized countries (NIC's) was collected from world development indicators (WDI) for the period from 1991 to 2013 where data for all concerned variables are available, leading to a balanced panel for 230 observations. This group of ten NICs namely Brazil, India, China, South Africa, Mexico, Indonesia, Philippines, Malaysia, Thailand, and Turkey,

<sup>2</sup> Supplementary data related to this article can be found at <https://doi.org/10.1016/j.econmod.2018.01.006>.

**Table 2**  
Description of Variables and Units.

Variable	Measurement/ Definition	Measurement Unit	Mean	Min	Max
CO <sub>2</sub> emission (CO <sub>2</sub> EM)	Total carbon dioxide emissions	Kilotonne	859761.3	43930.66	1.02e+07
Population (POP)	Mid-year population	Number	3.14e+08	1.87e+07	1.36e+09
GDP per capita (GDPPC)	GDP divided by mid-year population	Constant 2011 PPP US\$	5203.198	536.4321	11797.45
Productivity of labor (LBPD)	GDP per employed person	Constant 2011 PPP US\$	24936.12	2915.14	55963.27
Level of urban employment (UEL)	Ratio of total population employed to urban population	Percent	1.266656	.5831112	2.746046
Population carrying intensity of real economy (POPCI)	Total population divided by industrial value added	Number of people/ Constant 2011 PPP US\$	8905994	444349.9	4.27e+07
Energy mix (EMX)	Fossil fuel consumption divided by total energy consumption	Percent	75.14186	44.28031	95.11674
Trade Openness (TOPN)	Percentage of gross import and export value to GDP	Percent	68.79972	15.63556	220.4074
CO <sub>2</sub> emission intensity (CO <sub>2</sub> EI)	Carbon dioxide emissions per unit energy use	Kilotonne of carbon/ Million tonne of oil equivalent	2.507671	1.526896	3.627587
Energy intensity (ENGINT)	Energy use per unit of GDP	kg of oil equivalent per \$1,000 GDP	142.0396	72.12224	447.7528

was selected because 42 percent of world CO<sub>2</sub> emissions is contributed by these countries. These countries have a key role in upsurging of CO<sub>2</sub> emissions as their level of industrialization is higher as compared to other developing countries (Zhang et al., 2017). Also, selected period of investigation (1991–2013) was the era of rapid industrialization in the world as well as in selected countries as the production level was at its peak.

The Sample data comprised of CO<sub>2</sub> emissions (CO<sub>2</sub>EM), population (POP), GDP per capita (GDPPC), CO<sub>2</sub> emission intensity (CO<sub>2</sub>EI), energy intensity (ENGINT), productivity of labor (LBPD), level of urban employment (UEL), population carrying intensity of real economy (POPCI), energy mix (EMX), and trade openness (TOPN). Table 2 describes each variable with its definition and unit of measurement along with some key descriptive statistics. For analysis, all variables are transformed into logarithmic form to make analysis more meaningful.

Brief graphical summary of original data (before converting into logarithmic form) is presented from Fig. 1 to Fig. 5 for the period of 1991 to 2013 for each newly industrialized country (NIC's). Fig. 1 portrays the picture of the recent situation of CO<sub>2</sub> emissions level in the world and as well as in NIC's. It is obvious from the figure that after 2002 CO<sub>2</sub> emissions level is dangerously increasing with very high rates. Fig. 2 describes the CO<sub>2</sub> emissions level for each country and a clear idea can be obtained that China has the largest CO<sub>2</sub> emissions level counting about 62% of total NICs emissions. India is the second largest country with 13% emissions for CO<sub>2</sub> emissions in NICs.

India and China experienced a reduction in energy intensity level gradually but China still has the highest level as well as South Africa as demonstrated in Fig. 3. Malaysia and Thailand have shown the highest level of trade openness during this study period as exhibited in Fig. 4. However, labor productivity level is high for Turkey, Malaysia and Mexico for the period observed as shown in Fig. 5. Overall selected newly industrialized countries are important in the world economy and have a significant impact on environmental degradation as concluded from the above graphical analysis.

## 5. Extended STIRPAT estimation, results and analysis

In the start of the analysis, to infer evidence of the stationary process, all variables are tested through Im, Pesaran and Shin (IPS) unit root test developed by Im et al. (2003), to check the stationarity and to find the integration order of concerned variables. Results reported in Table 3 show that all concerned variables of study have unit roots at level but after taking first difference of series they became stationary, concluding that all series are following the process of I(1).

