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Unravelling the non-linear Impact of Energy Diversification on CO^2 Emissions: Evidence from Emerging Economies

Sidra Rehman[1], Mehtab Arif[2]

[1]Higher Education Department, Punjab, Pakistan
lhreconomist@gmail.com

[2] Lahore College for Women University, Lahore, Pakistan
mehtab.arif@lcwu.edu.pk

[2]ORIC ID: 0009-0009-6324-4540

Abstract

Global warming is a global issue. Goal 13 of the Sustainable Development Goals (SDGs) of the United Nations (UN) emphasizes the reduction of carbon emissions. Fossil fuel energy is a major source of carbon emissions. A transition to a cleaner energy mix can be helpful, however, this dynamic is less explored. Therefore, this study assesses the nonlinear effect of energy diversification on carbon emissions in case of emerging economies including Brazil, India, Russia, Turkiye, China, Mexico and Indonesia. These countries are among the highest polluters. Results suggest that a significant U-shaped relation prevails between carbon emissions and energy diversification. An initial increase in energy diversification lowers the carbon 443emissions. This relation reverses at very high levels of energy diversification. After a certain threshold point, further increase in energy diversification increases the carbon emissions. Growth, trade openness and urbanization are among the other significant contributing factors. Dataset spanning from 1991-2023 is used for estimation. Results of the study suggest a careful selection of energy mix to optimally handle the issue of carbon emissions.

Keywords: carbon emissions, energy diversification, growth, panel regression

1. Introduction

One of the important targets of the Sustainable Development Goals (SDGs) is to reduce carbon emissions among other greenhouse gases. SDG-13 calls for urgent actions to combat the global temperature rise to 1.5 °C as agreed under the Paris Agreement. As to the World Meteorologist Organization (WMO), 2023 to 2025 are the warmest years on the earth.

Energy diversification can be viewed as a strategy for enhancing carbon neutrality by reducing the consumption of fossil fuels and including the renewable energy sources in the energy mix. Previous research has explored the impact of energy diversification on carbon emissions (Nibedita & Irfan, 2024). It can also serve as a source of energy security by reducing the likelihood of disruptions (Solarin et al., 2025). The energy production processes can increase carbon emissions through an extensive fossil fuel mix. Thus, increasing energy diversification by adding green energy sources can support carbon neutrality (Nibedita & Irfan, 2024). Nevertheless, very high levels of energy diversification can amplify carbon emissions (Zahra & Fatima, 2024). This impact can be attributed to the "rebound effect" owing to greater usage of pollution causing inputs during production (Hoang et al., 2024).

Nibedita and Irfan (2024) find in case of following emerging economies including Brazil, Turkiye, Indonesia, India, Mexico, China and Russia that energy diversification has a shrinking impact on carbon emissions. Gozgor et al. (2022) apply the energy diversification index to assess its impact on economic growth and find energy diversification to be an important ingredient that may accelerate or reduce the speed of growth. Hoang et al., (2024) observe a varying effect of energy diversification on carbon emissions in different s in case of data set covering 66 countries from 1995 to 2018. Saboori et al. (2024) find the effect of energy diversification on carbon emissions is conditional to income level of the country. Their study is based on 76 countries and data spanning from 1990 till 2020. They also conclude that urbanization escalates CO^2 emissions. The Environmental Kuznets Curve (EKC) demonstrates a non linear impact of growth and carbon emissions. According to this hypothesis, environmental degradation initially increases with GDP growth and eventually starts falling after a certain threshold. Various studies support this trajectory of the Environmental Kuznet Curve (EKC). Li and Haneklaus (2022) find the presence of EKC in

G7 nations. In addition, they observe that trade openness also exacerbates carbon emissions by fostering production. It uses data from 1979 to 2019. Acaroglu et al. (2023) also validate the presence of EKC in Turkiye. Their study also supports the notion that trade openness amplifies emission levels. Nevertheless, enough literature is not available on examining the nonlinear relation between carbon emissions and energy diversification. Zahra and Fatima (2024) have analyzed the nonlinear effect of energy diversification but it is a time series analyses in case of China based on data from 1990 to 2020.

Thus, to address this research gap, the present study endeavors to examine the nonlinear effect of energy diversification on carbon emissions in 7 emerging economies i.e China, India, Mexico, Russia, Turkiye, Brazil, and Indonesia. These economies had a joint share of energy consumption at 44 % and 48.5 % contribution in global emission levels in 2021 (Nivedita & Irfan, 2024). Therefore, these nations have been included in this study.

2. Methodology

2.1. Energy Diversification Index

The Energy Diversification index (HHI) is estimated using the Herfindahl-Hirschman index. It indicates the level of energy diversification in a country showing its dependency on various energy sources (Nibedita & Irfan, 2024; Saboori et al., 2024).

