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Examining the Drivers of Carbon Intensity: China's Outward Foreign Direct Investment in the RCEP

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Abstract

This study analyzes the impact of China's outward foreign direct investment (OFDI) on carbon intensity in RCEP countries (2003–2023). Grounded in environmental economics theory, it distinguishes between short-term and long-term effects using a CS-ARDL model that accounts for cross-country interdependence. Results show that while OFDI may temporarily increase carbon intensity due to economic expansion, it significantly reduces carbon intensity in the long run through technology transfer and industrial upgrading. The significant error correction term confirms gradual adjustment toward sustainable equilibrium. These findings support the pollution halo hypothesis in the RCEP context and offer evidence-based insights for promoting green investment under regional cooperation frameworks.

Keywords: *China's OFDI; Carbon Intensity; RCEP; CS-ARDL; Technology Spillover; Environmental Economics*

1. Introduction

Global climate change has emerged as one of the most severe challenges of the 21 century, and controlling carbon emissions the primary source of greenhouse gases has gradually become an international consensus. Against this backdrop, outward foreign direct investment (OFDI), as a key vehicle of economic globalization, exerts profound influences on the carbon emission patterns of both home and host countries through multiple channels, including cross-border capital flows, technology diffusion, and industrial restructuring. As one of the world's largest carbon emitters and an increasingly important source of outward investment, China has experienced a rapid expansion of its OFDI since the early 2000s. China's OFDI stock increased from approximately USD 57.2 billion in 2005 to about USD 2.96 trillion in 2023, with an average annual growth rate of 27.96%. Meanwhile, China's carbon emissions account for nearly 30% of global total emissions. This coexistence underscores the urgency and policy relevance of systematically evaluating the environmental effects of China's OFDI.

The Regional Comprehensive Economic Partnership (RCEP), currently the world's largest free trade agreement in terms of both geographic coverage and economic scale, comprises 15 diverse economies

(Australia, Brunei, Cambodia, China, Indonesia, Japan, Laos, Malaysia, Myanmar, New Zealand, the Philippines, Singapore, South Korea, Thailand, and Vietnam). These member countries differ substantially in their stages of economic development, industrial structures, energy consumption patterns, and environmental regulatory stringency. Such pronounced heterogeneity provides a representative and meaningful empirical setting for examining the environmental impacts of China's OFDI. However, the existing literature on the relationship between FDI and environmental quality has long revolved around the competing "pollution haven" and "pollution halo" hypotheses, often yielding mixed or even contradictory empirical results across different regional contexts.

These inconsistencies can be largely attributed to three factors. First, substantial differences in economic structures and institutional environments across regions may lead to heterogeneous environmental outcomes. Second, variations in sample selection and econometric methodologies may affect empirical findings. Third, and most critically, many existing studies fail to adequately account for cross-sectional dependence and the dynamic adjustment processes underlying the environmental effects of foreign investment. In highly integrated regional economies, macroeconomic shocks, technological spillovers, and policy interactions tend to transmit across national borders, and neglecting these interdependencies may result in biased estimation outcomes.

In light of these considerations, this study focuses on RCEP member countries and systematically examines the impact of China's OFDI on host-country carbon intensity while explicitly accounting for cross-sectional dependence and dynamic heterogeneity. Specifically, this study seeks to address the following core questions: Does China's OFDI exacerbate or alleviate carbon intensity in RCEP countries? Do its environmental effects differ between the short run and the long run? By addressing these questions, this study aims to provide more robust empirical evidence on the environmental consequences of China's outward investment and to offer policy-relevant insights for regional low-carbon transitions and the coordination of outward investment strategies.

2. *Literature Revie*

The relationship between foreign direct investment and environmental outcomes has been extensively examined, yet no consensus has been reached. The dominant theoretical debate centers on the Pollution Haven Hypothesis and the Pollution Halo Hypothesis. The Pollution Haven Hypothesis posits that multinational firms relocate pollution-intensive activities to countries with weaker environmental regulations, thereby increasing host-country emissions (Birdsall & Wheeler, 1993; Copeland & Taylor, 1994). Empirical evidence supporting this hypothesis has been documented mainly in developing economies and resource-dependent regions (Cole et al., 2011; Sapkota & Bastola, 2017; Azam & Khan, 2016). In contrast, the PHoH argues that foreign investment can improve environmental performance through technology transfer, managerial spillovers, and the diffusion of cleaner production practices (Zarsky, 1999; Acheampong et al., 2019; Neves et al., 2020).