Results of four extended STIRPAT models with dynamic common correlated effects estimator (DCCE) for a panel of Brazil,

**Table 3**  
Im, Pesaran and Shin (IPS) Panel unit roots test.

Variables	Level		First difference	
	IPS (W-statistic)	p value	IPS (W-statistic)	p value
CO <sub>2</sub> EM	1.359	0.913	-2.549***	0.005
POP	1.115	0.867	-7.947***	0.000
GDPPC	-0.628	0.264	-1.688**	0.045
CO <sub>2</sub> EI	0.413	0.660	-3.061***	0.001
UEL	0.376	0.646	-4.102***	0.000
POPCI	-0.402	0.343	-3.815***	0.000
EMX	0.819	0.793	-4.056***	0.000
TOPN	-0.328	0.371	-5.167***	0.000
LBPD	-0.748	0.227	-4.269***	0.000
ENGINT	1.047	0.852	-4.510***	0.000

The Akaike information criterion was used to determine the optimum lag length.

\*\*\* Represents significance at 1% level.

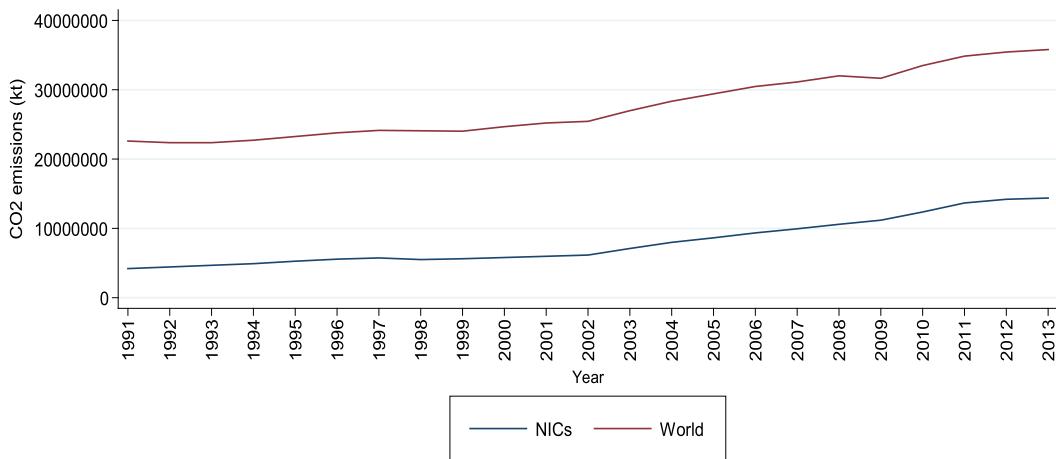
\*\* Represents significance at 5% level.

\* Represents significance at 10% level.

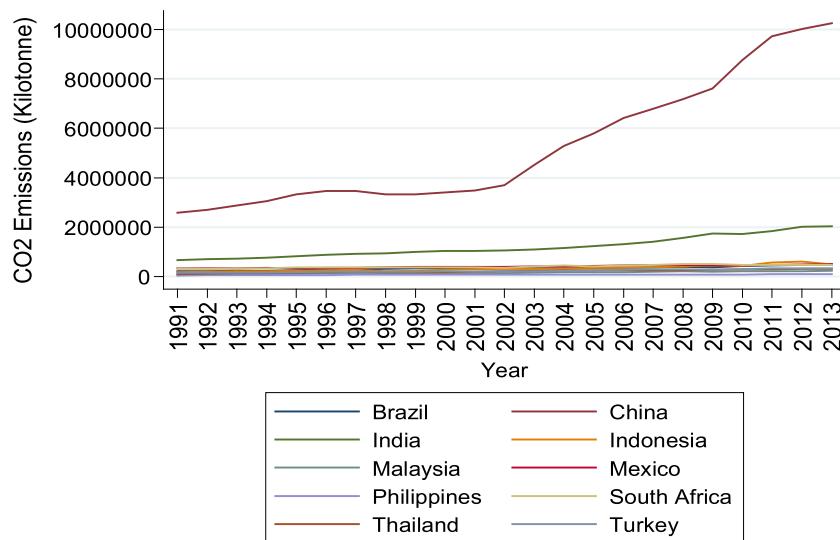
China, India, Indonesia, Malaysia, Mexico, Philippine, South Africa, Thailand, and Turkey for the period from 1991 to 2013 are presented in Table 4 from column 2–5.