The inverse of Herfindahl-Hirschman index for energy diversification (HHII) is applied in this study following Nibedita and Irfan (2024) and Zahra and Fatima (2024). The energy diversification index (HHI) is developed by taking the summation of squared shares of different energy sources. It is as follows:

$$HHI_{it} = \sum_{e=1}^{E} q^2{}_{eit}$$

Where e= 1, 2, 3,…, E represents various sources of energy whereas . Taking inverse of the index ensures that the higher values are representing greater energy diversification as follows:-

$$HHII_{it} = \frac{1}{HHI_{it}}$$

2.2. Tests for Unit Root and Panel Cointegration

Cross-sectional Augmented Dickey-Fuller (CADF) test and Cross-sectionally augmented Im-Pesaran-Shin (CIPS) test are applied due to non validity of first generation unit root tests when there is cross section dependence among cross sections.. Pesaran (2007) introduced the following statistics based on the CADF tests.

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF$$

The presence of mixed order of integration warrants the investigation of cointegration status. Pedroni and Kao tests are employed to examine the null hypothesis about the non-existance of cointegration. The existence of cointegration is validated by alternative hypothesis. The diagnostics are carried out, to address cross-sectional dependence, the series are adjusted by subtracting cross-sectional means before estimation, as proposed by Levin et al. (2002).

2.3. Data

This research is based on panel data of E7 nations (China, India, Mexico, Russia, Turkiye, Brazil, Indonesia) for a period that spans from 1991 to 2023. The data for estimation purpose is sourced from the BP Statistical Review (2024) for calculation of energy diversification index (HHII), CO_2 emissions and Population (only for calculation of per capita CO_2). Rest of the variables including the real GDP, Trade Openness and urbanization are obtained thorough the World Development Indicators (WDI). Energy diversification index (HHII) is based on six different sources of energy consumption including coal, oil, gas, hydro, nuclear, and renewables.

Table 1: Detail of Variables

Variable	Symbols	Description	Source
CO_2 Emissions	**CO2K**	Per capita CO_2 Emissions	Author's calculation based on data of total CO_2 emissions (Million tonnes of CO2) & population from BP.
Energy Diversification	**HHII**	Energy Diversification Index	Author's calculation based on data from BP

Squared Energy Diversification Index	**$HHII^2$**	Squared Energy Diversification Index	BP
Growth	**GDP**	GDP (constant 2015 US$)	WDI
Trade Openness	**TO**	Trade (% of GDP)	WDI
Urbanization	**UNP**	Urban population (% of total population)	WDI

The following model is used in this study

$$CO2K\ emissions = f(HHII, HHII^2, GDP, TO, UNP)$$

3. Results

The descriptive statistics is provided in table 2. The mean LNCO2K is 1.252 whereas the mean value of HHII is 2.708. All variables are transformed through natural log except the energy diversification index and its squared term.

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
LNCO2K	231	1.252	.779	-.211	2.874
HHII	231	2.708	.54	1.6	4.162
$HHII^2$	231	7.623	3.033	2.56	17.323
LNGDP	231	27.806	.834	26.388	30.475
LNTO	231	3.751	.374	2.75	4.706
LNUNP	231	4.043	.374	3.25	4.475

Table 3 indicates the correlation analysis. The squared term has highest correlation, which is expected. The preliminary analysis depicts no multicollinearity. But, it shows that the model suffers from the problem of heteroskedasticity (modified wald test) and autocorrelation (Woolridge test for autocorrelation).

Table 3: Pairwise Correlations

Variables	LNCO2K	HHII	HHII2	LNGDP	LNTO	LNUNP
LNCO2K	1.000					
HHII	0.158	1.000				
HHII2	0.168	0.991	1.000			
LNGDP	0.301	-0.279	-0.256	1.000		
LNTO	0.438	0.123	0.139	-0.067	1.000	

LNUNP	0.580	0.463	0.451	0.003	0.102	1.000

In the next step of estimation, the cross sectional dependence is assessed through CD test. Results are mentioned in Table 4 which give indication of strong dependence between the E7 nations. CADF and modified IPS test are suitable in this scenario for assessment of unit root problem in the data.

