Contents list available at CBIORE journal website

International Journal of Renewable Energy Development

Journal homepage: https://ijred.cbiore.id

Research Article

The polluters' paradox: Exploring the impact of green transition potential on carbon emissions in top ten emitters

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Abstract. Understanding the determinants of CO2emissions and the real possibilities for energy transition is essential to supporting sustainable growth, particularly for the world's ten largest emitters. These countries present a notable paradox: despite high economic complexity and efforts towards green transition, their emissions remain among the highest, revealing a persistent structural dependence on carbon-intensive activities and thus calling into question their effective capacity to sustainably reduce their emissions. This study fills a gap by simultaneously analyzing polluting specialisation and green transition potential using two indicators derived from economic complexity: the Brown Lock-In Index (BLI) and the Green Complexity Potential (GCP). The analysis, conducted on a panel of the ten largest CO2 emitters between 1999 and 2023 using FMOLS and PCSE estimators, shows that a carbon-intensive economic structure significantly increases emissions, while a higher green complexity potential contributes to their reduction. Furthermore, while economic growth and the use of non-renewable energies intensify environmental pressure, the consumption of renewable energies plays an important mitigating role. By highlighting the combined effect of polluting specialization and transition potential, this study offers decision-makers a structured understanding of the sources of their emissions and the real margins for transitioning to a low-carbon economy.

Keywords: CO2 Emissions; Brown Lock-In; Green Complexity Potential

Received: 27th Nov 2025; Revised: 7th January 2026; Accepted: 25th January 2026; Available online: 10th Feb 2026

1. Introduction

The ten largest CO2emitters provide a central analytical framework for understanding global carbon pollution dynamics. According to the Global Carbon Project (2024), these economies account for nearly 70% of global emissions, highlighting both their historical and current responsibility for environmental degradation. Their influence also extends through their strategic role in international trade and integration into diversified global value chains, where they are distinguished by the production and export of manufactured goods and energy resources. Economic literature has long established the link between trade structure and CO2emissions, particularly via the composition effect (Grossman and Krueger, 1991; Gozgor, G,2017; Antweiler *et al.*, 2001, Daghbagi, 2025). Moving beyond traditional approaches based on aggregate trade indicators such as nominal trade openness (Jebli *et al.*, 2016; Ansari *et al.*, 2020), the economic complexity framework (Hidalgo and Hausmann, 2009) provides a finer measure of the technological sophistication of exports and the underlying productive capabilities. This approach reveals that products of similar value can have vastly different carbon footprints, giving rise to a growing literature linking economic complexity and CO2emissions (Stojkoski *et al.*, 2023; Hamrouni *et al* 2025, Daghbagi, Hasni and Ben Jebli,2025). The major emitters are characterized by particularly high economic complexity indices. Japan (3rd), Germany (4th), and South Korea (5th) rank among the most technologically sophisticated economies, while the United States (13th) and China (19th) maintain significant productive sophistication (OEC, 2025). Literature suggests that higher complexity is generally associated with lower emissions due to specialization in high-value-added, low-carbon goods (Rafique *et al.*, 2022; Chu and Le, 2022; Daghbagi et El., 2025; Ouerghi and Hasni, 2025). According to standard economic complexity theory, the expected outcome is clear: more complex and diversified economies should exhibit lower emission levels as they move away from carbon-intensive activities. However, the empirical reality of the ten largest emitters contrasts sharply with this theoretical prediction. Despite their high level of productive sophistication, these economies continue to account for a disproportionate share of global CO_2 emissions. This discrepancy between predicted and observed emission patterns is what we refer to as the 'polluter's paradox

At the same time, these countries have shown increasing commitment to energy transition. Studies indicate that a higher share of renewables and improvements in energy mix quality significantly reduce long-term emissions (Mohsin *et al.,* 2021; Ehigiamusoe and Dogan, 2022; Li and Haneklaus, 2022). However, the effectiveness of this transition varies according to