For a deep understanding of extended STIRPAT model, the basic STIRPAT model using the DCCE in column 2 of Table 4 is estimated to find the impact of the population (POP), affluence (GDPPC) and technology (CO<sub>2</sub>EI) on carbon dioxide emissions (CO<sub>2</sub>EM). The extended STIRPAT model comprising only one extended variable that is energy intensity (ENGINT) is used, and results are reported in column 3 of Table 4, productivity of labor (LBPD) as well as energy intensity is used in extended STIRPAT model as results displayed in column 4 of Table 4, urban employment (UEL), population carrying intensity of real economy (POPCI), energy mix (EMX) and trade openness (TOPN) are used as extended variables in column 5 of Table 4. In most dynamic models, the lagged dependent variable is used as explanatory variables (Chudik and Pesaran, 2015). As Jorgenson et al. (2017) used a lag of dependent variable CO<sub>2</sub> emissions as an independent variable for their model, correspondingly, this study also used a lag of carbon dioxide to capture the influence of prior CO<sub>2</sub> emissions on current CO<sub>2</sub> emissions applying DCCE models.

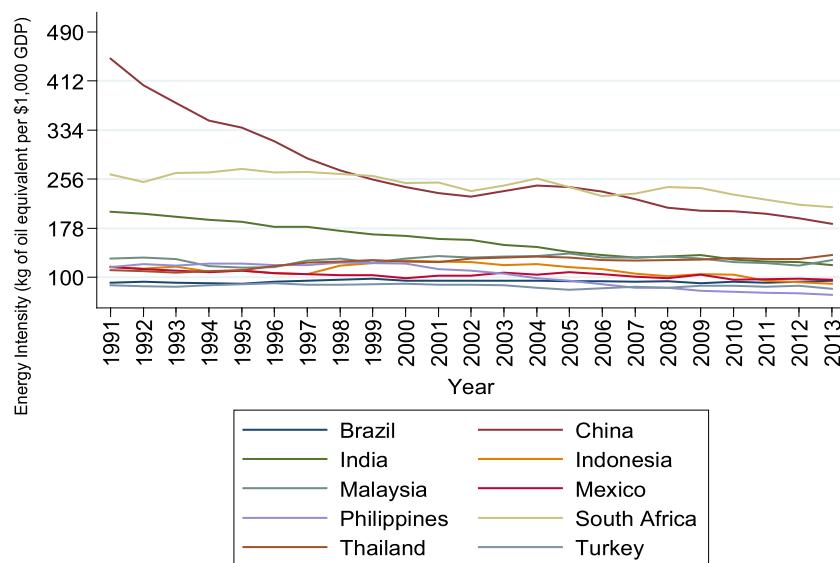
Table 4 reports significant R-squared and F-statistics values for all models. Cross-sectional dependence (CD) is confirmed applying Pesaran (2015) cross-sectional dependence (CD) test in all DCCE estimations. Results in DCCE (1) in Table 4 support the STIRPAT phenomena for newly industrialized countries as population (POP), affluence (GDPPC) and technology (CO<sub>2</sub>EI) are positively and significantly affecting CO<sub>2</sub> emissions (CO<sub>2</sub>EM). The findings are similar with the work of Liddle (2015), Lin et al. (2017) and Fan et al. (2006). Lagged dependent variable is found statistically significant and have a negative relation with the



