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Effect of foreign direct investments, economic development and energy consumption on greenhouse gas emissions in developing countries

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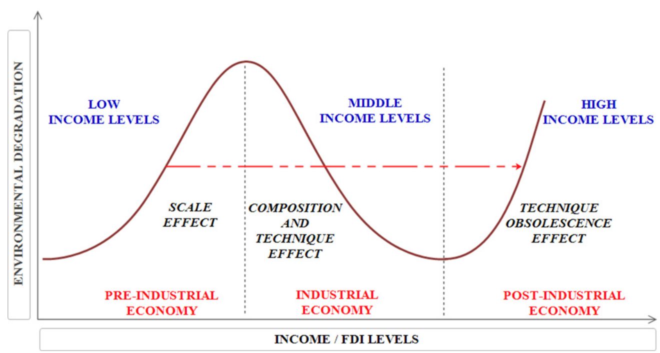
HIGHLIGHTS

- The environmental Kuznets curve hypothesis is valid for China and Indonesia.
- The pollution haven hypothesis is valid for China, India, Indonesia, Iran and South Africa.
- The study found a strong positive effect of energy consumption on CO_2 emissions.
- Foreign direct investment increases the level of CO_2 emissions in Indonesia.
- Clean and modern energy technologies will improve industrial-based pollution levels.

GRAPHICAL ABSTRACT



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ABSTRACT

In accordance with the Sustainable Development Goal 17 of improving global partnership for sustainable development, this study examined the effect of foreign direct investment inflows, economic development, and energy consumption on greenhouse gas emissions from 1982 to 2016 for the top five emitters of greenhouse gas emissions from fuel combustion in the developing countries, namely; China, India, Iran, Indonesia and South Africa. The study employed a panel data regression with Driscoll-Kraay standard errors, *U* test estimation approach and panel quantile regression with non-additive fixed-effects. The study found a strong positive effect of energy consumption on greenhouse gas emissions and confirmed the validity of the pollution haven hypothesis. The environmental Kuznets curve hypothesis is valid for China and Indonesia at a turning point of US$ 6014 and US$ 2999; second, a U-shape relationship is valid for India and South Africa at a turning point of US$ 1476 and US$ 7573. Foreign direct investment inflows with clean technological transfer and improvement in labour and environmental management practices will help developing countries to achieve the sustainable development goals. Mitigation of greenhouse gas emissions depends on enhanced energy efficiency, adoption of clean and modern energy technologies, such as renewable energy, nuclear, and the utilization of carbon capture and storage for fossil fuel and biomass energy generation processes.

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1. Introduction

The pollution haven hypothesis postulates that dirty industries migrate from high-income countries to low and middle-income countries through the trading of goods and foreign direct investment. Foreign direct investment (FDI) inflows remain one of the main sources of

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external funding for developing countries, yet, the relocation of carbon-intensive and energy-intensive industries from jurisdictions with more stringent environmental regulation to weak locales results in pollution haven. The transfer, dissemination, and diffusion of FDI inflows with polluting technologies, goods, and services to developing countries become the most important part of the challenge to achieve the sustainable development goals (SDGs). On the contrary, the environmental Kuznets curve (EKC) hypothesis postulates that the initial growth of a country's economic development leads to gradual deterioration of environmental quality and improves environmental conditions after reaching a threshold in economic development (Grossman and Krueger, 1991). Thus, both the pollution haven hypothesis and the EKC hypothesis are important policy derivatives for developing countries. Considering the importance of climate change mitigation and its impacts, as accentuated in SDG 13, the effect of FDI inflows, economic development, and energy consumption on greenhouse gas emissions in developing countries needs further attention to be able to alleviate the impacts.

Studies on pollution haven hypothesis (Zakarya et al. (2015) Behera and Dash, 2017; Solarin et al. (2017) Sun et al. (2017), support the validity of this hypothesis. Solarin et al. (2017) validated the pollution haven hypothesis for Ghana using the autoregressive distributed lag (ARDL) bounds testing approach. Sun et al. (2017) examined the impact of FDI inflows, economic growth, energy use, economic freedom, urbanization, financial development, and trade openness on CO_2 emissions using the autoregressive distributed lag model. The study confirmed the validity of the pollution haven hypothesis in China and that the positive effect of FDI inflows stems from the large contribution of manufacturing, mining and electricity shifted from the developed countries. Using the fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares regression, Behera and Dash (2017) found a positive impact of FDI inflows and energy consumption on CO_2 emissions in 17 south and southeast Asian countries, thus, confirming the pollution haven hypothesis. Zakarya et al. (2015) found a long-run effect of FDI inflows and energy consumption on CO_2 emissions in Brazil, Russia, India, and China, thus, validating the pollution haven hypothesis via panel causality and FMOLS regression. On the contrary, studies like Zhu et al. (2016) and Zhang and Zhou (2016), rejected the pollution haven hypothesis. Zhu et al. (2016) employed panel quantile regression to examine the heterogeneous effect of FDI inflows, economic growth, and energy consumption on CO_2 emissions in Indonesia, Malaysia, Philippines, Singapore, and Thailand from 1981 to 2011. The study found insufficient support for the pollution haven hypothesis but rather found the halo effect hypothesis in high emission countries. Zhang and Zhou (2016) argue that FDI inflows of modern technologies contribute to CO_2 emissions reduction in China rather than environmental deterioration. Dasgupta et al. (1999, 2001) and Dean et al. (2004) revealed that developing countries depend on sophisticated technology transfer through FDI inflows from developed countries as their primary source of acquiring technology. Hence, clean and upgrading from vintage to modern technologies help in the reduction of emission levels.

The EKC hypothesis posits that the initial stages of economic development are characterized by high emission levels and environmental stress, however, as the economy grows and reaching a specific turning of income level, pollution levels decline (Grossman and Krueger, 1991). Panayotou (1993) argued that the initial stages of economic development increase the natural resource extraction leading to an increase in waste generation. However, at higher levels of economic development, the improvements in technology, stringent environmental regulations and a structural change in the economy from pollution-intensive industries to services and information declines environmental deterioration (Grossman and Krueger, 1991; Panayotou, 1993; Sarkodie, 2018). A number of recent studies on the EKC hypothesis (Lau et al. (2014); Al-Mulali and Ozturk (2016) Abdallh and Abugamos (2017) Sarkodie (2018) Sarkodie and Strezov (2018) support this hypothesis while Özokcu and Özdemir (2017) and Zoundi (2017) reject the validity of the EKC hypothesis. The opposing arguments on both the pollution haven and the EKC hypothesis due to the mixed outcomes in existing literature prompt on the need for further empirically tests of the validity of both hypotheses by examining the effect of FDI inflows, economic development, and energy consumption on GHG emissions.