To reconcile these competing views, subsequent studies incorporate the Environmental Kuznets Curve (EKC)framework and emphasize the scale, composition, and technique effects as key transmission channels linking investment and environmental quality (Grossman & Krueger, 1995; Begum et al., 2015). In the short run, FDI or OFDI may increase carbon emissions through scale effects associated with expanded production and energy consumption. In the long run, however, composition shifts toward less carbon-intensive sectors and technology spillovers may offset these pressures, leading to improvements in environmental efficiency (Ali et al., 2016; Asumadu-Sarkodie & Owusu, 2017).

Recent empirical studies increasingly highlight the importance of econometric methodology. Traditional panel estimators often neglect cross-sectional dependence and dynamic heterogeneity, which are prevalent in economically integrated regions and may result in biased or inconsistent estimates (Mahadevan & Sun, 2020). To address these issues, second-generation panel techniques—such as the CS-ARDL framework—have been widely adopted. Evidence based on these approaches commonly reveals asymmetric dynamics, whereby foreign investment exacerbates environmental pressure in the short run but contributes to emission reductions in the long run through delayed technology and efficiency effects (Danish et al., 2019; Azam et al., 2022a; Azam et al., 2022b).

With the rapid expansion of China's outward foreign direct investment, a growing body of literature examines its environmental consequences in host countries. Studies focusing on Belt and Road Initiative (BRI) economies suggest that China's OFDI may increase carbon emissions when concentrated in energy- and resource-intensive sectors, particularly in countries with weak environmental regulations (Dong et al., 2022; Liu & Wang, 2022). Conversely, evidence from ASEAN and other emerging economies indicates that China's OFDI can reduce carbon intensity by promoting industrial upgrading and technology diffusion, especially in countries with stronger institutional capacity (Su et al., 2022; Huang et al., 2021).

Despite these advances, three gaps remain. First, relatively few studies investigate China's OFDI within RCEP countries as an integrated economic system, despite strong regional interdependence and exposure to common shocks. Second, cross-sectional dependence arising from global and regional spillovers is often insufficiently addressed. Third, empirical evidence distinguishing between short-run and long-run environmental effects remains limited. To fill these gaps, this study applies a CS-ARDL framework to examine the dynamic impact of China's OFDI on carbon intensity in RCEP member countries, explicitly accounting for cross-sectional dependence, mixed integration orders, and heterogeneous adjustment dynamics.

3. *Methodology*

3.1 Cross-Sectional Dependence Test

This study begins by testing for cross-sectional dependence in the panel data of RCEP countries. Given the significant interconnections among member states in terms of trade structure, energy prices, industrial chain linkages, and policy coordination, changes in variables are often influenced by regional common shocks, leading to synchronous movements. The CD test proposed by Pesaran (2004) confirms the presence of significant cross-sectional dependence, demonstrating that traditional panel estimation methods are no longer appropriate and providing a methodological foundation for adopting the CS-ARDL model, which can account for common factors.

The Pesaran (2004) CD test is employed:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \sim N(0,1) \qquad (1)$$

where $\hat{\rho}_{ij}$ is the residual correlation coefficient between individual i and j. The test results strongly reject the null hypothesis of "no cross-sectional dependence" ($p < 0.01$ for all variables), confirming the existence of significant cross-sectional correlation.

3.2 Panel Unit Root Test

The study proceeds to examine variable stationarity and integration orders. Since macro-level indicators like carbon intensity, OFDI, energy use, and economic development exhibit clear time trends, it is crucial to verify that all variables are I(0) or I(1) and avoid I(2) series that would invalidate long-run estimation. Unlike traditional IPS or LLC tests that ignore cross-sectional dependence, this study applies Pesaran's CIPS test, which filters out common factors and accounts for regional synchrony. The CIPS results confirm a mixed order of I(0) and I(1) variables, satisfying the theoretical requirements for the CS-ARDL model.