**Fig. 1.** CO<sub>2</sub> emissions Comparison for World and NICs.



**Fig. 2.** CO<sub>2</sub> emissions of NICs.



**Fig. 3.** Energy intensity of NICs.

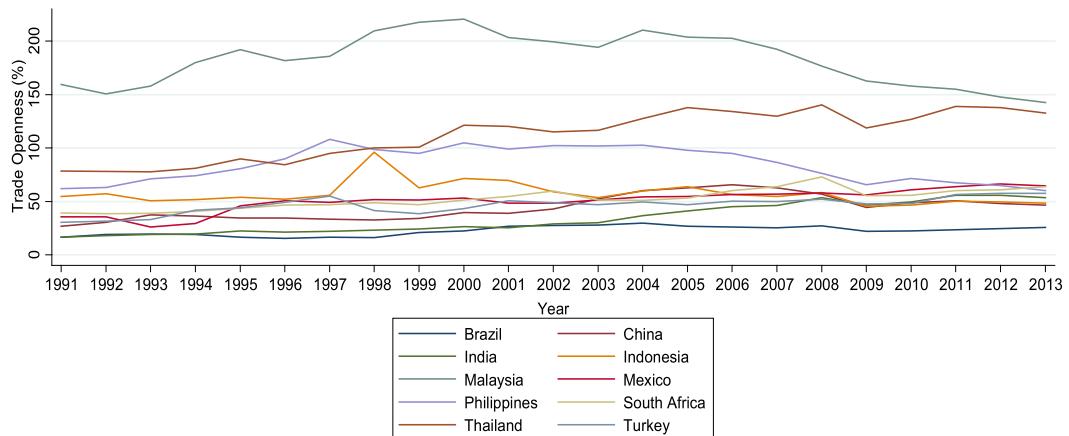


Fig. 4. Trade openness for NICs.

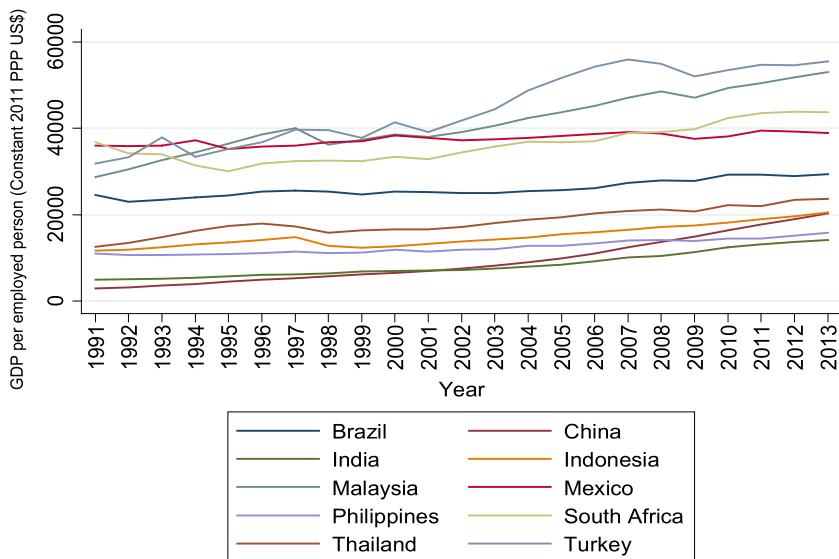


Fig. 5. Labor productivity for NICs.

CO<sub>2</sub> emissions at 1% significance in all DCCE estimations in Table 4, suggesting that prior CO<sub>2</sub> emission levels have a significant impact on current CO<sub>2</sub> emission levels.

In DCCE (2) estimation STIRPAT model is extended incorporating energy intensity (ENGINT), results show that population, affluence, technology and energy intensity is positively related with CO<sub>2</sub> emissions at 1% significant level. Results are in line with Zhang et al. (2017), Lin et al. (2017) and Abou-Ali et al. (2016). Further, DCCE (3) model is extended with a combination of productivity of labor (LBPD) and results show a significant relationship with the dependent variable.

For more reliability of extended STIRPAT model estimates, more estimators are added in the DCCE (4) model that are urban employment level (UEL), population carrying intensity of real economy (POPCI), energy mix (EMX) and trade openness (TOPN). However, DCCE (4) also showed significant outcomes as with the increase of one unit of population CO<sub>2</sub> emission level increases 0.35 units at 1% significance level as similar outcomes reported by Liddle (2013), Sadorsky (2014) and Jorgenson and Clark (2010). GDP per capita was estimated and results explain that with a unit increase in GDPPC causes 1.56 units increase in CO<sub>2</sub> emission level at 1% level of significance. Poumanyong and Kaneko (2010) and Martínez-Zarzoso and Maruotti (2011) found same results for high income, middle-income countries, and OECD respectively.

Level of urban employment has a negative association with CO<sub>2</sub> emissions at 1% significance level as this finding is corroborated with results of Lin et al. (2017).

Subsequently, trade openness (TOPN) was estimated in DCCE(4), and the positive association is found with CO<sub>2</sub> emissions, but results were statistically insignificant whereas productivity of labor (LBPD) has a significant negative association with CO<sub>2</sub> emission levels at 1%, hence, the result is similar with the findings of Lin et al. (2017).