The aim of this study is to investigate both pollution haven and EKC hypotheses to determine the effect of foreign direct investments, economic development, and energy consumption on greenhouse gas emissions in developing countries. The study selects the top five greenhouse gas emitting developing countries, namely China, India, Iran, Indonesia and South Africa. Contrary to existing literature, which adopts econometric methods that have challenges with cross-sectional dependence and issues when the time dimension becomes large, this study employs the Driscoll-Kraay covariance estimator that does not restrict the limiting behaviour of the panels and produces robust standard errors. As most of the results from previous studies neglect the distributional heterogeneity which may adversely impact the findings, this study considers distributional heterogeneity using panel quantile regression. The study employs Powell (2016) estimator with non-additive fixed-effects and non-separable disturbance term in the panel quantile estimation, which can correct the additive fixed-effects and separate disturbance terms when panel quantile regression is employed in the analysis. In order to produce robust estimations, the panel quantile regression is estimated using an adaptive Markov Chain Monte Carlo optimization based on 1000 draws. The study contributes to the global debate on greenhouse gas emissions from the top five emitters of carbon emissions from fuel combustion in developing countries by assessing the determinants of disaggregate greenhouse gas emissions throughout the quantiles.

2. Materials and methods

2.1. Data

To meet the outlined objectives, the study employs data from the World Development Indicators (World Bank, 2016) from 1982 to 2016 for the top five emitters of greenhouse gas emissions from fuel combustion in developing countries, namely; China, India, Iran, Indonesia and South Africa. The selection of the five countries stems from the Global Energy Statistical Yearbook 2018 ranking on CO_2 intensity by Enerdata (2017). Five study variables, Foreign direct investment net inflows (FDI), GDP per capita (GDPP), CO_2 emissions (CO_2E), total greenhouse gas emissions (GHG) and Energy use (ENE) are adopted in the study, as presented in Table 1. The World Bank defines FDI inflows as the inward direct investment to the indigenous economy made by foreigners (World Bank, 2016). GDP per capita is an indicator which measures the total economic output reflecting the changes in the production of goods and service excluding the cost of social and environmental production and consumption (Disano, 2002). CO_2 emissions measure anthropogenic emissions from fossil fuel energy combustion, industrial processes like cement manufacturing, and agricultural, forestry and land-use (World Bank, 2016). GHG emissions measure the six main GHG namely CO_2 emissions, methane, sulphur hexafluoride, nitrous oxide, hydrofluorocarbons, and perfluorocarbons. Thus, the data on non-CO_2 greenhouse gas emissions (NCO_2E) is extracted by deducting CO_2 emissions from the total greenhouse gas emissions to derive the data series. Energy use is an indicator which measures the primary energy consumption before end-use (World Bank, 2016). The selection of the data is based on the United Nations' Indicators of Sustainable Development: Guidelines and Methodology and the Sustainable Development Goals (SDGs) (United Nations, 2015). Due to the availability of data, missing data points are filled with Microsoft Excel interpolation method by aggregating duplicates using average at 99.99% confidence interval presented in Appendix A.

2.2. Panel regression

To examine the pollution haven hypothesis, the study employs a panel data regression with Driscoll-Kraay standard errors for coefficients estimated by the fixed-effects estimator. Cross-sectional dependence is one of the challenges in panel data settings, thus, yielding inconsistent estimates. Unlike standard techniques, Driscoll and Kraay (1998) algorithm accounts for cross-sectional dependence which results in a consistent and robust estimated standard errors. The Driscoll-Kraay algorithm assumes that the error structure is heteroskedastic, autocorrelated up to some lag and correlated between the groups in the panel. The Driscoll-Kraay estimator is a non-parametric technique which is more flexible without any restriction imposed on limiting behaviour of the number of panels and more useful when the time dimension becomes larger, thus, the estimator is based on large T asymptotics. The Driscoll-Kraay covariance estimator is capable of handling missing values and applicable in balanced and unbalanced panel data. The study takes the absolute of all negative values to prevent missing data after logarithmic transformation.

This study employs Driscoll-Kraay standard errors for pooled ordinary least squares (OLS) estimation by considering a linear model expressed as:

$$y_{i,t} = x'_{i,t}\beta + \varepsilon_{i,t}, \ \ i = 1, \ldots, N, \ \ t = 1, \ldots, T \tag{1}$$

where $y_{i,\ t}$ is the dependent variable (CO_2E| NCO_2E) and is a scalar, $x_{i,\ t}$ denotes the independent variables (FDI, FDI^2, FDI^3, GDPP, $GDPP^2$, $GDPP^3$ and ENE) with a $(K+1)\times 1$ vector, whose first element is 1, and β denotes the unknown coefficients with $(K+1)\times 1$ vector, i denotes the individual/cross-sectional units at time t.

Stacking all the observation, the formulation is expressed as:

$$y = \left[y_{1,t_{1,1}}, \ldots, y_{1,T_1} \ y_{2,t_{2,1}}, \ldots, y_{N,T_N}\right]' \text{ and } X = \left[x_{1,t_{1,1}}, \ldots, x_{1,T_1} \ x_{2,t_{2,1}}, \ldots, x_{N,T_N}\right]' \tag{2}$$

This is assumed that $x_{i,\ t}$ are uncorrelated with the scalar error term $\varepsilon_{i\ s}$ for all s, t (strong exogeneity). Nevertheless, $\varepsilon_{i,\ t}$ can exhibit heteroscedasticity, autocorrelation and cross-sectional dependence. Based on the outlined assumptions, β can be consistently estimated by OLS regression which results in (Hoechle, 2007):

$$\hat{\beta} = (X'X)^{-1}X'y \tag{3}$$

For brevity, the coefficient estimates of the Driscoll-Kraay standard errors are derived as a "square roots ($\hat{S}_T$) of the diagonal elements of the asymptotic covariance matrix" expressed as (Driscoll and Kraay, 1998):

$$V\left(\hat{\beta}\right) = (X'X)^{-1}\hat{S}_T \ (X'X)^{-1} \tag{4}$$

After the estimation of the panel regression, the study employs the U test algorithm by Lind and Mehlum (2010) to test the EKC and pollution haven hypothesis in individual countries.

Table 1
Description of variables.

Series	Series name	Units
FDI	Foreign direct investment, net inflows	Current US$
GDPP	GDP per capita	Current US$
CO_2E	CO_2 emissions	kt
GHG	Total greenhouse gas emissions	kt of CO_2 equivalent
ENE	Energy use	kg of oil equivalent per capita

2.3. Quantile regression for panel data

This subsection introduces panel quantile regression estimator by Powell (2016) with non-additive fixed-effects and maintains the non-separable disturbance term related with quantile estimation in panel data settings. It is contrary to other panel quantile regression estimators (Zhu et al., 2016) with additive fixed-effects and separable disturbance term incorporated into the quantile estimation, with the assumption that time-varying components only affect the variability of parameters.