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structural characteristics: technologically advanced large economies tend to benefit more from this dynamic (York and McGee, 2017; Thombs, 2017). China has emerged as a global hub for green technologies (solar panels, electric vehicles, batteries) (IEA, 2023), Germany has demonstrated the feasibility of large-scale renewable deployment through its "Energiewende," and the United States has undertaken a strategic shift with the Inflation Reduction Act (2022)[*], stimulating domestic green technology production (Rhodium Group, 2023). South Korea focuses on batteries and hydrogen, Japan pursues a balanced path between renewables and nuclear, and India and Indonesia rapidly expand renewable capacity driven by energy security and local pollution concerns. Even oil-exporting economies such as Russia, Saudi Arabia and Iran are making slow progress, mainly through pilot projects.

Thus, despite high economic complexity generally being associated with lower CO2emissions and a clear commitment to energy transition, these countries remain paradoxically among the largest global polluters. This paradox exposes a critical gap in the literature: classical measures of complexity, which consider total exports without carbon differentiation, do not fully explain the current situation of major emitters. In parallel, given the technological sophistication of these economies, it is crucial to assess their real transition potential, i.e., their current productive capacities and scope for diversification into green sectors.

This apparent coexistence of high economic complexity, growing green investment, and persistently high CO_2 emissions highlights a critical limitation of conventional economic complexity measures. By aggregating exports without distinguishing their environmental content, standard indices may mask carbon-intensive specializations behind high complexity scores. As a result, advanced economies may simultaneously display strong technological sophistication and remain structurally locked into emission-intensive production patterns.

To address this, we adopt a more nuanced approach that evaluates both the current productive structure and its direct links to CO_2 emissions, as well as the potential for diversification into sophisticated green products. We introduce two complementary indicators derived from economic complexity: the Brown Lock-In Index (BLI) (Andres *et al.*, 2023), which measures structural dependence on carbon-intensive exports, and the Green Complexity Potential (GCP) (Mealy and Teytelboym, 2022), which assesses a country's proximity to complex green technologies in which it is not yet competitive. These indicators were chosen to overcome a key limitation of traditional economic complexity metrics, such as the Economic Complexity Index (ECI), which assess productive sophistication without distinguishing its environmental content, a shortcoming that may mask carbon-intensive specialization behind high complexity scores, a phenomenon central to the "polluter's paradox." Their combined use thus offers a finer and more policy-relevant analysis of emission trajectories than aggregate complexity measures alone. Such an approach is essential for guiding strategic decisions, as the green transition could fundamentally reshape global competitive dynamics in favour of countries already capable of producing advanced green goods.

Empirically, our study is the first to integrate these two dimensions for the ten largest CO_2 emitters. Within this framework, our empirical strategy examines their effects separately to accurately quantify each dimension's contribution to emissions. A high BLI indicates structural dependence on carbon-intensive exports and is theoretically expected to exert upward pressure on emissions. In contrast, a high GCP reflects a latent capacity to diversify into sophisticated green products, revealing a structural potential for future emission reductions. We explicitly distinguish "brown" sophistication, associated with carbon-intensive products, from "green" sophistication, which signals transition potential. We further assess these economies' ability to leverage existing productive capabilities to drive a transition toward a low-carbon economy.

Our analysis covers the period 2000–2023, using the FMOLS estimators, complemented by PCSE estimators for more robust results. Control variables in this study include GDP, which captures the effect of overall economic activity on emissions (Grossman & Krueger, 1995; Kongkuah, 2023), renewable and non-renewable energy consumption, reflecting the impact of different energy sources on CO_2 emissions (Hasni, 2025; Cao *et al.*, 2022), and urbanization, accounting for demographic and spatial concentration effects on emissions (Wang *et al.*, 2021; Sarwar *et al.*, 2024). Meanwhile, the Brown Lock-In Index (BLI) and Green Complexity Potential (GCP) are the main variables of interest, used to assess the dichotomy between carbon-intensive specialization and the potential for green structural transformation.