The short-run and long-run association are also investigated through STIRPAT model and the results of four models (DCCE(5), DCCE(6), DCCE(7), DCCE(8)) are presented in Table 5. Similar results were found as reported in Table 4 except lagged CO<sub>2</sub> emission that is statistically insignificant in the short run with smaller coefficients values. While lagged dependent variable have a negative significant association with the CO<sub>2</sub> emission level (in 3 out of 4 DCCE models) for the long run. Similarly, in long run actors like population (POP), GDP per capita (GDPPC), CO<sub>2</sub> emission intensity (CO<sub>2</sub>EI) and energy intensity (ENGINT) are found to have a significant positive influence on CO<sub>2</sub> emission levels in NIC's. This suggests that energy intensity (ENGINT) is promoting CO<sub>2</sub> emissions level for NIC's over time along with population, affluence, and technology. Same results were reported by Zhang et al. (2017), Lin et al. (2017), Abou-Ali et al. (2016) and Liddle

**Table 4**

Extended STIRPAT equations with dynamic common correlated effects estimator (DCCE) by Chudik and Pesaran (2015). Panel 10 NICs, 1991–2013. CO<sub>2</sub> EM as the dependent variable.

Variables	DCCE(1)	DCCE(2)	DCCE(3)	DCCE(4)
Lagged CO <sub>2</sub> emissions (LCO <sub>2</sub> EM)	−0.798*** (0.000)	−0.995*** (0.000)	−0.996*** (0.000)	−0.868*** (0.000)
Population (POP)	0.700* (0.071)	0.808*** (0.000)	0.962*** (0.000)	0.353*** (0.000)
GDP per capita (GDPPC)	0.510*** (0.000)	0.930*** (0.000)	0.866*** (0.000)	1.563*** (0.001)
CO <sub>2</sub> emission intensity (CO <sub>2</sub> EI)	1.020*** (0.000)	0.929*** (0.000)	0.952*** (0.000)	1.077*** (0.000)
Level of urban employment (UEL)				−1.002*** (0.012)
Population carrying intensity of real economy (POPCI)				0.036 (0.743)
Energy mix (EMX)				0.877** (0.064)
Trade openness (TOPN)				0.007 (0.759)
Productivity of labor (LBPD)			0.067** (0.047)	−1.112*** (0.002)
Energy intensity (ENGINT)		0.968*** (0.000)	0.998*** (0.000)	
Cross-sections	10	10	10	10
Observations	210	210	210	202
R-squared	0.85	0.99	0.99	0.95
CD Test by Pesaran (2015) (p)	−0.24 (0.808)	−1.14 (0.255)	−0.93 (0.354)	−0.23 (0.821)
F-Stat (p)	24.82 (0.000)	134.71 (0.000)	99.03 (0.000)	20.65 (0.000)

All variables are in natural logarithms. p-values for coefficients are in parentheses.

\*\*\* Represents significance at 1% level.

\*\* Represents significance at 5% level.

\* Represents significance at 10% level.

(2015). While the productivity of labor (LBPD) is found to have no significant relation with CO<sub>2</sub> emission levels.

It is obvious from all DCCE models' results that population, GDP per capita, CO<sub>2</sub> emission intensity and energy intensity have a large and significant impact on CO<sub>2</sub> emissions in long run. While in short-run level of urban employment, energy mix, trade openness and productivity of labor have a marginal impact on CO<sub>2</sub> emissions, moreover population carrying intensity of real economy have no impact on CO<sub>2</sub> emissions for newly industrialized countries.

## 6. Robustness analysis

Although, the results estimated through dynamic common correlated effects estimator (DCCE) approach indicate strong evidence that population, affluence, and technology along with energy intensity, urban employment and energy mix have an impact on CO<sub>2</sub> emissions level. It is inevitable to check the robustness of DCCE regressions outcomes through other investigation techniques. To achieve this objective, in the first step study investigates the cointegration by implementing the Pedroni panel cointegration approach to investigate the presence of long run association in concerned panel series. After finding cointegration relationship between specified variables, methods of Fully Modified Ordinary Least Square (FMOLS) and Dynamic Ordinary Least Square (DOLS) are used to find long run relationship of actors of selected extended STIRPAT model. At the end, to check the direction of causality, the latest technique by Dumitrescu and Hurlin (2012) is used.