Table 4: Cross Sectional Dependence & Unit Root Analysis

	CD Test	**CADF**		**CIPS**	
		Level	Δ	Level	Δ
LNCO2K	14.420***	-2.706***	-3.330***	-2.235 *	-4.358***
HHII	8.150***	-1.695	-3.786 ***	-2.282*	-5.447***
$HHII^2$	8.20***	-1.684	-3.814 ***	-2.345**	-5.445***
LNGDP	24.860***	-2.151	-3.007 ***	-1.924	-3.931***
LNTO	4.270***	-2.122	-4.575 ***	-2.567***	-5.634***
LNUNP	24.810***	-2.622***	-2.255*	-1.509	-2.384**
*** p-value<.01, ** p-value<.05& * p-value<.1					

Results of CADF indicate that only lnCO2K is stationary at level whereas the rest of the variables suffer from unit root. All of these variables become stationary at first difference. CIPS test indicate that only LNGDP and LNUNP exhibit unit root but become stationary at first difference.

Table 5: Cointegration Tests

Pedroni		
	Modified Phillips–Perron t	2.7394***
	Phillips–Perron t	1.7632**
	Augmented Dickey–Fuller t	2.5528***
KAO		
	Modified Dickey–Fuller t	-2.6196***
	Dickey–Fuller t	-2.1641**
	Augmented Dickey–Fuller t	-2.0053**
	Unadjusted modified Dickey–Fuller t	-3.1668***
	Unadjusted Dickey–Fuller t	-2.3598***

*Significance levels are indicated as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*

Results of CADF and CIPS show that a mixed stationarity status is prevalent in the data. Therefore, it is essential to check the cointegration status. Pedroni (1999) and Kao (1999) tests are performed for this purpose which indicate cointegration. The results of panel regression using Driscoll and Kraay standard errors are provided in Table 7. This technique is robust to heteroscedasticity, autocorrelation and provides reliable results in presence of dependence among nations. Hausman test favours in validity of random effect model. Outcomes indicates strong evidence of U shaped relation between HHII and LNCO2K, where initially the energy diversification (HHII) generates a negative impact on carbon emissions (LNCO2K). This relation reverses at some point after which further energy diversification (HHII) augments the carbon emissions (LNCO2K).

Table 6: Robustness Check: Panel Regression with Driscoll-Kraay Standard Errors

Variables	**FE**		**RE**	
HHII	-0.767*** (0.076)		-0.765*** (0.091)	
$HHII^2$	0.116*** (0.009)		0.116*** (0.013)	
LNGDP	0.237*** (0.026)		0.235*** (0.038)	
LNTO	0.072*** (0.025)		0.080** (0.039)	
LNUNP	1.291*** (0.123)		1.294*** (0.124)	
c	-9.632***		-9.625***	
No. of Observations	231		231	
Hausman Test		$\chi^2(5)$ =0.29, p-value= 0.9979		

*Significance levels are indicated as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.*
Standard errors are reflected in ().

Growth (LNGDP), trade openness (LNTO) and urbanization (LNUNP) also positively contribute towards carbon emissions (LNCO2K). At higher levels, if energy diversification leads to lower the energy prices, it may generate a rebound effect which leads to higher energy consumption and

ultimately contributing towards carbon emissions. Also, after a certain level, further diversification may result in including non renewable energy sources which will also generate positive effect.

Table 7: Autoregressive Distributed Lag Model (ARDL)

Variables	**Long run**	**Short run**
ecm		-0.178**
		(0.0699)
D.HHII		0.454
		(0.590)
D.HHII2		-0.0859
		(0.114)
D.LNGDP		0.687***
		(0.116)
D.LNTO		0.0571**
		(0.0258)
D.LNUNP		1.622
		(2.306)
L.HHII	-2.162***	
	(0.799)	
L.HHII2	0.337**	
	(0.146)	
L.LNGDP	0.214***	
	(0.0574)	
L.LNTO	0.199***	
	(0.0375)	
L.LNUNP	1.912***	
	(0.304)	
Constant		-1.715**
		(0.668)
Observations	224	224

Significance levels are indicated as *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$.
Standard errors are reflected in().

The robustness of results is examined with the help of Autoregressive Distributed Lag Model (ARDL). Results are provided at Table 8. Findings confirm the U shaped relation between carbon emissions and energy diversification in the long run.

4. Conclusion

Carbon emissions are a source of increasing the temperature levels. The present study is an attempt to explore how energy diversification can possibly affect CO2 emission levels in E-7 countries. Outcomes suggests the presence of a nonlinear U shaped relation between energy diversification and CO2 emissions. Energy diversification is helpful to combat carbon emissions only when diversification is biased towards adding renewable sources of energy. Growth, trade openness and urbanization are some other significant contributing factors.

These results are important to comprehend the diverse and complex relationship of energy diversification in environmental context. Further, research is suggested to examine the threshold levels of energy diversification and position of countries in pre or post threshold levels. A policy recommendation of enhancing the energy diversification after careful examination of potential benefits is suggested.

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