The remainder of the paper is structured as follows: Section 2 presents the literature review, Section 3 presents the empirical analysis, Section 4 presents the methodology and results, and Section 5 concludes with policy recommendations tailored to the major emitters.

2. Literature review

The literature on energy transition initially emphasized the importance of investments in renewable energy as a lever for reducing CO2emissions, before gradually incorporating the concepts of Brown Lock-In (BLI) and Green Complexity Potential (GCP), highlighting their roles in structural and potential decarbonization. Empirical studies using international panels, such as those by Mohsin *et al.* (2021) and Ehigiamusoe and Dogan (2022), indicate that increasing renewable energy consumption constitutes an effective long-term decarbonization strategy. Li and Haneklaus (2022) confirm that, in G7 countries, technological specialization in low-carbon energy systems promotes emissions reduction, while Dóci, Vasileiadou, and Petersen (2015) show, through the analysis of Renewable Energy Communities in the Netherlands, that social innovation and energy decentralization also contribute to reducing dependence on centralized fossil fuel systems. Moreover, Bergougui and Ben-Salha (2025) and Hamrouni (2025) highlight those stringent environmental policies, which include support for renewable energy, catalyze innovation and strengthen regulatory frameworks, thereby creating a favorable environment for the adoption of green technologies. However, Baz *et al.* (2022) caution that the manufacturing processes for complex green technologies, such as solar panels, can themselves be carbon-intensive, emphasizing the need to decarbonize the entire supply chain to fully realize environmental benefits.

Simultaneously, a growing body of literature on energy transition moves beyond traditional approaches, focused on trade volumes or income levels, by applying the economic complexity framework. This approach demonstrates that the sophistication and structure of a country's export basket are essential determinants of CO2emission trajectories (Hidalgo and Hausmann, 2009). This literature review thus shows that a

[*] Inflation Reduction Act of 2022, Pub. L. No. 117-169, 136 Stat. 1818.

country's environmental performance is not solely a function of its overall economic development but is strongly conditioned by its position between two poles: the persistence of Brown Lock-In in carbon-intensive specializations and a latent transition capacity, captured by Green Complexity Potential. A country may therefore be trapped in a high BLI, reflecting carbon-intensive specializations, or benefit from a high GCP, enabling it to diversify its exports toward sophisticated green products.

A dominant finding in this literature is that a country's dependency on a limited range of low-complexity, high-emission exports, quantified as a high BLI, constitutes a primary structural driver of CO2emissions and a significant source of transition risk. Andres *et al.* (2023) pioneer this measure, demonstrating that a high BLI, characteristic of petrostates such as Iraq and Libya with undiversified, low-complexity brown specializations, is strongly associated with higher CO2emissions and a diminished capacity to adapt to a decarbonizing global economy. This brown lock-in is not confined to resource exporters. At a subnational level, Pérez-Hernández *et al.* (2021) show that Mexican states with productive structures distant from the green product space are effectively locked into high-carbon development trajectories. Similarly, Tian *et al.* (2023) and Qayyum *et al.* (2021) illustrate how specialization within global value chains, particularly in low- and medium-technology manufacturing, creates carbon-intensive lock-in, increasing both domestic and embodied emissions.

In direct contrast, the concept of GCP has emerged as a crucial metric for assessing a country's capacity to overcome this inertia and transition toward a sustainable export profile. GCP measures the proximity of a country's existing productive capabilities to sophisticated green products it has yet to export, effectively quantifying feasible pathways for green diversification (Mealy and Teytelboym, 2022). A high GCP indicates lower transition risk and a greater inherent ability to reduce emissions through structural change. For instance, Stojkoski *et al.* (2023) show that synergistic advancement in trade, technology, and research complexities, captured by the notion of potential, is a powerful driver of emissions reduction. Countries such as Sweden and Austria, which excel across these dimensions, successfully avoid brown lock-in by transforming their productive structures. This is further corroborated by Lee *et al.* (2023), who find that in high-risk, often developing economies, export diversification systematically builds foundational green complexity, but only when the diversification aligns with a country's adjacent possible, as measured by GCP.