Pedroni (2004) proposed a cointegration test for panel data, we employed the same to analyze cointegration among CO<sub>2</sub> emissions and different actors of environmental degradation for our panel. The presence of long run association among the above variables can be tested on the bases of results of unit root test already reported in Table 3. For this purpose Pedroni (2004) cointegration technique is applied to check the long run association

among concerned variables of study (CO<sub>2</sub>EM, POP, GDPPC, CO<sub>2</sub>EI, LBPD, ENGINT). The outcomes of Pedroni cointegration test is presented in Table 6, reporting seven statistics divided into two parts (within dimensions and between dimensions). Statistics from the results furnish the significant evidence that there is a long run relationship among variables as from these seven statistics four are significant. The evidence from results of cointegration test states that variables, in long run, move together.

After the sufficient evidence of long run relationship among variables, the elasticities and their significance of main actors of extended STIRPAT model must be investigated. For this purpose, two techniques (FMOLS and DOLS) are used. The FMOLS technique is proposed by Pedroni (2001) while DOLS is proposed by Stock and Watson (1993), both are used to analyze heterogeneous data with cointegrated panels. These techniques are consistent, provides efficient estimates and can handle the issue of autocorrelation and simultaneity.

The results of FMOLS and DOLS regressions are reported in Table 7, and explains long run relationship among variables of extended STIRPAT model. The results reported by both FMOLS and DOLS regressions are similar in term of significance and sign of explanatory variables. The estimated models explain that in long run population, affluence, technology along with energy intensity are promoting CO<sub>2</sub> emissions level for NIC's. The variables used in the analyses are in logarithmic form so coefficients of explanatory variables are treated as elasticities. These results report that with 1% increase in population, increases CO<sub>2</sub> emissions level by 1–1.2%, while 1% increase in affluence (GDP per capita) causes 0.97–0.99% increase in CO<sub>2</sub> emissions level. Same findings are concluded from DCCE regression results, which confirms the robustness of the DCCE estimator.

Finally, panel causality is tested for the extended STIRPAT model using the Dumitrescu and Hurlin causality tests, which report the results of W statistics and Z bar statistics presented in Table 8. The findings of this test report that there is unidirectional

**Table 5**

Extended STIRPAT equation with dynamic common correlated effects estimator (DCCE) by Chudik and Pesaran (2015). Panel 10 NICs, 1991–2013. CO<sub>2</sub> EM as dependent variable.

Variables	DCCE(5)	DCCE(6)	DCCE(7)	DCCE(8)
Short Run Estimates				
Lagged CO <sub>2</sub> emissions (LCO <sub>2</sub> EM)	0.030 (0.566)	−0.007 (0.628)	−0.002 (0.887)	−0.004 (0.735)
Population (POP)	2.216 (0.254)	2.335 <sup>**</sup> (0.002)	3.402 <sup>***</sup> (0.000)	3.286 <sup>***</sup> (0.000)
GDP per capita (GDPPC)	0.371 <sup>***</sup> (0.000)	0.502 <sup>***</sup> (0.000)	0.910 <sup>***</sup> (0.000)	0.883 <sup>***</sup> (0.000)
CO <sub>2</sub> emission intensity (CO <sub>2</sub> EI)	0.914 <sup>***</sup> (0.000)	0.494 <sup>***</sup> (0.000)	0.456 <sup>***</sup> (0.000)	0.439 <sup>***</sup> (0.000)
Level of urban employment (UEL)			−0.393 <sup>*</sup> (0.086)	−0.426 <sup>*</sup> (0.070)
Trade openness (TOPN)				0.007 <sup>*</sup> (0.033)
Productivity of labor (LBPD)		−0.062 (0.445)	−0.499 <sup>**</sup> (0.015)	−0.486 <sup>**</sup> (0.022)
Energy intensity (ENGINT)		0.487 <sup>***</sup> (0.000)	0.455 <sup>***</sup> (0.000)	0.440 <sup>***</sup> (0.000)
Long Run Estimates				
Lagged CO <sub>2</sub> emissions (LCO <sub>2</sub> EM)	−0.233 (0.459)	−0.493 <sup>***</sup> (0.009)	−0.534 <sup>**</sup> (0.027)	−0.547 <sup>***</sup> (0.010)
Population (POP)	0.426 (0.454)	1.025 <sup>***</sup> (0.009)	1.103 <sup>**</sup> (0.054)	1.105 (0.211)
GDP per capita (GDPPC)	1.014 <sup>**</sup> (0.000)	1.078 <sup>***</sup> (0.014)	1.023 <sup>*</sup> (0.088)	1.036 (0.252)
CO <sub>2</sub> emission intensity (CO <sub>2</sub> EI)	0.526 (0.449)	0.955 <sup>**</sup> (0.000)	0.933 <sup>***</sup> (0.009)	0.932 <sup>***</sup> (0.000)
Productivity of labor (LBPD)		−0.071 (0.886)	−0.022 (0.975)	−0.040 (0.965)
Energy intensity (ENGINT)		0.968 <sup>***</sup> (0.000)	0.963 <sup>**</sup> (0.035)	0.959 <sup>***</sup> (0.016)
Cross-sections	10	10	10	10
Observations	210	210	210	202
R-squared	0.86	0.99	0.99	0.99
CD Test by Pesaran (2015) (p)	−1.02 (0.307)	−1.09 (0.277)	−0.61 (0.543)	−0.25 (0.799)
F-Stat (p)	22.86 (0.00)	369.42 (0.00)	328.45 (0.00)	282.93 (0.00)