The distribution of the outcome variable $Y_{i,\ t}$ is estimated using the quantile panel regression for treatment variables $D_{i,\ t}$. To maintain the non-separable disturbance term usually linked with panel quantile estimation, the study employs non-additive fixed-effects to model the outcome, expressed as:

$$Y_{i,t} = D'_{i,t}\beta(U^*{}_{i,t}), \qquad U^*{}_{i,t} \sim U(0,1) \tag{5}$$

where $D_{i,\ t}'\beta(\tau)$ strictly increases in quantile τ, $U^*{}_{i,t}$ denotes the function of the disturbance terms and proneness for the outcome. The structural quantile function for Eq. (5) is expressed as:

$$S_Y(\tau/d) = d'\beta(\tau), \qquad \tau \in (0,1) \tag{6}$$

The structural quantile function explains the quantile of the latent outcome variable $Y_d = d'\beta(U^*)$ for randomly selected $U^* \sim U(0,1)$ and a fixed potential value of the treatment effect d.

Based on the above algorithm, the study specifies the panel quantile regression to test the effect of FDI and per capita GDP on carbon dioxide emissions and greenhouse gas emissions as:

$$\begin{aligned}(CO_2E|NCO_2E)_{i,t}(\tau|\alpha_i, \delta_t, x_{i,t}) = \alpha_i + \delta_t + \beta_{1,\tau}FDI_{i,t} + \beta_{2,\tau}FDI^2{}_{i,t} \\ + \beta_{3,\tau}FDI^3{}_{i,t} + \beta_{4,\tau}GDPP_{i,t} \\ + \beta_{5,\tau}GDPP^2{}_{i,t} + \beta_{6,\tau}GDPP^3{}_{i,t} \\ + \beta_{7,\tau}ENE_{i,t}\end{aligned} \tag{7}$$

where, α_i denotes the non-adaptive fixed-effects, x denotes the matrix of the independent variables at individual countries i and time t. In order to improve the results of the panel quantile regression, the study performs a numerical optimization via adaptive Markov chain Monte Carlo sampling using a multivariate normal proposal distribution by Baker (2014).

The study specifies the cointegrating relationship as:

$$\begin{aligned}(CO_2E|NCO_2E)_{i,t} = \gamma_i + \beta_1 FDI_{i,t} + \beta_2 FDI^2{}_{i,t} + \beta_3 FDI^3{}_{i,t} + \beta_4 GDPP_{i,t} \\ + \beta_5 GDPP^2{}_{i,t} + \beta_6 GDPP^3{}_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{8}$$

where γ_i denotes the panel-specific fixed-effects, β_1, …, β_6 denote the cointegrating parameters which are the same across the panel, and ε

Table 2
Panel unit root tests.

	lnFDI	$\ln CO_2E$	$\ln NCO_2E$	lnGDPP	lnENE
Level					
Breitung	1.3509	6.6682	1.5927	4.8141	6.3624
p-Value	0.9116	1.0000	0.9444	1.0000	1.0000
IPS	−1.4531	1.9348	1.8576	4.2605	4.3570
p-Value	0.0731	0.9735	0.9684	1.0000	1.0000
Hadri	36.8638	47.3130	21.9341	42.9495	46.4008
p-Value	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
1st diff					
Breitung	−4.1102	−6.5870	−6.8856	−6.4326	−4.0060
p-Value	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
IPS	−8.0031	−6.1878	−7.2197	−5.6604	−6.7919
p-Value	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]	0.0000[a]
Hadri	−1.7984	−1.0196	−1.9159	0.8258	0.9721
p-Value	0.9639	0.8461	0.9723	0.2045	0.1655

[a] Rejection of the null hypothesis at 1% significance level.

Table 3
Results of Kao test for cointegration.

Kao test statistic	CO_2E		NCO_2E	
	−14.8016	0.0000[a]	−13.4722	0.0000[a]
Modified Dickey-Fuller t	−7.2251	0.0000[a]	−4.2012	0.0000[a]
Dickey-Fuller t	−4.8266	0.0000[a]	−3.3882	0.0004[a]
Augmented Dickey-Fuller t	−14.6411	0.0000[a]	−11.3254	0.0000[a]
Unadjusted modified Dickey-Fuller	−7.2173	0.0000[a]	−4.0505	0.0000[a]
Unadjusted Dickey-Fuller t	−14.8016	0.0000[a]	−13.4722	0.0000[a]

[a] Denotes the rejection of the null hypothesis of no cointegration at 1% significance level.

represents the white noise. The Kao cointegration test employs Bartlett Kernel for an automatic lag selection and proposes five test statistics namely, modified Dickey-Fuller t, Dickey-Fuller t, augmented Dickey-Fuller t, unadjusted modified Dickey-Fuller, and unadjusted Dickey-Fuller t.

3. Results

3.1. Panel unit root & cointegration test

Prior to the estimation of the panel data regression with Driscoll-Kraay standard errors for coefficients and panel quantile regression, the study performs three variety of tests for stationarity in a strongly balanced panel data series. The variety of tests includes Breitung (1999), Im-Pesaran-Shin (IPS) (Pesaran et al., 2003) and Hadri (2000) Lagrange multiplier (LM). Both Breitung and IPS tests have the same null hypothesis that all the data series contain a unit root while Hadri LM test has the null hypothesis that all the panel data series are stationary. Breitung (1999) test transforms the data series before the regression to make the standard t statistics usable. Even though the IPS test (Pesaran et al., 2003) does not require a strongly balanced panel like Breitung and Hadri LM tests it allows each panel to have its own rho_i. Hadri (2000) LM test conducts an alternative test to provide strong evidence to reject the null hypothesis. The test assumes that the error terms in the model are normally distributed and is more appropriate for panel data series with a large period (T) and moderate to small cross-sectional units (N). Evidence from Table 2 reveals that the null hypothesis of unit root by the IPS and Breitung tests cannot be rejected at level but rejected at first difference. The null hypothesis of stationarity by the Hadri LM test cannot be rejected at level but rejected at first difference. Thus, all the three tests reveal that the data series under investigation are integrated of order one.

With evidence that the data series are integrated of order one, the study proceeds to test the long-run effect of FDI, squared of FDI, cubic of FDI, GDPP, squared of GDPP and cubic of GDPP on CO_2E and NCO_2E emissions using the Kao (1999) test for cointegration. Table 3 reveals that the null hypothesis of no cointegration is rejected at 1% significance level for all five test statistics under the two models.

3.2. Driscoll-Kraay panel regression

To enable comparison, the study first estimates the panel regression with Driscoll-Kraay standard errors. Table 4 presents the results of the level-log panel data with Driscoll-Kraay standard errors estimated by fixed-effect regression and average marginal effects for post-estimation. The results reveal that all the coefficients in the pollution haven hypothesis and EKC hypothesis are significant at 1% level.

The nexus between per capita GDP and CO_2/non-CO_2 GHG emissions are presented in Table 4. In both scenarios of CO_2 and non-CO_2 GHG emissions, economic development is initially positive, thus, increases CO_2 and non-CO_2 GHG emissions by 270,000 kt and 308,000 kt of CO_2 equivalent but decreases by 39,278 kt and 42,978 kt of CO_2 equivalent after reaching a turning point in economic development, and accelerates by 1876 kt and 1975 kt of CO_2 equivalent afterwards. Hence, the Driscoll-Kraay panel regression supports the EKC hypothesis for all the selected countries.