Strategic investment in renewable energy and green innovation is key to realizing a country's GCP and actively breaking brown lock-in. The generation and export of renewable energy technologies represent a direct manifestation of high green complexity. Mealy and Teytelboym (2022) classify such technologies as complex green products, whose specialization correlates with lower emissions. The adoption of renewables is also a critical enabling condition: Bergougui and Ben-Salha (2025) demonstrate that stringent environmental policies, often supporting renewables, catalyse the energy transition by stimulating innovation and strengthening regulation, thereby operationalizing a country's green potential. Nevertheless, Baz *et al.* (2022) warn that manufacturing complex green technologies, such as solar panels, can itself be carbon-intensive, highlighting the need to decarbonize the full green supply chain to maximize emissions reduction.

The interplay between BLI and GCP shapes a country's strategic outlook. Literature suggests that a high BLI combined with a low GCP represents a double exposure to economic and environmental risks (Andres *et al.*, 2023). Conversely, a low BLI, as seen in France (Peñasco, 2025), implies lower transition risk, while a high GCP provides a roadmap for future green growth. Policymakers are therefore encouraged to move beyond generic green investment, employing data-driven tools like GCP to identify and target high-potential green sectors, such as renewable energy systems, hydrogen, and environmental monitoring, through R&D incentives, green industrial policies, and aligned trade strategies (Grazini and Guarini, 2023; Can *et al.*, 2022; Pérez-Hernández *et al.,* 2021).

In conclusion, the literature consistently confirms that the sophistication of exported products and the nature of specialization are paramount. A high BLI is a robust predictor of elevated and persistent CO2emissions, reflecting structural dependence on polluting activities. Conversely, a high GCP captures a country's capacity to mitigate these emissions by diversifying into sophisticated, low-carbon export sectors, with renewable energy playing a pivotal role. Therefore, jointly analysing BLI and GCP provides a nuanced framework for understanding a country's pathway to decarbonizing its economy and trade.

However, despite these empirical advances, few studies simultaneously integrate Brown Lock-In and Green Complexity Potential to examine the paradox of the most polluting countries: they often undertake significant energy transition efforts while being among the most complex economies in terms of their export structure. This gap underscores the need for an analytical framework combining these two concepts to better understand the structural constraints and potential decarbonization trajectories of the top ten emitters.

3. Empirical Analysis and Methodology

3.1. Data and Variable Description

The Empirical analysis is based on a panel of the top ten CO2 emitting countries[*] over the period 1999–2023. The data were obtained from reliable international sources such as the World Bank and the International Energy Agency (IEA). Table 1 presents the list and description of the variables used in the model.

The energy variables (CO_2, RE, and NRE), from the EIA, 2024, and the GDP and URB variables from the WDI, 2024, allow us to distinguish the effects of different energy sources and other relevant factors on CO2emissions. In addition, the Brown Lock-In Index (BLI) and Green Complexity Potential (GCP), provided by the Green Transition Navigator (GTN, 2024), capture the carbon intensity of the economic structure and the potential for green diversification, respectively. These indices are constructed using product-level trade data (HS6) from the BACI database and follow the methodologies developed by Andres *et al.* (2023) for the BLI and Mealy & Teytelboym (2022) for the GCP, situating them within the economic complexity framework.

The Brown Lock-In Index (BLI) measures a country's degree of specialization in and dependence on "brown" sectors. Formally, it calculates the total revealed comparative advantage (RCA) a country holds in products that are both carbon-intensive ("brown") and of low complexity. A higher BLI score signals a deeper structural lock-in of a comparative advantage

[*] China, Germany, India, Indonesia, Iran, Japan, Republic of Korea, Russia, Saudi Arabia, USA.