All variables are in natural logarithms. p-values for coefficients are in parentheses.

\*\*\* represents significance at 1% level.

\*\* represents significance at 5% level.

\* represents significance at 10% level.

**Table 6**  
Pedroni panel cointegration test.

Within dimensions (Common coefficients)				
	t-stat	Prob.	Weighted	
			t-stat	Prob.
Panel v-stat	−3.167	0.999	−6.030	1.000
Panel $\rho$ -stat	3.379	0.999	2.842	0.997
Panel PP-stat	−22.594 <sup>***</sup>	0.000	−3.976 <sup>***</sup>	0.000
Panel ADF-stat	−9.336 <sup>***</sup>	0.000	−4.314 <sup>***</sup>	0.000
Between dimensions (Individual coefficients)				
	t-stat	Prob.		
Group $\rho$ -stat	4.692	1.000		
Group PP-stat	−15.584 <sup>***</sup>	0.000		
Group ADF-stat	−4.754 <sup>**</sup>	0.000		

The Akaike information criterion was used to determine the optimum lag length.

\*\*\* Represents significance at 1% level.

\* Represents significance at 10% level.

causality running from GDPPC to CO<sub>2</sub>EM, CO<sub>2</sub>EI to CO<sub>2</sub>EM and ENGINT to CO<sub>2</sub>EM. However, there is bidirectional causality relationship between POP and CO<sub>2</sub>EM, while no causality is reported between LBPD and CO<sub>2</sub>EM. These findings conclude that these actors of extended STIRPAT model have predictive power for CO<sub>2</sub> emissions level for NIC's.

**Table 7**

Long run estimates via FMOLS and DOLS, Panel 10 NICs, 1991–2013. CO<sub>2</sub> EM as dependent variable.

Variables	FMOLS	DOLS
Population (POP)	1.295 (0.000) <sup>***</sup>	1.008 (0.000) <sup>***</sup>
GDP per capita (GDPPC)	0.974 (0.000) <sup>***</sup>	0.990 (0.000) <sup>***</sup>
CO <sub>2</sub> emission intensity (CO <sub>2</sub> EI)	0.995 (0.000) <sup>***</sup>	1.001 (0.000) <sup>***</sup>
Productivity of labor (LBPD)	0.008(0.572)	0.001(0.948)
Energy intensity (ENGINT)	0.969 (0.000) <sup>***</sup>	0.994 (0.000) <sup>***</sup>

All variables are in natural logarithms. p-values for coefficients are in parentheses.

\*\*\* Represents significance at 1% level.

\*\* Represents significance at 5% level.

\* Represents significance at 10% level.

## 7. Conclusion and policy recommendations

This study examined the extended STIRPAT model for a panel of ten newly industrialized countries for the period from 1991 to 2013 using dynamic panel DCCE method. To achieve this objective, study first applied IPS unit root test to check whether the panel series used in analysis are stationary or not. Then panel

**Table 8**

Results of the Dumitrescu and Hurlin panel causality test.