The initial effect of FDI on CO_2 emissions is positive and becomes negative at the first turning point ($\ln FDI^2$) of development after reaching an extreme point but becomes positive at the second turning point ($\ln FDI^3$) of development. Quantitatively, the initial impact of FDI increases CO_2 emissions by 265,000 kt, thus, confirming the pollution haven hypothesis. However, CO_2 emissions decline by 13,772 kt at the first turning point and increases by 236 kt thereafter. This means that the pollution haven hypothesis affects the shape of the EKC (Dinda, 2004). Similarly, FDI accelerates non-CO_2 GHG emissions by 60,791 kt of CO_2 equivalent until it reaches a threshold, then declines by 3070 kt of CO_2 equivalent and accelerates by 51 kt of CO_2 equivalent afterward, hence, the initial positive effect confirms the pollution haven hypothesis.

A positive impact of energy use on CO_2 emissions and non-CO_2 GHG emissions is evidenced in Table 4. 1% increase in energy use propels CO_2 emissions and non-CO_2 GHG emissions by 14,640 kt and 3327 kt of CO_2 equivalent.

To verify and validate the results of the Driscoll-Kraay panel regression, the study employs the average marginal effects as a post-estimation technique. The corresponding results of the average marginal effects are presented in columns 6–9 of Table 4. The post-

Table 4
Results of panel data regression and average marginal effects.

	Coef.	Drisc/Kraay std. err.	t	P > t	dy/dx	Std. err.	z	P > z
CO_2E								
lnGDPP	270,000	139,000	1.94	0.0610	270,000	139,000	1.94	0.0520
$\ln GDPP^2$	−39,278	18,909	−2.08	0.0450	−39,278	18,909	−2.08	0.0380
$\ln GDPP^3$	1876	855	2.19	0.0350	1876	855	2.19	0.0280
lnFDI	265,000	34,652	7.64	0.0000	265,000	34,652	7.64	0.0000
$\ln FDI^2$	−13,772	1687	−8.16	0.0000	−13,772	1687	−8.16	0.0000
$\ln FDI^3$	236	27	8.69	0.0000	236	27	8.69	0.0000
lnENE	14,640	3060	4.78	0.0000	14,640	3060	4.78	0.0000
_cons	−2,370,000	444,000	−5.35	0.0000	R-squared	0.92	Prob > F	0.0000
NCO_2E								
lnGDPP	308,000	90,094	3.42	0.0020	308,000	90,094	3.42	0.0010
$\ln GDPP^2$	−42,978	12,456	−3.45	0.0020	−42,978	12,456	−3.45	0.0010
$\ln GDPP^3$	1975	569	3.47	0.0010	1975	569	3.47	0.0010
lnFDI	60,791	13,860	4.39	0.0000	60,791	13,860	4.39	0.0000
$\ln FDI^2$	−3070	680	−4.52	0.0000	−3070	680	−4.52	0.0000
$\ln FDI^3$	51	11	4.64	0.0000	51	11	4.64	0.0000
lnENE	3327	1822	1.83	0.0770	3327	1822	1.83	0.0680
_cons	−1,130,000	282,000	−4.02	0.0000	R-squared	0.29	Prob > F	0.0000

Table 5
U test estimation results.

Country		CO_2E-GDPP		CO_2E -FDI		NCO_2E -GDPP		NCO_2E -FDI	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
China	Interval	203.3349	8123.181	4.30E + 08	2.91E + 11	203	8123	4.30E + 08	2.91E + 11
	Slope	0.0006	−0.0002	1.31E − 11	−2.70E − 12	1.89E − 04	2.13E − 05	6.71E − 12	−1.66E − 12
	t-Value	14.1947	−4.4986	17.8293	−3.0833			8.1789	−1.6772
	P > t	2.18E − 16	0.0000	1.93E − 19	0.0020			0.0000	0.0512
		Turns[a]	6014	**Turns**	2.41E + 11	**Turns**	9126	**Turns**	2.33e + 11
		Shape[b]	Inverse U shape	**Shape**	Inverse U shape	**Shape**	Monotone	**Shape**	Inverse U shape
India	Interval	271.3336	1709.592	5,640,000	4.45E + 10	2.71E + 02	1.71E + 03	5.64E + 06	4.45E + 10
	Slope	0.0023	−0.0004	7.09E − 11	−2.00E − 11	1.23E-03	−1.64E − 03	3.20E − 11	−4.43E − 11
	t-Value	6.5755	−1.0916	5.9385	−1.4061	6.2867	−6.6996	5.20E + 00	−5.76E + 00
	P > t	6.79E − 08	0.1412	4.65E − 07	0.0843	0.0000	0.0000	0.0000	0.0000
		Turns	1476	**Turns**	3.47E + 10	**Turns**	889	**Turns**	1.86e + 10
		Shape	U shape	**Shape**	Inverse U shape	**Shape**	Inverse U shape	**Shape**	Inverse U shape
Indonesia	Interval	471	3688	−4.55E + 09	2.51E + 10	4.71E + 02	3.69E + 03	1.45E + 08	2.51E + 10
	Slope	0.0011	−0.0003	6.29E − 11	2.32E − 11	0.0003	−0.0011	0.0000	0.0000
	t-Value	7.1031	−1.9177			0.6782	−2.5032		
	P > t	0.0000	0.0317			0.2510	0.0086		
		Turns	2999	**Turns**	4.25E + 10	**Turns**	1153	**Turns**	−1.43e + 11
		Shape	Inverse U shape	**Shape**	Monotone	**Shape**	U shape	**Shape**	Monotone
Iran	Interval	1081	7833	−3.62E + 08	4.66E + 09	1.08E + 03	7.83E + 03	2.00E + 06	4.66E + 09
	Slope	0.0001	0.0002	6.41E − 10	−2.49E − 10	8.93E − 05	2.88E − 04	0.0000	0.0000
	t-Value			6.0527	−1.8032			3.0777	−0.1657
	P > t			3.29E − 07	0.0400			0.0020	0.4347
		Turns	−4456	**Turns**	3.25E + 09	**Turns**	−1955	**Turns**	4.31e + 09
		Shape	Monotone	**Shape**	Inverse U shape	**Shape**	Monotone	**Shape**	U shape
South Africa	Interval	2052	7976	−4.53E + 08	9.89E + 09	2.05E + 03	7.98E + 03	3.36E + 06	9.89E + 09
	Slope	0.0002	0.0000	1.16E − 10	−5.73E − 11	1.50E − 04	2.95E − 04	5.81E − 10	−6.13E-10
	t-Value	5.2522	−0.3378	4.5952	−1.7379			3.28E + 00	−2.50E + 00
	P > t	3.74E − 06	0.3688	0.0000	0.0455			0.0012	0.0086
		Turns	7573	**Turns**	6.47E + 09	**Turns**	−4102	**Turns**	4.81e + 09
		Shape	U shape	**Shape**	Inverse U shape	**Shape**	Monotone	**Shape**	Inverse U shape

NB: **CO_2-GDPP** represents the relationship between CO_2 emissions, per capita GDP and the square of per capita GDP; **NCO_2-GDPP** represents the relationship between non-CO_2 GHG emissions, per capita GDP and the square of per capita GDP; **CO_2-FDI** represents the relationship between CO_2 emissions, FDI inflows and the square of FDI inflows; **NCO_2-FDI** represents the relationship between non-CO_2 GHG emissions, FDI inflows and the square of FDI inflows.