Table 1
Variables and data source

Variable	Description	Unit	Source
CO2	Carbon dioxide emissions	Million metric tons (MMt)	WDI, 2024
GDP	Gross Domestic Product	Constant USD	WDI, 2024
URB	Urban population	Number of people living in urban areas	WDI, 2024
RE	Renewable energy	Quadrillion BTU	IEA, 2024
NRE	Non-renewable energy	Quadrillion BTU	IEA, 2024
BLI	Brown Look Index	Index	GTN,2024
GCP	Green Complexity Potential	Indicator of potential green complexity	GTN,2024

based on low-complexity, high-emission production, representing a significant barrier to decarbonization and a source of long-term transition risk (Andres *et al*., 2023). In our model, an increase in BLI corresponds to a strengthening of this locked-in, carbon-intensive productive structure.

The Green Complexity Potential (GCP) quantifies a country's latent capacity to transition by estimating the proximity of its existing productive capabilities to sophisticated green products it does not yet export. A higher GCP indicates that a country's industrial ecosystem is closely related to complex green technologies, indicating its potential to diversify into complex green products. Our core finding, a significant negative relationship between GCP and emissions, confirms that this latent potential acts as a lever for structural decarbonization (Mealy & Teytelboym, 2022).

These two indices are complementary: the BLI captures the inertia of the current carbon-intensive structure, while the GCP captures the opportunity for green structural change. In our econometric specifications, both indices are transformed using the natural logarithm, allowing coefficients to be interpreted as elasticities, i.e., the percentage change in CO_2 emissions associated with a 1% change in either brown lock-in or green potential. For complete technical details on the construction of these indices, we refer the reader to the seminal works cited above and the Green Transition Navigator, documentation.

3.2. Descriptive statistics and correlation analysis

Table 2 presents the descriptive statistics of the panel reveal important characteristics of the studied variables. The mean of LNCO2 (7.08) is slightly higher than its median (6.78), indicating a positive skewness and the presence of high extreme values. Similarly, LNRE and LNNRE show that some high observations increase the mean, while LNBLI exhibits negative skewness and LNGCP is nearly symmetric. The standard deviation shows moderate dispersion for LNCO2, LNGDP, and LNURB and greater variation for LNGCP (1.41), reflecting substantial differences in green complexity potential among countries. Kurtosis coefficients indicate that LNRE and LNBLI are slightly leptokurtic, LNGCP is platykurtic, and the other variables are slightly flattened. Jarque-Bera tests reject the normality hypothesis for all variables except LNURB, confirming the presence of skewness and extreme values. These results justify the use of logarithmic transformations and robust methods such as FMOLS to produce reliable and interpretable coefficients.

The analysis of the figure1 reveals a contrasting dynamic between the carbon-intensive economic structure and green complexity in the top CO2-emitting countries. The LNBL graph shows that the carbon economic structure remains relatively high and stable over the observed period, oscillating between 3 and 4 on the logarithmic scale. However, a significant drop is recorded around 2016–2017, followed by a gradual recovery. This volatility illustrates the persistence of reliance on fossil fuels despite transition efforts.

Simultaneously, the LNGCP graph indicates a positive evolution of green complexity, characterized by an overall increasing trend with notable peaks around 2015 and 2020, exceeding the level of 4.5. This progression suggests that emitting countries are progressively developing more sophisticated technological capacities in green production and environmental innovations.