The Pesaran CIPS test is used, with the model specified as:

3.2.1 Level Test Specification

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \delta_i \Delta\bar{y}_t + \sum_{j=1}^{p} \theta_{ij}\, \Delta y_{i,t-j} + \varepsilon_{it} \qquad (2)$$

3.2.2 First-Difference Test Specification

$$\Delta^2 y_{it} = \alpha_i + \beta_i \Delta y_{i,t-1} + \gamma_i \overline{\Delta y}_{t-1} + \delta_i \Delta^2 \bar{y}_t + \sum_{j=1}^{p} \theta_{ij} \Delta^2 y_{i,t-j} + \varepsilon_{it} \qquad (3)$$

Where:

• Δy_{it} represents the first difference of the variable
• $\bar{y}_{t-1}$ is the lagged cross-sectional mean, and $\Delta\bar{y}_t$ is the contemporaneous cross-sectional mean of the first differences. These two cross-sectional mean terms are used to capture common trends and shocks among the data of various countries, constituting the core innovation of the CIPS test.
• The term p denotes the optimal lag length determined based on information criteria, employed to ensure that the residual term.
• ε_{it} satisfies the white noise assumption.The null hypothesis of the test is $H_0: \beta_i = 0$, indicating that a unit root is present in all cross-sections and that the series is non-stationary.

3.3 edroni Cointegration Test

After establishing the integration properties of the variables, the Pedroni (1999, 2004) heterogeneous panel cointegration test is applied to assess long-run equilibrium relationships. This method allows intercepts, trends, and long-run coefficients to vary across RCEP countries, making it suitable for a highly heterogeneous panel. The results confirm a stable long-run cointegration relationship among China’s OFDI, carbon intensity, and control variables, forming the basis for the ECM and the estimation of short-run and long-run effects.

The Pedroni test is developed based on the following regression model:

$$y_{it} = \alpha_i + \delta_{it} + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \cdots + \beta_{Mi} x_{Mi,t} + e_{it} \qquad (4)$$

Where: y_{it} the dependent variable (in this study, ln carbon), $X_{mi,t}$ The independent variables (in this study, including ln ofdi,ln industry, ln energy,ln gdp etc.), α_t the individual intercept term (fixed effect), δ_{it} the individual-specific trend term, allowing each country to have its own distinct time trend, β_{Mi} the individual-specific coefficients, which reflect the heterogeneity of the cointegration vectors and represent the core feature of the Pedroni test , e_{it} the regression residual.

3.4 CS-ARDL Model Estimation

The core empirical model using the CS-ARDL (Cross-Sectionally Augmented Autoregressive Distributed Lag) framework. CS-ARDL provides several key advantages for this study. First, by incorporating cross-sectional averages, it effectively controls for unobserved common factors across RCEP countries, reducing bias caused by cross-sectional dependence. Second, it accommodates variables with mixed integration orders (I(0) and I(1)), making it suitable for the macro-panel properties of the dataset. Third, the model simultaneously estimates short-run dynamics and long-run equilibrium effects, allowing this study to distinguish the short-run impact of Chinese OFDI on carbon intensity from its long-run technological or structural effects. Finally, CS-ARDL allows for heterogeneous parameters across countries, which aligns with the substantial differences in development, environmental regulation, and industrial structure within the RCEP. These features make CS-ARDL the most appropriate and robust econometric approach for this study.

The study specifies the following baseline CS-ARDL model:

$$CI_{it} = \alpha_i + \sum_{k=1}^{p} \phi_{ik} CI_{i,t-k} + \sum_{k=0}^{q} \beta 1_{ik} OFDI_{i,t-k} + \sum_{k=0}^{q} \beta 2_{ik} X_{i,t-k} + \gamma_i \bar{CI}_t + \delta_i \bar{OFDI}_t + \theta_i \bar{X}_t + \varepsilon_{it} \quad (5)$$

Where :CI $_{it}$ Carbon Intensity of country i at time t ,OFDI $_{it}$ China's Outward FDI to country i at time t, X $_{it}$ Control Variables (GDP per capital, industry, energy consumption), $\bar{CI}_t$Cross-sectional mean of CI, α_i Country fixed effect, ε_{it} Error term.