Null hypothesis: no causality	W statistic	Z bar statistic	p value
POP → CO <sub>2</sub> EM	8.016***	3.053	0.002
GDPPC → CO <sub>2</sub> EM	6.021**	1.839	0.065
CO <sub>2</sub> EI → CO <sub>2</sub> EM	5.820**	1.933	0.063
ENGINT → CO <sub>2</sub> EM	5.945*	1.742	0.082
LBPD → CO <sub>2</sub> EM	3.931	0.566	0.570
CO <sub>2</sub> EM → POP	13.179***	6.195	0.000
CO <sub>2</sub> EM → GDPPC	3.393	0.239	0.810
CO <sub>2</sub> EM → CO <sub>2</sub> EI	1.958	-0.634	0.526
CO <sub>2</sub> EM → ENGINT	7.205	2.559	0.010
CO <sub>2</sub> EM → LBPD	5.177	1.324	0.185

All variables are in natural logarithms.

\*\*\* Represents significance at 1% level.

\*\* Represents significance at 5% level.

\* Represents significance at 10% level.

estimation is done with the help of DCCE approach. For robustness cointegration test is also applied to check the existence of cointegration relationship among the variables. The results from the DCCE method are also compared with FMOLS and DOLS techniques. Lastly, study applied Dumitrescu and Hurlin causality tests to investigate the directional causalities.

The study to explore relevant factors that are the main cause to enhance CO<sub>2</sub> emissions is very relevant when emissions are sharply increasing overall the globe. Especially, NICs are emitting a large number of emissions due to the high pace of industrialization. Evidence from the results suggests that main actors or driving forces contributing a large level of environmental degradation for newly industrialized countries are populations, GDP per capita, CO<sub>2</sub> emission intensity and energy intensity. Hence, it can be concluded that with a higher level of population, GDP per capita, and CO<sub>2</sub> emission intensity are the response for promoting a level of CO<sub>2</sub> emissions and reduction in energy intensity can lead to control the level of CO<sub>2</sub> emissions. On the other hand labor productivity in NICs have no significant impact on the level of CO<sub>2</sub> emissions in long run. Consequently, it can be proposed with the support of estimates that the use of more productive labor during industrialization will not cause environmental degradation. Similarly, the population carrying capacity of the real economy is not contributing to increasing level of CO<sub>2</sub> emissions significantly which suggest that development of real economy will not harm the level of CO<sub>2</sub> emissions. Energy mix and trade openness are some other factors which are marginally contributing in enhancing CO<sub>2</sub> emissions, suggesting that as sample countries are in the process of rapid growth and industrialization and in these countries absence of conservative energy and trade openness related policies are promoting the CO<sub>2</sub> emissions level. Moreover, results suggest that main factors that can reduce CO<sub>2</sub> emission level are energy intensity, urban employment level and labor productivity.

In all NIC's actors of extended STIRPAT (population, economic development, technology and energy intensity) are promoting environmental degradation in long run. These findings provide useful information for a policymaker to manage both healthy pace of industrialization and CO<sub>2</sub> emission level. Industrialization is a necessary element for economic development and cannot be restricted while CO<sub>2</sub> emission is the main cause of environmental degradation. Policy makers in newly industrialized countries may suggest introducing new industrial units with supportive environmental technologies consuming low energy levels which may lead to low level of pollution. The focus should also be on environment favorable energy mix, promoting trade (import and export) of goods with low carbon use and encouraging foreign direct investment in the projects with low CO<sub>2</sub> emission levels. Energy intensity management can be one of a key contributor

to reducing CO<sub>2</sub> emissions level especially for the industrial sector in newly industrialized countries, and effective policies with government support can make this possible.

These newly industrialized countries must adopt more conservative energy policies for nonrenewable energy sources on short term and long term and should spend more budget on research and development to adopt environment-friendly energy sources. Renewable and alternative energy sources should be explored and used at large scale which are alternative to nonrenewable energy (oil energy), such as solar energy. Most importantly, gradually fossil fuel energy should be replaced by renewable energy as there is a huge cost reduction in renewable energy recently due to research and improvement in technology. The policy makers in NIC's should take some measures to customize the energy usage and promote the usage of renewable energy sources at an industrial and commercial level by developing policies, like fiscal subsidies for the users. One of the important measures to restrict the environmental degradation in NIC's can be the promotion of efficient energy utilization at industrial as well as household level.

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