A global panel analysis comparing carbon emissions across levels of economic development

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Abstract

This study compares carbon emissions across panels of high-income countries (HICs) and low- and middle-income countries (LMICs). Using the Environmental Kuznets Curve (EKC) hypothesis as a theoretical framework, this study observes the curve for each income panel using random effects panel regression, controlling for the scale, composition, technological, and pollution outsourcing effects. With a dataset ranging 30 years from 1990 to 2019 and a panel of 18 HICs and 20 LMICs, the regression results validate the presence of an EKC-like relationship between emissions and income per capita for both panels. Key findings show that LMICs are on a path of growth that emits fewer emissions than HICs at the same income level due to access to less emission-intensive technologies. This suggests that, in contrast to previous theoretical understanding, the effects observed in the EKC occur simultaneously rather than sequentially and may be leveraged to dominate at any point on the curve. In practice, LMICs are urged to dismiss the “grow now, clean later” ethos and instead, adopt cleaner production methods through energy efficiency initiatives, technological transfers, and technological leapfrogging to manage economic growth without a corresponding growth in emissions.

Keywords: environmental Kuznets curve; panel data; robust random effects; carbon emission

JEL Classification: Q56; O44

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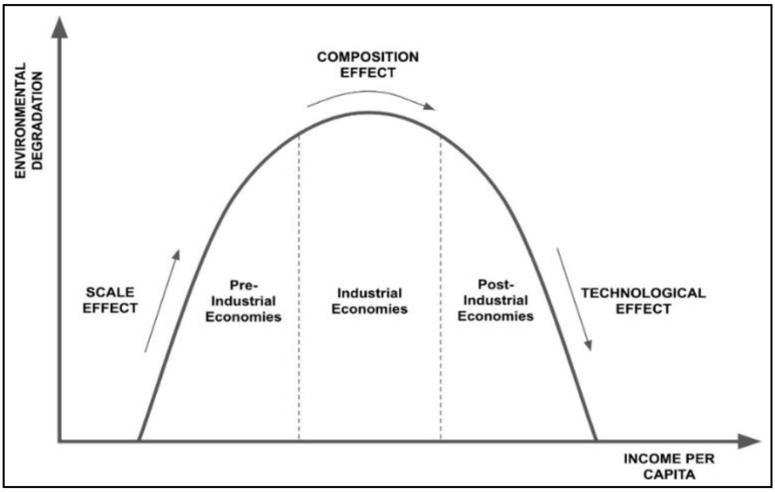
1. Introduction

The Paris Agreement was adopted by low-, middle-, and high-income countries alike and was made with the overarching goal of limiting the increase in global average temperature (UNFCCC, 2015). This new agreement requires nations to submit non-binding pledges through Nationally Determined Contributions (NDCs) covering emissions mitigation. In formulating their NDCs, low- and middle-income countries (LMICs) are given leniency to reduce emissions from a business-as-usual baseline. In contrast, high-income countries (HICs) are expected to reduce emissions below the baseline of a given year (Fransen, 2021). This distinction subtly implies an acceptance of continued emissions from LMICs. Such an ethos finds theoretical grounding in the Environmental Kuznets Curve (EKC) Hypothesis, which posits that as nations grow economically, the environment would degrade up to a certain point where it would then start to improve (Grossman & Krueger, 1991). This hypothesis has led institutions to prioritize pro-growth policies in LMICs–known as "grow now, clean later"-banking on the potential of an EKC-like growth trajectory to remedy the environment later (Azadi et al., 2011).