Long-term Equation：

$$CI_{it} = \lambda_i OFDI_{it} + \psi_i X_{it} + u_{it} \quad (6)$$

Where: CI $_{it}$ Carbon Intensity of country i at time t, OFDI $_{it}$ China's Outward FDI to country i at time t ,X $_{it}$ Control Variables (GDP per capital, industry, energy consumption), λ_i Long-run OFDI Coefficient , ψ_i Long-run Control Coefficients,u_{it} Error Term (Long-run).

3.5 Error Correction Model (ECM)

Error Correction Model (ECM) to characterize the speed and mechanism of the system's adjustment from short-run deviations back to the long-run equilibrium. The error correction term (ECM_{t-1}) in the ECM reflects the extent to which carbon intensity deviates from the long-run relationship and the speed of its adjustment towards equilibrium. If this term is negative and significant, it indicates the system possesses long-run stability, and the greater the deviation, the faster the return to equilibrium. Since the environmental impacts of OFDI often exhibit time lags.

$$\Delta CI_{it} = \phi_i ECM_{i,t-1} + \sum_{k=0}^{p-1} \pi_{ik} \Delta CI_{i,t-k} + \sum_{k=0}^{q-1} \rho_{ik} \Delta OFDI_{i,t-k} + \sum_{k=0}^{q-1} \eta_{ik} \Delta X_{i,t-k} + \varepsilon_{it} \quad (7)$$

Where: $ECM_{i,t-1}$: Represents the magnitude of the deviation of carbon intensity from the long-run equilibrium relationship in the previous period. Reflects the speed at which the system corrects itself back towards the long-run equilibrium , ϕ_i (Speed of Adjustment Coefficient) It is expected to be negative and statistically significant.

Short-run Dynamic Terms

•π_{ik}Captures the short-run impact of the past changes in carbon intensity on its current change.
• ρ_{ik}Captures the immediate/short-run impact of OFDI on carbon intensity.
•η_{ik} Capture the short-run impacts of the control variables. Note: These coefficients explain short-term fluctuations and do not represent long-term structural effects.
• ε_{it} The white-noise error term, containing unobserved random shocks.

4. *Empiric Alanalysis*

4.1 Cross-Sectional Dependence Test

Given the high degree of economic integration and common external shocks among RCEP countries, cross-sectional dependence is likely to exist in the panel data. To formally examine this issue, Pesaran's (2004) cross-sectional dependence (CD) test is employed.

Table 1: Cross-Sectional Dependence Test Result

Variable	CD Statistic	Sig.
carbon	24.33	***
ofdi	19.29	***
industry	9.33	***
energy	3.61	***
gdp	26.90	***
urban	24.82	***

As reported in Table 1, the CD statistics are large and statistically significant for all variables. For example, the CD statistic for carbon intensity (ln_carbon) reaches 24.33, while that for China's OFDI (ln_ofdi) is 19.29, both significant at the 1% level. Similar results are observed for all control variables. These findings provide strong evidence of cross-sectional dependence, indicating that ignoring common factors may lead to biased estimations. Accordingly, cross-sectionally augmented estimation methods are required.

4.2 Panel Unit Root Test

In the presence of cross-sectional dependence, second-generation panel unit root tests are employed. Specifically, the Cross-sectionally Augmented IPS (CIPS) test proposed by Pesaran (2007) is used to examine the stationarity properties of the variables.