[a] Denotes turning point.

[b] Denotes interpretation.

estimation technique estimates and reports statistics based on a fitted model where some or all of the covariates are fixed. The results of the average marginal effects produce the same results as the Driscoll-Kraay panel regression but with robust p-values, thus, confirming the initial outcome at 1% significance level.

3.3. U test estimation

After examining the Driscoll-Kraay panel regression, the study examines both the pollution haven and EKC hypothesis in the individual countries using the *U* test estimation algorithm by Lind and Mehlum (2010) to corroborate the empirical results of the panel regression. Table 5 presents the results of the *U* test estimation. The nexus between CO_2 emissions and economic development on a per capita basis reveals three outcomes.

First, based on a 5% significance level, the inverse U-shape hypothesis is valid for China and Indonesia at a turning point of US$ 6014 and US $ 2999; second, a U-shape relationship is valid for India and South Africa at a turning point of US$ 1476 and US$ 7573 and third, a monotone relationship exists between CO_2 emissions and economic development for Iran at a turning point of US$ −4456, signifying economic recession or impacts related to international economic sanctions. The nexus between non-CO_2 GHG emissions and economic development reveals three outcomes namely; inverse U-shape, U-shape, and monotonic shape presented in columns 7–8 of Table 5. The inverse U-shape hypothesis is valid for India at a turning point of US$ 889; the U-shape hypothesis is valid for Indonesia at a turning point of US$ 1153 while a monotonic relationship is valid for China, Iran, and South Africa at a turning point of US$ 9126, US$ −1955, and US$ −4102.

The relationship between CO_2 emissions and foreign direct investment inflows reveals two outcomes in Table 5. First, an inverse U-shape nexus between CO_2 emissions and FDI is valid for China, India, Iran, and South Africa at a turning point of FDI inflows of US$ 241 billion, US$ 34.7 billion, US$ 3.25 billion and US$ 6.47 billion, respectively, while monotonic relationship between CO_2 emissions and FDI is revealed for Indonesia at a turning of FDI inflows of US$ 42.5 billion. The results in Table 5 confirm the validity of an inverse U-shape relationship between non-CO_2 GHG emissions and FDI for China, India, and South Africa at a turning of FDI inflows of US$ 233 billion, US$ 18.6 billion, and US$ 4.81 billion, while Iran and Indonesia exhibit a U-shaped relationship and monotonic shape at a turning point of US$ 4.31 billion and −US$ 143 billion. The negative turning point exhibited by Indonesia denotes a larger disinvestment capital by foreign investors compared to the value of capital newly invested in the economy.

3.4. Panel quantile regression

This section employs a panel quantile regression estimator developed by Powell (2016) to address the limitation[1] of the Driscoll-Kraay panel regression and existing fixed-effect quantile estimators. The distributional and heterogeneous effect of FDI, GDPP, and ENE on CO_2 and non-CO_2 GHG emissions were examined with the panel quantile regression estimator and presented in Tables 6–7. The panel quantile results are reported for 5th, 10th, …, 90th and 95th percentiles of the conditional CO_2 emissions and non-CO_2 GHG emissions.

The results in Tables 6–7 reveal that the impact of treatment variables on CO_2 and non-CO_2 GHG emissions are heterogeneous and statistically significant at 1% level. The lnGDPP column of Table 6 shows that the economic development increases CO_2 emissions in the 5th to 70th

[1] Individual fixed-effects included in the model change the interpretation of the estimation coefficient on the explanatory variables.

Table 6
Panel quantile results with CO_2E as dependent variable.

Quantile	Model	lnGDPP	lnGDPP^2	lnGDPP^3	lnFDI	lnFDI^2	lnFDI^3	lnENE
5	Coef	212,000	−33,252	1640	367,000	−18,827	320	10,846
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	Coef	147,000	−23,904	1204	433,000	−22,112	374	10,260
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20	Coef	145,000	−23,952	1213	382,000	−19,589	333	11,206
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	Coef	111,000	−19,387	1016	394,000	−20,246	345	10,637
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
40	Coef	78,390	−14,763	793	381,000	−19,603	335	11,702
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	Coef	96,519	−17,769	946	302,000	−15,948	279	12,263
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
60	Coef	37,624	−10,701	680	275,000	−14,755	261	11,716
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
70	Coef	85,735	−16,755	928	295,000	−15,652	275	11,243
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
80	Coef	−18,641	−2591	298	237,000	−12,953	234	10,236
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
90	Coef	−287,000	35,719	−1471	245,000	−13,300	239	4392
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
95	Coef	285,000	−46,402	2386	267,000	−14,502	260	7124
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

quantiles, declines in the 80th to 90th quantiles and accelerates at 95th quantile. In the lnGDPP^2 column of Table 6, CO_2 emissions decrease with increasing economic growth from the 5th to 80th quantiles, but, accelerate in the 90th quantile and decline thereafter (95th quantile). However, the aggregated weight of the economic impact on CO_2 emissions is negative. In lnGDPP^3 column of Table 6, CO_2 emissions are positive with income levels from the 5th to 80th quantiles but decline in the 90th quantile and accelerate in the 95th quantile.

On the contrary, the relationship between non-CO_2 GHG emissions and income level in Table 7 becomes homogeneously positive in the 5th to 80th quantiles of lnGDPP; homogeneously negative in the 5th to 80th quantiles of lnGDPP^2 and homogeneously positive in the 5th to 80th quantiles of lnGDPP^3. The effect of income levels on non-CO_2 GHG emissions turns insignificant above 80th quantile. Notwithstanding, the aggregate effect of economic development on non-CO_2 GHG emissions agrees with results in Table 4.

Tables 6–7 reveal that the quest to improve income levels in low-income countries increases greenhouse gas emissions at the initial stages of economic development, however, CO_2 emissions decline in the middle to high-income countries at a specific turning point in economic development, accentuated in Table 5 of the *U* test estimation. The results support the validity of the EKC hypothesis in the five countries and agree with the previous studies (Sarkodie (2018); Sarkodie and Strezov (2018).

In columns 6–8 of Table 6, the nexus between CO_2 emissions and FDI is homogeneously positive from the 5th to 95th quantiles but becomes homogeneously negative at the second polynomial of FDI and becomes homogeneously positive at the third polynomial of FDI. Thus, the results corroborate the validity of the pollution haven hypothesis expounded in Tables 4–5. The relationship between non-CO_2 GHG emissions and FDI shows a different scenario. The effect of FDI on non-CO_2 GHG emissions is homogeneously positive from the 5th to 80th quantiles and turns negative and insignificant afterward. Similarly, the impact of FDI on non-CO_2 GHG emissions turns negative in lnFDI^2 and positive in lnFDI^3 from the 5th to 80th quantiles and becomes insignificant thereafter. The influx of foreign direct investment affects the anthropogenic

Table 7
Panel quantile results with NCO_2E as dependent variable.