Figure 1. The Environmental Kuznets Curve



Source: Authors (2024) adopted from Grossman and Krueger (1991)

The objective of this research is, therefore, to understand the relationship between emissions and per capita income by comparing LMICs and HICs. With different economic structures and development stages of LMICs and HICs, the strength of the relationship between the two variables will differ. Conceptually, the relationship between the two variables cannot be expected to be similar in LMICs that depend on the agriculture and manufacturing sectors (within pre-industrial economies and industrial economies) and in HICs that rely on the services sector (within post-industrial economies) as seen in Figure 1. In this context, this research contributes to the literature that relates emissions to per capita income in two aspects. First, by comparing the EKC across different income panels (LMICs and

HICs), the research offers a nuanced understanding of how economic structure and development stage impact emissions differently across income levels. This comparative approach highlights the varying inflection points and emission trajectories between LMICs and HICs. Second, the classification of LMICs and HICs allows for the establishment of policy implications for each country group based on the results obtained, with broad empirical support from some countries and a long period of time analysed.

To achieve the research objective, the following research questions have been formulated: 1) What is the shape of the relationship between emissions and per capita income in LMICs compared to HICs? This question aims to determine whether the EKC hypothesis holds true for both income panels and to identify the specific shape of the relationship. 2) Do LMICs exhibit different inflection points, where emissions begin to decline as per capita income increases, compared to HICs? This question explores whether the inflection points differ between LMICs and HICs. 3) How do the scale, composition, technological, and pollution outsourcing effects influence the EKC in LMICs and HICs? This question aims to dissect the various factors contributing to the EKC and understand their simultaneous impacts on emissions across different income levels. 4) What policy recommendations can be made to promote the increase in per capita income with less of an increase in emissions in LMICs? This question focuses on deriving actionable insights and policy recommendations to help LMICs, including Indonesia, achieve sustainable economic growth and economic structure transformation without compromising the environment.

The growth and industrialization witnessed in LMICs of today, a mechanism outlined as the scale effect, invariably results in increased production and, consequently, waste generation. However, with concerns for the ecological limits to growth, it is necessary for all nations to "clean now" irrespective of the emitter. This creates a dilemma for LMICs as mitigating emissions appears contrary to economic growth; some nations are too poor to be green.

Post-industrialization economies typically see a shift in the composition of output away from manufacturing and toward services (Rodrik, 2015). HICs, having undergone the composition effect, can achieve economic growth with diminishing marginal emissions as service-driven economies are seen as less polluting (Roberts et al., 2021). Despite this, debatable concerns exist about pollution outsourcing from HICs to LMICs (Levinson, 2022). Pollution outsourcing is an oft-used premise used to attribute global emissions to the consumption patterns of HICs. The liberalization of trade has allowed the exchange of goods to act as a channel for the transfer of pollution from one nation to another (Aklin, 2015). Today, climate agreements are merely commitments for unilateral emission reductions based on production-based emissions (PBEs), which fail to account for the displacement of production emissions by HICs to LMICs.

An alternative method to accounting for emissions is consumption-based emissions (CBEs). CBEs reflect the emissions of products consumed within a nation’s borders by subtracting embodied emissions in exports and adding embodied emissions in imports (Ghosh & Agarwal, 2013). Industrialized countries tend to be net importers of emissions, whereas LMICs and commodity-dependent countries tend to be net exporters. However, while CBEs hold nations accountable for emissions outsourced through trade, they fail to capture emission shifts resulting from technological advancements (Ghosh & Agarwal, 2013). The technological effect is last. It refers to advanced technological capabilities, often found in HICs, as a reversal mechanism that would enable emission-intensive production and consumption to continue as emissions are reduced through newly developed technological practices. An example is the higher utilization rates of electric vehicles (EVs) in HICs (World Resources Institute, 2023). However, the benefits of EVs are significantly smaller in LMICs with coal-intensive electricity generation (Hausfather, 2019). While some LMICs are too poor to be green, China has been observed to leapfrog over technologies used by HICs. A strong case can be made that LMICs do not need to abide by the "grow now, clean later" maxim if the technological effects can be reached sooner through technological leapfrog and transfers.

General studies concerning the EKC typically employ a proxy variable for environmental degradation, such as CO2 emissions (Ntim-Amo et al., 2021; Ahmad et al., 2017) or other GHG emissions (Day & Grafton, 2003). The common econometric methodology for observing the EKC includes the use of a linear and quadratic term of an economic variable, typically GDP per capita, to model the parabolic curve of the EKC.