The comparison of the two indicators highlights that the energy transition process remains incomplete: although green complexity is improving, reflecting innovation and diversification efforts toward sustainable production, the carbon-intensive economic structure is still relatively high, indicating continued dependence on fossil-based activities. technologies, the carbon economic structure remains deeply entrenched, reflecting the structural challenges these economies face in decarbonizing their productive systems

Table 2
Descriptive Statistics

	LNCO2	LNGDP	LNURB	LNRE	LNNRE	LNBLI	LNGCP
Mean	7.084730	28.27203	18.51279	0.945879	2.944851	3.706999	3.398974
Median	6.779806	28.01988	18.48475	0.915216	2.652452	4.025192	3.496508
Maximum	9.408835	30.72490	20.62994	2.849855	5.096331	5.141664	5.433722
Minimum	5.525097	26.21963	16.32659	-0.002300	1.313535	0.693147	0.693147
Std. Dev.	1.007971	1.194452	1.020250	0.826462	0.960932	1.230914	1.410090
Skewness	0.700604	0.414167	0.190953	0.864997	0.635897	-1.062843	-0.188220
Kurtosis	2.518999	2.217649	2.376248	3.020073	2.462185	3.345287	1.801382
Jarque-Bera	22.86192	13.52303	5.572064	31.18003	19.86153	48.31003	16.44157
Probability	0.000011	0.001157	0.061665	0.000000	0.000049	0.000000	0.000269
Observations	250	250	250	250	250	250	250

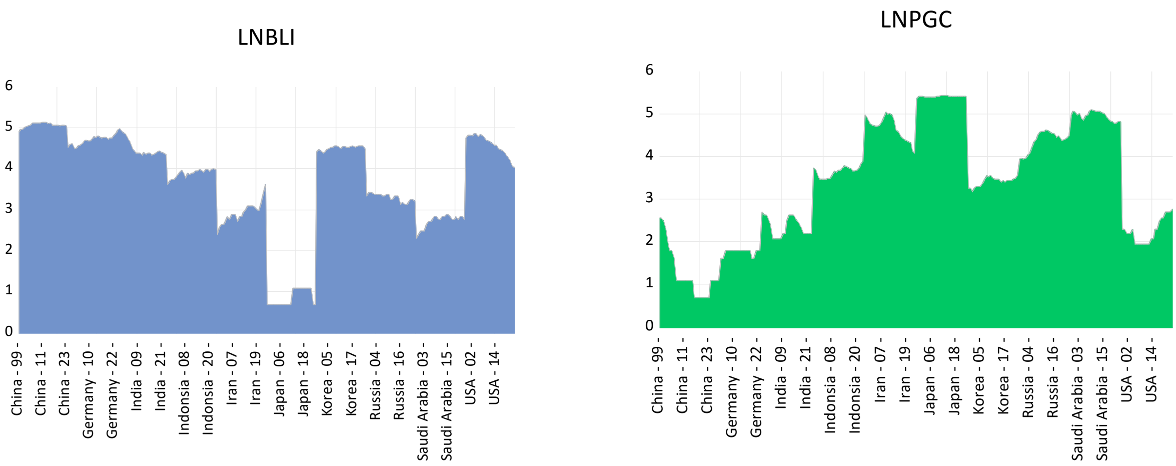

Fig. 1. Evolution of BLI and GCP

Table 3 presents the correlation matrix for model 1 reveals overall positive relationships among the explanatory variables. GDP (LNGDP) shows a strong correlation with both renewable (LNRE, 0.894) and non-renewable energy consumption (LNNRE, 0.851), indicating that economic growth is accompanied by increased energy use from both sources. This is consistent with the literature emphasizing the energy dependence of expanding economies.

Similarly, urban population (LNURB) is moderately correlated with GDP (0.634) and more strongly with non-renewable energy (0.721), suggesting that greater urbanization tends to increase energy demand, often met by non-renewable sources. By contrast, the Brown Look Index (LNBL) exhibits relatively weak correlations with the other variables (below 0.40), implying that it captures an environmental dimension distinct from economic and energy dynamics.