Quantile	Model	lnGDPP	lnGDPP^2	lnGDPP^3	lnFDI	lnFDI^2	lnFDI^3	lnENE
5	Coef	139,000	−21,598	1062	82,481	−4270	73	3139
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
10	Coef	89,978	−14,310	708	91,383	−4710	81	2031
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
20	Coef	116,000	−17,575	844	87,553	−4531	78	1426
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
30	Coef	128,000	−19,047	903	102,000	−5234	89	1550
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
40	Coef	98,273	−15,117	734	80,680	−4215	73	1459
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
50	Coef	77,116	−12,114	592	59,923	−3231	58	1251
	p-Value	0.0010	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
60	Coef	29,724	−5589	295	71,034	−3733	65	1204
	p-Value	0.0240	0.0040	0.0020	0.0000	0.0000	0.0000	0.0010
70	Coef	106,000	−16,702	828	66,168	−3596	65	265
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5860
80	Coef	154,000	−23,360	1135	56,894	−3199	59	221
	p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.6450
90	Coef	3.78E + 20	−4.62E + 19	1.89E + 18	−9.75E + 19	4.01E + 18	−5.35E + 16	−1.29E + 19
	p-Value	0.8310	0.8400	0.8480	0.6910	0.6910	0.6940	0.7470
95	Coef	8.69E + 17	−1.41E + 17	7.33E + 15	−8.19E + 17	4.13E + 16	−6.88E + 14	2.31E + 16
	p-Value	0.6860	0.6260	0.5720	0.3590	0.3590	0.3580	0.3270

emission levels due to the displacement effect in developing countries. Pollution-intensive industries migrate to developing countries with lax environmental regulations and cheaper cost of production, as such, the levels of greenhouse gas emissions increase (Dasgupta et al., 1999, 2001; Dean et al., 2004). Hence, developing countries have a comparative advantage in pollution-intensive and energy-intensive goods compared to developed countries. The study further reveals that the effect of foreign direct investment inflows is more severe on CO_2 emissions compared to non-CO_2 GHG emissions, demonstrating that domestic investments and initiatives have a greater contribution to the non-CO_2 emissions.

Table 6 shows a strong positive effect of energy consumption on CO_2 emissions. The positive effect becomes insignificant from the 70th to 80th quantiles, turns insignificant negative in the 90th quantile and turns insignificant positive thereafter. The study is in line with Jayanthakumaran et al. (2012), Shahbaz et al. (2013), Wang et al. (2016) and Sarkodie (2018) who found a strong relationship between energy consumption and CO_2 emissions in China, India, Indonesia and South Africa. Various studies argue that the eagerness of developing countries to improve economic development adjures them to be reliant on fossil fuel energy technologies. Table 7 reveals that the effect of energy consumption on non-CO_2 emissions is weak. This may be because the non-CO_2 emissions depend on other processes, such as waste management, food production, and manufacturing.

To test the robustness of the results, the study employs average marginal effects as a post-estimation technique. The marginal effects examine and report changes in the response for alteration in some or all the covariates fixed at different values based on a fitted model. The results reveal that the estimated coefficients and p-values are in line with the output of the average marginal effects, thus, validating the models. Figs. 1–2 present the stability plots for the 5th quantile, 50th quantile and 95th quantile and show that these line plots fall within the red spikes which denote the 95% confidence interval, thus, confirming the robustness of the panel quantile regression models.

4. Discussion

The results of the study can be summarized in a diagrammatic format presented in Fig. 3 as a pictorial interpretation of the EKC and pollution haven hypothesis presented in all the models applied in this study. Using the second and third-degree polynomial of GDPP and FDI, the study presents the results in three scenarios.

All the models reveal a positive coefficient of per capita GDP in low-income levels coupled with its negative coefficient in the second-degree polynomial, providing evidence to support the EKC hypothesis for the selected developing countries. According to the EKC hypothesis, low echelons of a country's development is characterized by a low intensity and quantity of environmental deterioration. This is due to the limited impacts of economic development on the natural resource base (Panayotou, 1993; Sarkodie, 2018), thus, leading to a vast ecological reserve. The individual *U* test estimation reveals that CO_2 and GHG emissions for Iran and South Africa in Table 5, to some extent, follow a monotonic relation with income level, thus, confirming the scale effect, which is contrary to Sarkodie (2018). As economic development intensifies, the extraction of natural resources, such as oil, natural gas, coal, the mineral ores and agricultural productivity increases. Economic development propels industrialization, thus adding value to the extracted natural resources, and intensifies agricultural output leading to increasing rate of natural resource depletion, while exceeding the regenerative natural resource capacity (i.e. ecological deficit), and the quantity and toxicity of waste generation increases (Sarkodie and Strezov, 2018). Due to the middle-income status of Iran and South Africa, a composition and technique economic effect was expected but it appears that their economies depend on carbon-intensive industries and fossil fuels to maintain their economic status. As presented in Table 5, the country-wise estimation, based on the nexus between CO_2 emissions and