Furthermore, several studies utilized the decomposition method as an alternative method of observing the EKC. These studies disaggregate the scale, composition, and technological effects driving the EKC hypothesis in an attempt to observe the intensity of each variable across various points of the EKC. Stern (2002) separated each effect using the coefficient estimate of income per capita for the scale effect, value-added shares of agriculture, manufacturing, and other related sectors as a proxy for the composition effect, and total energy consumption to measure the technological impact. Bouvier's (2004) attempt at the disaggregation of these effects includes assessing its effects on various sources of global and local air pollutants. Meanwhile, in an attempt to validate pollution outsourcing in HICs, econometric models for the EKC evolved to use FDI as an economic variable (Shahbaz et al., 2015) and CBEs as an environmental variable (Frodyma et al., 2022). Currently, the narrative told by such studies points the finger at HICs having deliberately outsourced pollution at the expense of LMICs (Aldy, 2005).

Based on empirical evidence from existing literature, the following research hypotheses have been formulated: 1) There exists a significant inverted U-shaped relationship between carbon emissions and per capita income in LMICs and HICs. 2) There are different inflection points of income and emissions in LMICs and HICs. 3) Scale, composition, technological, and pollution outsourcing effects occur simultaneously. The hypotheses challenge the traditional sequential understanding of the EKC depending on economic structure transformation and development stages. This new perspective can significantly alter how researchers and policymakers approach the EKC and related environmental policies. In addition, the hypotheses focus on technology leapfrogging of LMICs that can adopt advanced and less emissions-intensive technologies earlier in the development stages. The role of technological leapfrogging of LMICs in studies of the EKC is relatively underexplored in the literature and offers new understanding.

This study will take a distinct approach in several ways. Firstly, this study will conduct a comparative analysis between two income panels: the high-income panel (HIP) versus the low- and middle-income panel (LMIP). This will provide a deeper understanding of the EKC across different income levels. Secondly, this study will employ the decomposition method to incorporate a more exhaustive set of control variables, including the formulation of a binary variable to represent pollution outsourcing by having a net emission transfer (NET) formulation. The NET is one if a country is a net importer of emissions, meaning the emissions embodied in its imports exceed those embodied in its exports. Meanwhile, NET is zero if a country is a net exporter of emissions, meaning the emissions embodied in its exports exceed those embodied in its imports. Lastly, while this study will examine the inflection point, the discussion will be more nuanced around the effects observed.

2. Methodology

Panel data spans from 1990 to 2019, covering a panel of 38 countries of varying wealth levels sourced from the World Bank, the Penn World Table 10.01, the Global Carbon Budget, and the Energy Institute Statistical Review of World Energy. Since the World Bank classifies income groups into four, that is, low, lower-middle, upper-middle, and high-income, this research aggregates the low-, lower-middle, and upper-middle income groups into low- and middle-income for a more robust dataset.
A standard regression with panel data can be written as follows:

$$Y_{rit} = \beta_0 + \beta_1 X_{rit} + \varepsilon_{rit} \quad (1)$$

Subscript i indicates the country, t is the time dimension, and β is a constant term.

$$lnPRO_{\mathrm{rit}} = \beta_0 + \beta_1 lnPRO_{\mathrm{rit}} + \beta_2 lnGDP2_{\mathrm{rit}} + \beta_3 NET_{\mathrm{rit}} + \beta_4 lnENE_{\mathrm{rit}} + \beta_5 lnDEI_{\mathrm{rit}} + \beta_6 lnREN_{\mathrm{rit}} + \varepsilon_{\mathrm{rit}} \quad (2)$$