Overall, although some correlations are relatively high, particularly between LNGDP, LNRE and LNNRE, they remain below the critical threshold of 0.90. Therefore, while there is no evidence of severe multicollinearity, the Variance Inflation Factor (VIF) test is still necessary to confirm the robustness of the econometric results.

The results of the variance inflation factor (VIF) shown in Table 4 confirm the absence of significant multicollinearity between the explanatory variables. The VIF values range between 1.23 and 7.54, with an average of 4.84, well below the commonly accepted threshold of 10 in econometric analysis.

The relatively higher VIF values for LNRE (7.54), LNNRE (6.57), and LNGDP (6.21) indicate moderate correlation among these variables, consistent with the correlation matrix findings. This is expected, as economic growth is closely linked to both renewable and non-renewable energy consumption. However, these values remain within acceptable limits and do not threaten model validity.

Conversely, LNURB (2.66) and LNBLI (1.23) exhibit low VIF values, suggesting that they contribute unique and independent information to the regression. These results confirm that the model does not suffer from multicollinearity

Table 3
Correlation Matrix

	Model 1						**Model 2**				
	LNGDP	LNURB	LNRE	LNNRE	LNBL		LNGDP	LNURB	LNRE	LNNRE	LNGCP
LNGDP	1					LNGDP	1				
LNURB	0.634	1				LNURB	0.634	1			
LNRE	0.894	0.536	1			LNRE	0.894	0.536	1		
LNNRE	0.851	0.721	0.867	1		LNNRE	0.851	0.721	0.867	1	
LNBL	0.275	0.398	0.307	0.323	1	LNGCP	-0.561	-0.590	-0.514	-0.521	1

Table 4
Multicollinearity test

	Model 1			**Model 2**	
	VIF	**1/VIF**		**VIF**	**1/VIF**
LNRE	7.54	0.132	LNRE	7.42	0.134
LNNRE	6.57	0.152	LNNRE	6.68	0.149
LNGDP	6.21	0.161	LNGDP	6.20	0.161
LNURB	2.66	0.376	LNURB	2.86	0.353
LNBLI	1.23	0.810	LNGCP	1.73	0.578
Mean VIF	4.84		Mean VIF	4.84	

issues, ensuring that the FMOLS estimates are robust and interpretable.

The analysis of the correlation matrix for model 2 highlights expected relationships among the model variables. LNGDP, LNURB, LNRE, and LNNRE exhibit positive and relatively high correlations with each other (ranging from 0.53 to 0.89), reflecting the structural link between economic growth, urbanization, and energy consumption, whether renewable or non-renewable.

In contrast, LNGCP shows negative correlations with all other explanatory variables, notably with LNGDP (-0.561), LNURB (-0.590), LNRE (-0.514), and LNNRE (-0.521). This inverse relationship suggests that countries with higher productive capacity tend to emit less CO2, likely due to more efficient resource use and better technological and institutional integration. This finding is consistent with the economic rationale that improving productive capacities supports more sustainable, less polluting growth (Daghbagi *et al* 2025b).

The Variance Inflation Factor (VIF) results further confirm the absence of problematic multicollinearity among the explanatory variables. VIF values range from 1.73 to 7.42, with a mean of 4.84, well below the commonly accepted threshold of 10. The higher VIF values for LNRE (7.42), LNNRE (6.68), and LNGDP (6.20) reflect moderate interdependence between economic and energy components, without compromising model stability. The VIFs for LNURB (2.86) and LNGCP (1.73) are low, indicating that these variables provide unique and independent information in explaining CO2 emissions.

Overall, these results indicate that the model is econometrically sound, and no variable suffers from excessive multicollinearity, ensuring the reliability of the FMOLS estimates. All estimations were conducted using Stata 17 software.

3.3. Empirical Model

To examine the determinants of CO2 emissions, two empirical models are proposed:

$$CO2_{it} = f(GDP_{it}, URB_{it}, RE_{it}, NRE_{it}, BLI_{it}) \quad (1)$$

$$CO2_{it} = f(GDP_{it}, URB_{it}, RE_{it}, NRE_{it}, GCP_{it}) \quad (2)$$

where *i* denotes the country and *t* the time period.