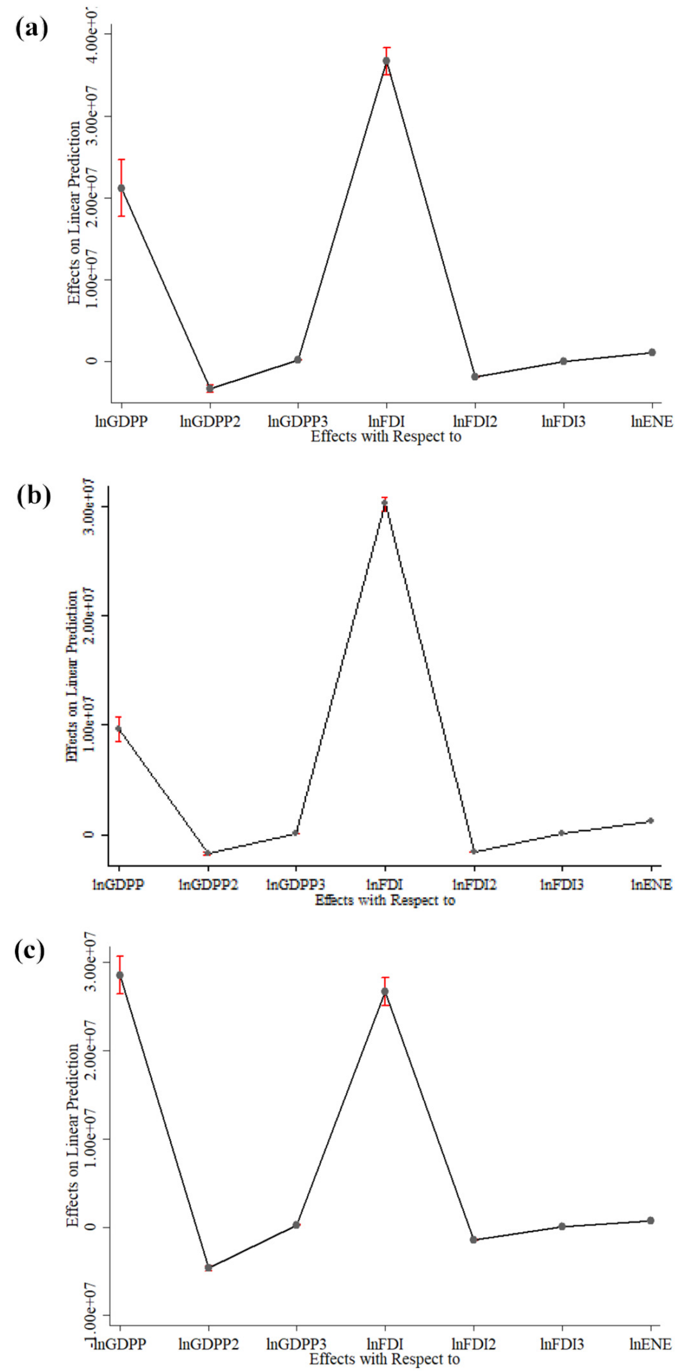

Fig. 1. Stability of panel quantile with CO_2E as the dependent variable (a) 5th quantile (b) 50th quantile and (c) 95th quantile. NB: The red spikes denote the 95% Confidence Interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

economic development, reveals that the inverse U-shape hypothesis is valid for China (is in line with Dong et al. (2018)) and Indonesia at a turning point of US$ 6014 and US$ 2999, on a per capita basis. However, based on the relationship between non-CO_2 GHG emissions and economic development, the inverse U-shape hypothesis is only valid for India at a turning point of US$ 889. At higher levels of economic development, as presented in Fig. 3, environmental awareness creation, enforcement of environmental laws, policies and regulations, high environmental expenditure, advancement in technology and structural change towards energy-intensive and carbon-intensive industries and services result in a gradual decline in environmental deterioration (Panayotou, 1993).

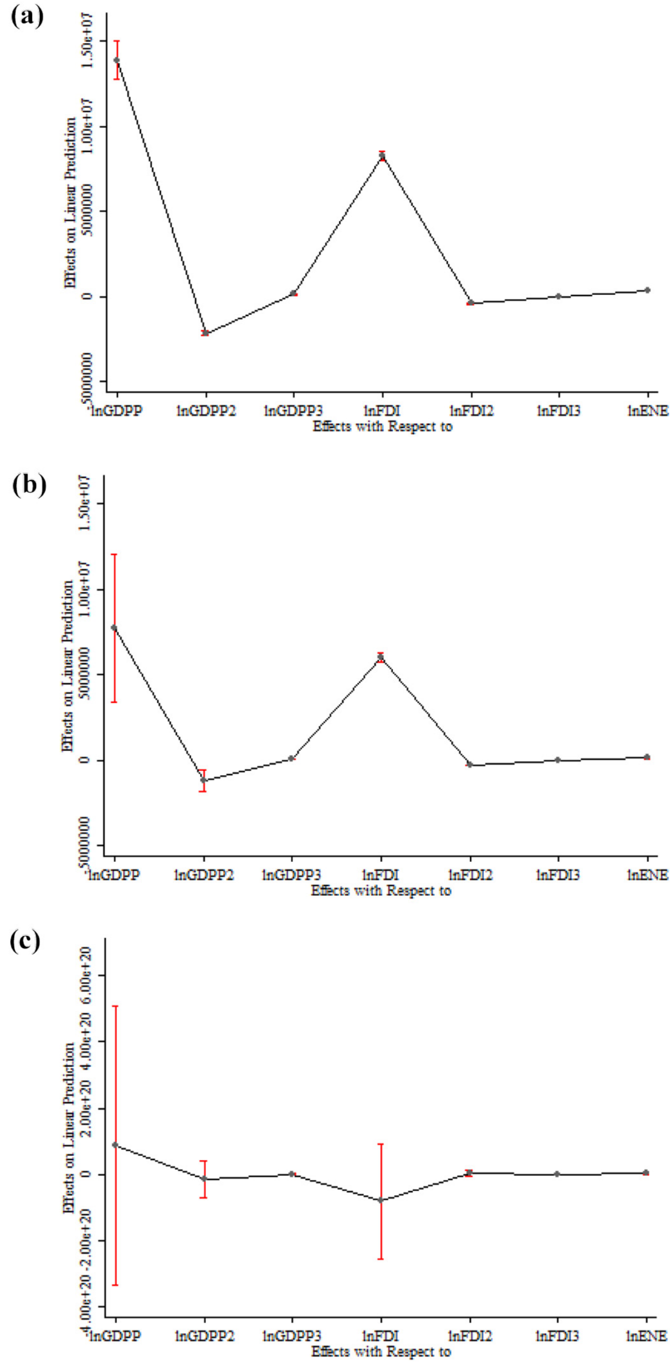

Fig. 2. Stability of panel quantile with NCO_2E as the dependent variable (a) 5th quantile (b) 50th quantile and (c) 95th quantile. NB: The red spikes denote the 95% Confidence Interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The panel quantile regression reveals that the heterogeneous effect of FDI on CO_2 and non-CO_2 GHG emissions still support the results of aggregate effect reported in Driscoll-Kraay panel regression and *U* test estimation. Contrary to Zhu et al. (2016), who found evidence of halo effect, the positive coefficient of FDI in all the models is significant and sufficient to support the pollution haven hypothesis in the five countries. The hypothesis posits that countries with weak environmental regulations attract polluting industries from countries with stringent environmental regulations. Due to stringent environmental regulations, the cost of the key inputs for products with pollution-intensive production increases, thus reducing the country's comparative advantage in those products. Propelling the transfer of pollution-intensive production to pollution haven countries is evidenced in the study. Since foreign direct investment inflows are a key source of external funding for developing countries, the study reveals that at a turning point of foreign investment inflows of US$ 241 billion, US$ 34.7 billion, US$ 3.25 billion and US$ 6.47 billion for China, India, Iran, and South Africa cause CO_2 emissions to decline. However, at a turning of foreign investment inflows of US$ 42.5 billion, the level of CO_2 emissions in Indonesia continue to rise unabated. In contrast, a country-wise effect of FDI on non-CO_2 GHG emissions reveals that at a turning point of foreign investment inflows of 233 billion, US$ 18.6 billion, and US$ 4.81 billion for China, India, and South Africa, greenhouse gas emissions excluding CO_2 emissions decline. A U-shaped relationship and monotonic shape at a turning point of US$ 4.31 billion and —US$ 143 billion were valid for Iran and Indonesia. In terms of per capita consideration, the turning point of FDI in China is US$ 174.81 (~2.15% of GDP) for CO_2 emissions and US$ 169 (~2.08% of GDP) for non-CO_2 GHG emissions; India is US$ 26.21 (~1.53% of GDP) for CO_2 emissions and US$ 14.05 (~0.82% of GDP) for non-CO_2 GHG emissions; Iran is US$ 40.48 (~0.78% of GDP) for CO_2 emissions and US$ 53.69 (~1.03% of GDP) for non-CO_2 GHG emissions; South Africa is US$ 115.50 (~2.19% of GDP) for CO_2 emissions and US$ 85.87 (~1.63% of GDP) for non-CO_2 GHG emissions; and Indonesia is US$ 162.76 (~4.56% of GDP) for CO_2 emissions and US$ -547.65 (~—15.34% of GDP) for non-CO_2 GHG emissions. The decline of CO_2 and non-CO_2 GHG emissions can be due to an improved investment climate, technological transfer, growth in the private sector, improved labour and managerial skills, and implementation of the sustainable development goals. While investments in Iran are impacted by economic sanctions, the negative turning point exhibited by Indonesia denotes a larger disinvestment capital by foreign investors compared to the value of capital newly invested in the economy, hence, affecting climate investment. Overall, the results show that the pollution haven hypothesis influences the shape of the EKC, which is in line with Dinda (2004).