Where:
$lnPRO_{\mathrm{rit}}$ = per capita production-based carbon emissions (metric tons);
$lnGDP_{\mathrm{rit}}$ = per capita real output-side GDP (2017 US$)
$lnGDP2_{\mathrm{rit}}$= the quadratic term of $lnPRO_{\mathrm{rit}}$
NET_{rit} = a binary term where net positive emission transfers register a value of 1 and net negative emission transfers register a value of 0;
$lnENE_{\mathrm{rit}}$ = per capita primary energy consumption (GJ)
$lnMAN_{\mathrm{rit}}$ = % of GDP that comes from value added in the manufacturing sector
$lnSER_{\mathrm{rit}}$ % = of GDP that comes from value added in the manufacturing sector
$lnDEI_{\mathrm{rit}}$ = $lnSER_{\mathrm{rit}}$ / $lnMAN_{\mathrm{rit}}$
$lnREN_{\mathrm{rit}}$ = % of total energy consumption that comes from renewable energy
β_0 = constant
β_{1-6} = coefficient estimates
$\varepsilon_{\mathrm{rit}}$ = error term
r = income group, that is, low, middle, and high income
i = country
t = year

The following procedure will be used for hypothesis testing:

1) Hypothesis 1
a) For Eq.2 and every income level (r), if the p-values of β_1 and β_2 are <0.05
b) (>0.05), the relationship between income per capita and carbon emissions is significant (not significant).

c) For Eq.2 and every income level (r), if $\beta_1 \geq 0$ $(\beta_1 \leq 0)$ and $\beta_2 \geq 0$ $(\beta_2 \leq 0)$. There exists a monotonic non-decreasing (monotonic non-increasing) relationship between income per capita and carbon emissions.
d) For Eq.2 and every income level (r), if $\beta_1 < 0$ $(\beta_1 > 0)$ and $\beta_2 > 0$ $(\beta_2 < 0)$There exists a U-shaped (inverted U-shaped) relationship between income per capita and carbon emissions.
2) Hypothesis 2 For Eq. 2 and every income level (r) that exhibits a non-monotonic relationship indicated by $\beta_1 > 0$ and $\beta_2 < 0$ or $\beta_1 < 0$ and $\beta_2 > 0$. The inflection point of income is found with the equation $e\,(-\beta_1/2^*\beta_2)$ and the inflection point of emissions is found by substituting $e\,(-\beta_1/2^*\beta_2)$ into the panel regression equation.

3. Results and Discussion

Based on the methodology that has been conducted, Table 1 presents the findings of the model. In this table, the author has categorized them into high-income, low-income, and middle-income. The summary provides key insights into the distribution of each variable, including their mean values, standard deviations, and range. This overview is essential for understanding the general characteristics and variability within the dataset.

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min.	Max.	Obv.
		High - Income Panel			
PRO	10.079	5.443	2.293	35.668	540
GDP	40,318.43	19,750.22	7127	144841	540
NET	0.826	0.380	0.000	1.000	540
ENE	216.750	124.408	42.004	754.346	540
MAN	15.877	5.290	5.605	31.726	540
SER	59.790	8.658	24.175	72.258	540
REN	14.423	13.350	0.01	52.87	540
		Low- and Middle-Income Panel			
PRO	3.118	2.406	0.137	10.673	600
GDP	9,891.747	5673.684	1430	27500	600
NET	0.575	0.495	0.000	1.000	600
ENE	48.326	34.046	2.348	160.857	600
MAN	17.662	5.586	3.988	44.444	600
SER	50.335	7.651	21.632	73.338	600
REN	24.023	19.075	0.440	78.09	600

Source: Processed by Author

Based upon Table 1, we continue our findings in Table 2, which displays the estimation results of the Random Effect Models for both high-income and low-middle income. This model was selected based on the suitability of the data structure and the assumption that unobserved effects are uncorrelated with the explanatory variables.