Table 2: Panel Unit Root Test Results (CIPS Test)

Variable	CIPS at Level	Stationary at Level	CIPS at 1st Diff	Stationary at 1st Diff
carbon	-1.363	No	-4.113***	Yes
ofdi	-3.978***	Yes (1%)	-5.607***	Yes
industry	-1.626	No	-4.872***	Yes
energy	-2.144*	Weak (10%)	-4.094***	Yes
gdp	-1.954	No	-3.752***	Yes
urban	-2.809***	Yes (1%)	-1.958	Yes

The results in Table 2 reveal a mixed order of integration. China's OFDI (ofdi) is stationary at levels, with a CIPS statistic of −3.978, exceeding the 1% critical value. Similarly, urban is also stationary at levels. In contrast, carbon, industry, energy, and gdp fail to reject the unit root null at levels but become stationary after first differencing. Importantly, no variable is integrated of order two, satisfying the preconditions for applying the CS-ARDL approach.

4.3 Panel Cointegration Test

Given the mixture of I(0) and I(1) variables, panel cointegration tests are conducted to assess the existence of a long-run equilibrium relationship. The Pedroni (1999, 2004) cointegration test is employed.

Table 3: Panel Cointegration Test Results

Statistic	Value	p-value
Modified PP t	3.2864	0.0005
PP t	−1.3953	0.0815
ADF t	−1.5052	0.0661

As shown in Table 3, several statistics reject the null hypothesis of no cointegration. In particular, the Modified Phillips–Perron statistic is significant at the 1% level, while the Phillips–Perron and Augmented Dickey–Fuller statistics are significant at the 10% level. These results provide empirical evidence of a stable long-run cointegrating relationship among carbon intensity, China's OFDI, and the control variables, justifying long-run estimation within a CS-ARDL framework.

4.4 CS-ARDL Long-Run Estimation Results

The long-run relationship is estimated using a fixed-effects CS-ARDL model that accounts for cross-sectional dependence through cross-sectional averages. China's OFDI enters the model with a two-period lag to capture delayed environmental effects.

Table 4: CS-ARDL Fixed Effects Results (Long-run)

Variables	Coefficient	Std. Err.	t-Statistic	P-value	95% Confidence Interval
ofdi	−0.0074	0.0030	−2.49	0.030	[−0.0140, −0.0009]
Industry	0.7319	0.3459	2.12	0.058	[−0.0293, 1.4931]
energy	0.4803	0.2272	2.11	0.058	[−0.0197, 0.9803]
gdp	−0.4530	0.1591	−2.85	0.016	[−0.8031, −0.1028]
urban	0.1141	0.5850	0.19	0.849	[−1.1735, 1.4017]
_cons	−0.0000	3.3075	−0.00	1.000	[−7.2797, 7.2797]

The estimation results, reported in Table 4, show that lagged OFDI exerts a negative and statistically significant impact on carbon intensity. Specifically, the coefficient of ofdit−2 is −0.0074, significant at the 5% level, indicating that an increase in China's OFDI is associated with a reduction in host-country carbon intensity in the long run. This finding supports the hypothesis that OFDI contributes to environmental improvement through technology spillovers and efficiency gains.

Regarding control variables, energy consumption has a positive and weakly significant effect on carbon intensity, while economic development (gdp) exhibits a negative and statistically significant coefficient (−0.453, 5% level), suggesting that higher income levels are associated with lower carbon intensity. Urbanization does not show a significant long-run effect.

4.5 Short-Run Dynamics and Error Correction Mechanism

To further examine short-run dynamics and the system's adjustment behavior toward long-run equilibrium, this study estimates an error correction model (ECM) derived from the CS-ARDL specification, with results reported in Table 5.

Table 5: Error Correction Model Results

Variables	Coefficient	Std. Err.	t-Statistic	P-value	95% Confidence Interval
ECT(t−1)	−0.2624	0.0602	−4.36	0.001	[−0.3949, −0.1300]
Δ_ofdi	−0.0036	0.0029	−1.24	0.242	[−0.0099, 0.0028]
Δ_industry	−0.1691	0.1473	−1.15	0.275	[−0.4932, 0.1550]
Δ_energy	0.4010	0.0941	4.26	0.001	[0.1939, 0.6080]
Δ_gdp	−0.6344	0.1902	−3.34	0.007	[−1.0531, −0.2158]
Δ_urban	0.7207	1.8436	0.39	0.703	[−3.3370, 4.7784]
_cons	−0.0095	0.0162	−0.59	0.569	[−0.0451, 0.0261]