The study reveals a strong positive effect of energy consumption on CO_2 emissions and a weak effect on non-CO_2 GHG emissions. This is because China, India, Indonesia, Iran and South Africa are industrial economies and depend mostly on fossil fuel energy technologies for energy-intensive foreign direct investment inflows and carbon-intensive industries to drive their economic development. The outcome of this study is in line with the Intergovernmental Panel on Climate Change (IPCC) 5th assessment report (IPCC, 2014). According to the IPCC report, energy consumption contributes to 34.6% of the global GHG by economic sectors. The rate of the emissions was due to higher energy demand coupled with a rapid economic development and an increase in the share of fossil fuels, especially coal. Thus, energy-related emissions reduction includes a paradigm shift from fossil fuel, the incorporation of clean and renewable energy technologies like renewables, nuclear power, and carbon capture and storage, improving energy efficiency, and among others (Owusu and Asumadu, 2016; Sarkodie and Adom, 2018), leading to a decarbonized electricity generation. Liobikienė and Butkus (2018); Sarkodie and Adams (2018) revealed that the promotion of higher energy efficiency, specifically in upper-middle-income countries is the most important climate policy opportunity that helps to mitigate GHG emissions.

5. Conclusion

The study examined the effect of foreign direct investment inflows, economic development, and energy consumption on disaggregate greenhouse gas emissions. The study employed data spanning from 1982 to 2016 for the top five emitters of carbon emissions from fuel combustion in the developing countries. The study revealed a strong positive effect of economic development on CO_2 emissions, thus, confirms the validity of the EKC hypothesis. The panel quantile regression showed a distributional and heterogeneous effect of FDI, GDPP and ENE on greenhouse gas emissions, however, the aggregate effect

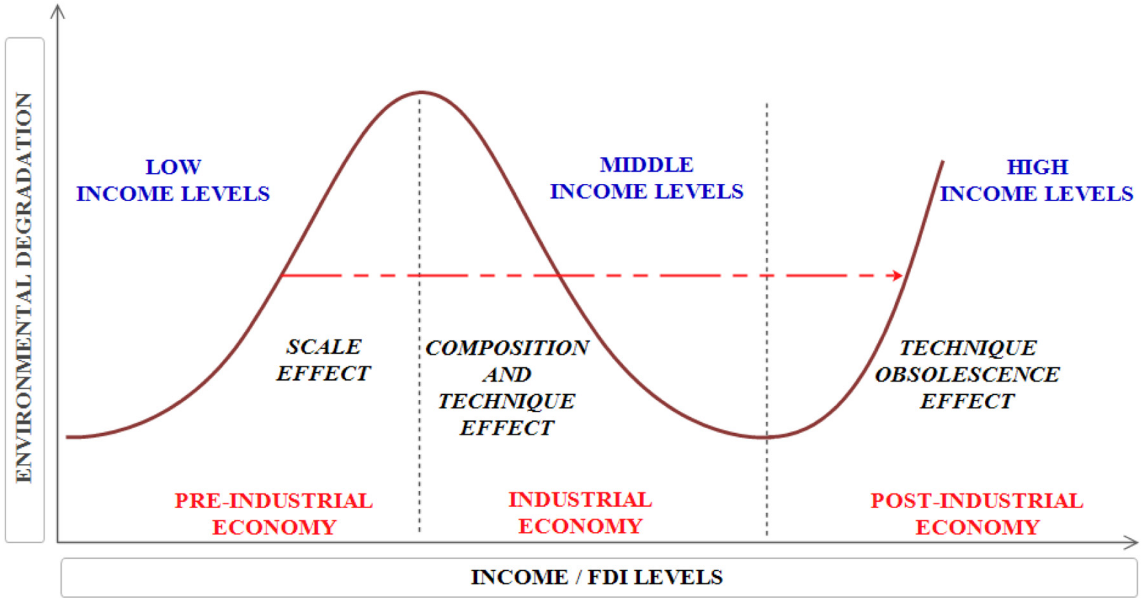

Fig. 3. Schematic representation of the EKC and pollution haven hypothesis.

confirmed the validity of the pollution haven hypothesis. Even though foreign direct investment inflows are considered a major source of external funding which improves the economic development of a country and grows the private sector. The study revealed that foreign direct investment inflows increase CO_2 emissions in the top five emitters of carbon emissions from fuel combustion from developing countries. In the process of globalization and the urge to improve economic development, many least developing and developing countries are eager to attract foreign direct investment inflows with polluting industries by engaging in an inefficient competition, such as weakening their environmental standards yet have poor environmental management systems and modern technologies to streamline polluting trends. The study revealed that there is more room for improvement as greenhouse gas emissions appear to decline at a sustained increase in foreign direct investment inflows.

The inverse U-shape hypothesis was for China, India, Iran, and South Africa at a turning point of foreign investment inflows of US$ 241 billion, US$ 34.7 billion, US$ 3.25 billion and US$ 6.47 billion. This means that foreign direct investment inflows with clean technological transfer and improvement in labour and environmental management practices will help developing countries in the achievement of the sustainable development goals. As a policy implication, there is a need for a global partnership that ensures promotion, transfer, and dissemination of clean and modern technologies in developing countries that will assist in the achievement of a long-term sustainability. Energy consumption has a strong positive effect on CO_2 emissions, as evidenced in the study. Deterioration of the environment stems from the overdependence on fossil fuel energy technologies to meet the growing energy demand for residential and commercial purposes. Pollution haven in developing countries also propels the adoption of fossil fuel energy technologies rather than renewables in order to accumulate low production cost of goods and services from energy-intensive and carbon-intensive industries. Therefore, a reduction of CO_2 emissions and environmental pollution will depend on enhanced energy efficiency, behavioural changes in political institutions that adopts inefficient competitive advantage to lure FDI inflows with polluting technologies, the adoption of clean and modern energy technologies such as renewables, nuclear power plants, the adoption of carbon capture and storage for fossil fuel and biomass energy generation processes.

While this study employed FDI inflows, future studies can possibly examine the role of international trade in pollution levels using both EKC and the pollution haven hypothesis. This will in effect help to understand the dynamics of the factors that determine the shape of the EKC.

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Declaration

There is no conflict of interest.

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