Table 2. Estimation Results of the Random Effect Model

Variable	Coefficient	Std.Error	z	P>|z
High-Income Panel				
lnGDP	3.557***	0.372	9.550	0.000
lnGDP2	-0.181**	0.018	-10.130	0.000
NET	-0.053**	0.022	-2.410	0.016
lnENE	0.859***	0.041	20.920	0.000
lnDEI	-0.033	0.044	-0.750	0.454
lnREN	-0.062***	0.012	-5.330	0.000
Constant	-19.449***	1.925	-10.110	0.000
R2	0.656		Prob>F	0.000
			N	540
Low and Middle-Income Panel				
Variable	Coefficient	Std.Error	z	P>|z
lnGDP	0.852***	0.143	6.010	0.000
lnGDP2	-0.046***	0.008	-5.690	0.000
NET	-0.011	0.010	-1.150	0.250
lnENE	0.897***	0.025	35.490	0.000
lnDEI	-0.071**	0.032	-2.230	0.026
lnREN	-0.055***	0.014	-3.980	0.000
Constant	-6.121***	0.642	-9.540	0.000
R2	0.960		Prob>F	0.000
			N	600

Note: *sig. 0,1 **sig. 0,05 ***sig 0,01
Source: Processed by Author

Table 3. Breusche-Pagan Langrange Multiplier and Hausman Test Result

Test	P-value	Alpha	Conclusion
Breusche-Pagan Langrange	0.000	<0.05	Accept H0 : REM
Hausman	0.472	<0.05	Accept H0 : REM

Source: Processed by Author

The Hausman test and the Breusche-Pagan Langrange Multiplier test were then completed to determine the best model (PLS, FEM or REM) to use. The Hausman tests between the random effects and the fixed effects model, while the Breusch-Pagan Lagrange Multiplier tests between the random effects and the pooled OLS (PLS) model. The results concluded that the random effects model was the best. To overcome problems of heteroskedasticity and autocorrelation in the data, the robust standard error is applied to the random effects panel regression. This is similar to the works of Ozokcu and Ozdemir (2017). As discussed by Woolridge (2013), specifying robust is equivalent to Specifying clustering on the panel variable results in the production of a consistent estimator when heteroskedasticity and autocorrelation are detected.

Table 4. Robust Standard Error Random Effects Estimation Results

High-Income Panel				
Variable	Coefficient	Std. Error	z	P>|z|
lnGDP	3.557**	1.654	2.150	0.032
lnGDP2	-0.181**	0.083	-2.190	0.029
NET	-0.053***	0.020	-2.690	0.007
lnENE	0.859***	0.142	6.070	0.000
lnDEI	-0.033	0.099	-0.330	0.740
lnREN	-0.062**	0.026	-2.350	0.019
Constant	-19.449**	7.730	-2.520	0.012
R2	0.656		Prob > F	0.000
			N	540
Low- and Middle-Income Panel				
Variable	Coefficient	Std. Error	z	P>|z|
lnGDP	0.852***	0.203	4.200	0.000
lnGDP2	-0.046***	0.011	-4.160	0.000
NET	-0.011	0.014	-0.820	0.415
lnENE	0.897***	0.059	15.130	0.000
lnDEI	-0.071	0.047	-1.490	0.136
lnREN	-0.055**	0.025	-2.130	0.033
Constant	-6.121***	0.875	-6.990	0.000
R2	0.960		Prob > F	0.000
			N	600

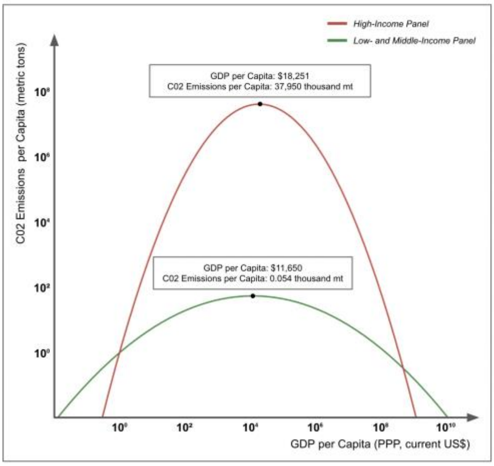
Note: *sig. 0,1 **sig. 0,05 ***sig 0,01
Source: Processed by Author

The Hausman test and the Breusche-Pagan Langrian Multiplier test were then completed to determine the best model (PLS, FEM or REM) to use. The Hausman tests between the random effects and the fixed effects model, while the Breusch-Pagan Lagrange Multiplier tests between the random effects and the pooled OLS (PLS) model. The results concluded that the random effects model was the best. To overcome problems of heteroskedasticity and autocorrelation in the data, the robust standard error is applied to the random effects panel regression. This is similar to the works of Ozokcu and Ozdemir (2017). As discussed by Woolridge (2013), specifying robust is equivalent to specifying clustering on the panel variable, resulting in the production of a consistent estimator when the heteroskedasticity and autocorrelation are detected.