The coefficient of the error correction term (ECT_{t–1}) is negative (–0.262) and statistically significant at the 1% level. This confirms the existence of a stable long-run equilibrium relationship between carbon intensity, China's OFDI, and the control variables. The magnitude of the coefficient indicates that approximately 26.2% of short-run deviations from the long-run equilibrium are corrected within one period, reflecting a relatively rapid self-adjustment capacity of the system.

The key finding regarding short-run effects is that the coefficient of the short-run change in lagged OFDI (Δ_ofdi) is statistically insignificant (coefficient = –0.0036, p-value = 0.242). This result indicates that in the short run, China's OFDI does not generate an immediate and significant environmental effect on the carbon intensity of host countries. This insignificance may stem from several factors. First, the environmental impacts of OFDI, particularly positive effects arising from technology spillovers and industrial upgrading, often exhibit a noticeable time lag, requiring a longer period to accumulate and manifest. Second, in the initial phase of investment, the economic expansion directly driven by OFDI (scale effect) may temporarily increase energy consumption and emissions, thereby offsetting potential green benefits in the short term. This stands in sharp contrast to the significant carbon reduction effect of OFDI observed in the long-run estimates, clearly revealing a dynamic asymmetry in its environmental impact that is, the coexistence of long-term structural dividends and short-term effect delays.

Regarding control variables, short-term increases in energy consumption (Δ_energy) significantly raise carbon intensity, whereas short-term economic growth (Δ_gdp) contributes to lowering carbon intensity, findings that align with theoretical expectations. Overall, the ECM results clearly distinguish between short-run fluctuations and long-run structural effects, emphasizing the importance of differentiating time dimensions when analyzing the environmental effects of OFDI, thereby further reinforcing the applicability and explanatory power of the CS-ARDL framework in the context of this study.

Conclusion

This study systematically examines the dynamic impact of China's outward foreign direct investment (OFDI) on the carbon intensity of host countries within the Regional Comprehensive Economic Partnership (RCEP) framework, using panel data from 2003 to 2023 and employing a Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) model. The findings reveal significant cross-sectional dependence among RCEP member states, and all variables meet the requirements of mixed integration orders, providing a methodological foundation for the application of the CS-ARDL model. Empirical results indicate that, in the long run, China's OFDI exerts a significantly negative effect on host countries' carbon intensity (coefficient = -0.0074, $p < 0.05$), supporting the applicability of the "Pollution Halo Hypothesis" within the RCEP region. This suggests that China's OFDI contributes to carbon emission reductions in host countries primarily through channels such as technology spillovers, industrial upgrading, and efficiency improvements. Error correction mechanism analysis shows that the system possesses a stable long-term equilibrium adjustment mechanism, with approximately 26.2% of short-term deviations corrected within one year. However, the short-term environmental effect of OFDI is not significant ($p > 0.1$), indicating a notable time lag in its environmental benefits, which are difficult to materialize immediately during the initial investment phase.

Based on these findings, this study proposes the following policy recommendations: Host countries should strengthen their environmental regulatory systems, enhance technological absorption capacity, and guide foreign investment toward green industries. China should promote the green transformation of its "Going Global" strategy by incorporating low-carbon standards into its overseas investment framework. The RCEP cooperation mechanism could explore the establishment of a regional green investment platform to coordinate environmental standards and jointly build a green value chain. At the same time, this study acknowledges several limitations: due to data availability constraints, it does not disaggregate investment industries and carbon emission sources; it does not quantify mechanism factors such as institutional quality; and it does not conduct subgroup tests based on development stages. Future research could further investigate the heterogeneous environmental effects of different types of investments and examine specific transmission mechanisms through mediation effect models, thereby providing more refined policy references for regional green investment cooperation.

References

1. Siddhartha Chib. 1995. “Marginal Likelihood from the Gibbs Output.” Journal of the American Statistical Association. 90: 1313-1321.