Overall, both the HIP and LMIP are statistically significant. The R-squared value is 0.66 for the HIP and 0.96 for the LMIP. This signifies that the independent variables explain approximately 66% of the variation observed for carbon emissions in the HIP, indicating that the variables observed in the HIP do not include all variables associated with a reduction in carbon emissions. However, this does not necessarily mean the model is bad (Gujarati, 2004). Meanwhile, the independent variables explain 96% of the variations observed in the LMIP. The model's statistical significance is further confirmed by the F test observed from the Prob > chi2 values being 0.000 for both models (Torres-Reyna, 2007).

The study observes a significant (** at 5% and *** at 1%) inverted U-shaped relationship between carbon emissions and income per capita in both the HIP and LMIP confirms Hypothesis 1 to be true. Furthermore, different turning points of income and emissions exist in the LMIP compared to the HIP, confirming the Hypothesis 2 to be true. Further observation of the coefficients reveals that in absolute terms, coefficients of GDP and $GDP2$ are higher in the HIP, which results in a steeper EKC than the LMIP. Consistently, Table 8 reveals that the LMIP exhibits a lower inflection point of income and emissions. A visual depiction of the EKCs is shown in Figure 3.

Figure 3. EKC Estimation for HIP and LMIP



Source: Processed by Author

Table 5. Inflection Points for High-Income and Low- and Middle-Income EKC

Inflection Point	High-Income	Low- and Middle-Income
GDP per Capita (PPP, 2017 US$)	\$18,251	\$11,650
CO2 Emissions per Capita (thousand metric tons)	37,950	0.054

Source: Processed by Author

Overall, the control variables (NET, ENE, DEI, and REN) exhibit variations in statistical significance. The coefficient of NET is negative and significant only in the HIP. Perhaps this is due to a higher incidence of positive net emission transfers in the HIP. This suggests that HICs observed to have positive net emission transfers would reduce carbon emissions by 0.05%. ENE is significant in both panels. A percentage increase of ENE would increase PRO by 0.86% for HICs and 0.9% for LMICs. DEI is insignificant and is observed to have a negative relationship with the dependent variable in both panels. Given the variable's insignificance, the study has ruled out the role of the composition effect. Lastly, REN is negative and significant in both panels. Within the HIP, a percentage increase in REN results in a decrease of 0.06% in PRO, while a decrease of 0.05% in PRO is observed for the LMIP. The econometric findings indicate that an EKC-like relationship can be observed in both panels. These findings are in line with several works done in the past observing a similar inverted U-shaped curve in their studies (e.g. Ahmad et al., 2017; Ntim- Amo et al., 2021; Saboori et al., 2012). Despite the similarity between the two panels, an investigation of each panel's respective coefficients reveals more. A higher inflection point is observed for the HIP compared with the LMIP.

This finding is supported by another study (Sayed & Sek, 2013). The authors suggest this to be due to the scale effect as represented by the significant variable ENE. HICs experienced rapid growth during the Industrial Revolution. Though this period is not captured within the dataset of this study, it is interesting to point out that the coefficient of the variable ENE in the HIP is significant and of similar magnitude to the LMIP despite having gone through the scale effect. This finding suggests the effects observed in the EKC occur simultaneously rather than sequentially. Different effects may dominate at different points along the curve, leading to the inflection point. Hence, a nation may leverage these effects at any point on the curve to achieve a desired outcome. Conversely, the HIP also boasts a steeper decline in emissions after reaching the inflection point. This phenomenon is probably largely due to two reasons. First, HICs were given more responsibility in the formulation of their NDCs early on compared to LMICs (Fransen, 2021).

In line with this reasoning, the variable REN is significant in the HIP with a negative coefficient. The expectation to reduce emissions below the baseline of a given year forces HICs to pivot their emissions trajectory imperatively. Such an urgency has not been felt by LMICs where mitigation contributions are committed conditional on factors (Fransen, 2021) and the "grow now, clean later" ethos is found to be commonplace (Azadi et al., 2011). The second reason pertains to pollution emission transfers, indicating that these countries consume more emissions than they produce. This is evidenced by the significant negative relationship between NET and PRO within the HIP, whereas a significant relationship was not observed in the LMIP. Consequently, the displacement of production emissions substantially contributes to reducing production emissions in HICs, a phenomenon not mirrored in LMICs.

While a large part of previous studies has focused on the history of HICs in reaching the inflection points, it is of greater importance to shine a light on the LMICs. Given the ecological limits to growth coupled with ever-growing emissions in emerging economies like China, India, and Indonesia, this begs the question of whether responsibility from LMICs should equally be demanded or forgiven for the sake of growth. Interestingly, coefficients in the LMIP indicate a flatter increase in emissions for every percentage increase in GDP before reaching the inflection point than the HIP. Concurrently, the LMIP boasts a lower income per capita in the inflection point of its EKC, specifically $11,650 compared to the $18,251 needed for the HIP. This finding is also found in the works of Sayed and Sek (2013). These results show that the LMICs have grown at a lower emission intensity and are on a trajectory to reduce emissions at a lower income per capita than the HIP.

Our finding suggests that this is due to a more significant technological effect present for LMICs than it was for HICs at the same GDP per capita, following our hypothesis that the effects observed in the EKC happen simultaneously rather than sequentially. An abundance of studies has documented how technology reduces carbon emissions through energy efficiency and the adoption of renewable energy sources (Khan et al., 2022; Altenburg et al., 2022; Milindi & Inglesi-Lotz, 2022; Singh, 2024). For example, advancements in technical energy efficiency across various sectors have lowered energy demand in numerous economic activities. Since 1990, the energy required to produce a unit of global GDP has decreased by 36% (Singh, 2024). Furthermore, the price of solar power has fallen by over 80% since 2010, and renewable energy is now more affordable than ever before (Armstrong, 2022), highlighting how LMICs now have greater access to better technologies.

The transfer and leapfrogging of less emission-intensive technologies are two ways the technological effect can be achieved early on. Technological transfer encompasses the transfer or investment in new hardware, training and knowledge transfer, R&D support and collaboration, energy efficiency improvements, related management practices, as well as other innovation strategies (Wiebe, 2018). On the other hand, technological leapfrogging is defined as a country's efforts in jumping directly on the latest technologies or exploring an alternative path of technological development involving emerging technologies with new benefits and new opportunities (Yayboke et al., 2022).

The literature on the effectiveness of technological transfers is limited. However, its effects are well-documented in China. One study found that technological transfers in parts of China led to technological progress and improved energy efficiency (Li et al., 2023). Another study found a positive relationship between low levels of technological transfer and CO2 emissions in a particular region of China (Mi et al., 2023). Technological transfers may also occur due to the involvement of international parties in decarbonization. Such an example can be found in Indonesia through the Just Energy Transition Partnership (JETP) launched in 2022 (PLN, 2022). With a plan to mobilize $20 billion worth of public and private financing to decarbonize Indonesia's energy sector, various HICs have committed to this endeavor. The second way in which LMICs can achieve the technological effect, albeit more challenging to assess (Altenburg et al., 2022) and less documented, is through technological leapfrogging to low-carbon technologies. China is observed to be one of the few countries to have done this through their advancements in EVs. One study found that several Chinese firms successfully leapfrog ahead of international competition in the field of electromobility, as shares and the quality of patents are improving (Altenburg et al., 2022). Their success demonstrates that policies targeting significant sectoral transformation towards sustainable technologies can foster innovation and create new competitive advantages.