2. Alam S, Fatima A, Butt MS (2007) Sustainable development in Pakistan in the context of energy consumption demand and environmental degradation. J Asian Econ18(5):825–837. https:// doi. org/10. 1016/j. asieco. 2007. 07. 005

3. Ali HS, Law SH, Zannah TI (2016) The dynamic impact of urbanization, economic growth, energy consumption, and trade openness on CO2 emissions in Nigeria.

4. Environ Sci Pollut Res 23(12):12435–12443. https:// doi. org/ 10. 1007/ s11356-016- 6437-3

5 Ali R, Bakhsh K, Yasin MA (2019) Impact of urbanization on CO2 emissions in anemerging economy: evidence from Pakistan. Sustain Cities Soc 48:101553. https://doi. org/ 10. 1016/j. scs. 2019.101553

6. Andjarwati T (2020) Impact of energy consumption, and economic dynamics on environmental degradation in ASEAN. Int J Energy Econ Policy 10(5):672–678.https:// doi. org/ 10. 32479/ ijeep. 10366

7. Anser MK, Alharthi M, Aziz B, Wasim S (2020) Impact of urbanization, economic growth, and population size on residential carbon emissions in the SAARC countries. Clean Technol Environ Policy 22(4):923–936. https:// doi. org/ 10. 1007/ s10098- 020- 01833-y

8. Asumadu-Sarkodie S, Owusu P (2017) Carbon dioxide emissions, GDP per capita, industrialization and population: an evidence from Rwanda. Environ Eng Res 22(1):116–124. https:// doi. org/10. 4491/ eer. 2016. 097

9. Cowan WN, Chang T, Inglesi-Lotz R, Gupta R (2014) The nexus of electricity consumption, economic growth and CO2 emissions in the BRICS countries. Energy Policy 66:359–368. https:// doi. org/10. 1016/j. enpol. 2013. 10. 081

10. Danish BMA, Mahmood N, Zhang JW (2019) Effect of natural Dietz T, Rosa EA (1997) Effects of population and affluence on CO2 emissions. Proc Natl Acad Sci 94(1):175–179. https:// doi. org/ 10.1073/ pnas. 94.1.

11. Elfaki KE, Khan Z, Kirikkaleli D, Khan N (2022) On the nexus between industrialization and carbon emissions: evidence from ASEAN+ 3 economies. Environ Sci Pollut Res 29(21):31476–31485. https:// doi. org/ 10. 1007/ s11356- 022- 18560-0

12. Friedman M (1937) The use of ranks to avoid the assumption of normality implicit in the analysis of variance. J Am Stat Assoc32(200):675–701 Ghosh S (2010) Examining carbon emissions economic growth nexus for India: a multivariate cointegration approach. Energy Policy38(6):3008–3014. https:// doi. org/ 10. 1016/j. enpol. 2010. 01. 040

13. Holdren JP, Ehrlich PR (1974) Human population and the global environment: population growth, rising per capital material consumption, and disruptive technologies have made civilization a global ecological force. Am Sci 62(3):282–292
14. Huang J, Li X, Wang Y, Lei H (2021) The effect of energy patents on China's carbon emissions: evidence from the STIRPAT model. Technol Forecast Soc Change 173:121110. https:// doi. org/ 10.1016/j. techf ore. 2021. 121110
15. Pesaran, M.H. and Yamagata, T. (2008), "Testing slope homogeneity in large panels", Journal of Econometrics, Vol. 142 No. 1, pp. 50-93.
16. Prakash, A. (2018), "Boiling point", Finance and Development. Int.Monetary Fund, Vol. 55 No. 3, pp. 22-26. Ren, S., Yuan, B., Ma, X. and Chen, X. (2014), "International trade, FDI and embodied CO2 emissions: a case study of China's industrial sectors", China Economic Review, Vol. 28, pp. 123-134.
17. Salahuddin, M., Alam, K., Ozturk, I. and Sohag, K. (2018), "The effects of electricity consumption, economic growth, financial development and foreign direct investment on CO2 emissions.