In contrast, the LMIP shows a slower decline in emissions for every increase in GDP after reaching the inflection point than the HIP. This is likely due to the scale effect, which simultaneously takes place, represented by the variable ENE, which is found to be significant. Unfortunately, LMICs are less attentive to the development of low-carbon technologies in expanding their economic growth. This results in significant investments in energy-intensive projects that do not consider carbon emissions (Milindi & Inglesi-Lotz, 2022). Not to mention, emissions have grown at the same rate as GDP in Southeast Asia (Singh, 2024). Here, the rising electricity demand has led to growing emissions as the share of coal in power generation and industrial energy demand has more than doubled since 1990 (Singh, 2024). It may be inferred that even though LMICs may activate the technological effect earlier, emissions reduction is not an autonomous sequence. Progress will remain slow without deliberate action to curb the scale effect.

Current LMICs may not face the same domestic and international conditions for growth as HICs of today have faced (Cole, 2004). External variables have influenced the shape of the curve experienced by LMICs as opposed to that experienced by HICs in the past. Some conditions have led to disadvantages for LMICs in reducing emissions. Overwhelmingly, however, the advantages found in the development of technology have led to conditions that would aid in reducing emissions at a faster rate. The findings illustrate that LMICs today may not need to "grow now" and "clean later," and emissions reductions can be achieved technologically. Most LMICs may lack easy access to necessary technology, which is often expensive even when available. Recommendations should therefore aim to maximize the technological effect and minimize the scale effect.

4. Conclusion

This study is evidence of an EKC for both HICs and LMICs using data from 1990 to 2019. The study employs robust random effects regression to examine carbon emissions relative to economic development in 38 countries, confirming an inverted U-shaped curve, which supports the EKC hypothesis. For HICs, the inflection point is at a higher income level than that of LMICs. This indicates that HICs began reducing emissions only after significant economic growth due to investments in cleaner technologies and strict environmental regulations. In contrast, LMICs have a lower turning point, suggesting these nations will start reducing emissions at a lower income per capita.

The research implies that LMICs can deviate from the "grow now, clean later" approach and prioritize "clean growth" through energy efficiency and renewable energy. This finding is positive news for LMICs, showing there is a path where policymakers can pursue economic objectives without trading off environmental integrity. This study recommends that governments pursue policies that minimize the scale effect using energy-efficient technologies and maximize the technological effect through technological transfers and technological leapfrog.

Local governments have a greater influence on promoting energy efficiency. To support supply-side energy efficiency approaches, the government can help the utilization of digital technologies that enable efficient energy generation and structure regulations to set specific efficiency targets. Meanwhile, the government can launch information campaigns to support demand-side energy efficiency approaches to influence consumers' behavior toward transitioning to more low-carbon alternatives. Additionally, efforts can be made to retrofit buildings to achieve greater energy efficiency. On the other hand, the transfer of technologies in low- and middle-income countries can be done by subsidizing local engineering, procurement, and construction (EPC) companies to acquire advanced, less emission-intensive technology licenses in renewable energy. Since operating energy plants using patented technologies would be costly in the long term, the discovery of nascent, less emission-intensive technologies should be sought out for acquisition.

Regarding technological leapfrogging, local governments would need to encourage technological innovation, which can be done by establishing market mechanisms and research facilities. Second, governments can develop local consortia dedicated to leapfrogging in renewable energy. Creating a separate consortium can alleviate state-owned electricity companies from the financial burdens associated with these projects, allowing existing power agreements to continue without disruption. However, it is essential to recognize that during technological transfers and technological leapfrogging, certain aspects of economic development cannot be bypassed with new technology. Nations will still need to provide the core infrastructure necessary for growth through the development of education, internet access, roads, and other forms of infrastructure, in addition to building strong social institutions. Based on the results and discussions, to further enrich the understanding of EKC and its implications, future research could incorporate spatial approaches by conducting spatially disaggregated analyses at sub-national levels (e.g., provinces or cities) to capture local variations in the EKC. This can reveal how local government policies, economic activities, and environmental conditions influence the EKC at finer spatial scales.

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