The first model evaluates the role of the carbon-intensive economic structure (BLI), whereas the second model incorporates the green complexity dimension (GCP) to capture the potential for ecological transition. In addition to BLI and GCP, both models include gross domestic product (GDP), urbanization (URB), renewable energy (RE), and non-renewable energy (NRE) as explanatory variables.

In accordance with econometric theory, all model variables have been log-transformed to reduce the influence of extreme values and to linearize potential non-linear relationships among them. This transformation is essential to ensure the validity of econometric estimates, as it allows for a better interpretation of the coefficients in terms of elasticity and improves the overall robustness of the model.

Accordingly, the two previously defined models can be expressed in their logarithmic form as follows:

$$LNCO2_{it} = \alpha_0 + \alpha_1 LnGDP_{it} + \alpha_2 LNURB_{it} + \alpha_3 LNRE_{it} + \alpha_4 LNNRE_{it} + \alpha_5 LNBLI_{it} + \varepsilon_{it} \quad (3)$$

$$LNCO2_{it} = \beta_0 + \beta_1 LnGDP_{it} + \beta_2 LNURB_{it} + \beta_3 LNRE_{it} + \beta_4 LNNRE_{it} + \beta_5 LNGCP_{it} + \mu_{it} \quad (4)$$

Where ε_{it} *and* μ_{it}represents the error term.

Given the long-term nature of the relationships studied, estimation is based on the Fully Modified Ordinary Least Squares (FMOLS) method. Developed by Pedroni (2000, 2001), this approach corrects for endogeneity and serial correlation biases in cointegrated relationships. FMOLS provides unbiased and asymptotically efficient estimators, particularly when the variables exhibit a stable long-term relationship.

Before applying the FMOLS method, several preliminary econometric tests are necessary to ensure the robustness and validity of the results. First, unit root tests are conducted to check the stationarity of the time series for each panel variable, using methods such as CIPS (Cross-sectionally Augmented IPS) and CADF (Cross-sectionally Augmented Dickey-Fuller,1979). Second, cointegration tests are performed to determine whether a long-term relationship exists among the model variables, employing the Pedroni (2004) and Kao (1999) tests. In addition, multicollinearity and correlation analysis are carried out to verify that the explanatory variables are not highly correlated, thereby avoiding bias in the estimated coefficients. Finally, error diagnostics are checked to detect heteroskedasticity and autocorrelation in the residuals, which are automatically corrected by the FMOLS procedure. These steps collectively ensure that applying FMOLS to the logarithmic models yields robust and interpretable estimates of the determinants of CO2 emissions.

3.4. Cross-sectional dependence tests

Before estimating the models using the FMOLS method, it is essential to check for cross-sectional dependence among the panel units, i.e., whether shocks experienced by one country may affect the others. The results of the CD test are reported in Table 5.

Table 5
CD tests

Model 1				Model 2			
Test	Statistic	d.f.	Prob.	Test	Statistic	d.f.	Prob.
Breusch-Pagan Chi-square	308.134	45	0.000	Breusch-Pagan Chi-square	290.278	45	0.000
Pearson LM Normal	26.682		0.000	Pearson LM Normal	24.800		0.000
Pearson CD Normal	-2.087		0.036	Pearson CD Normal	-1.443		0.148
Friedman Chi-square	7.725	24	0.999	Friedman Chi-square	10.743	24	0.990
Frees Q	2.449			Frees Q	1.923		
Asymtotic critical values*	1%	0.194		Asymptotic critical values*	1%	0.194	
	5%	0.134			5%	0.134	
	10%	0.103			10%	0.103	

*Frees (1995) Q distribution
*Frees (1995) Q distribution

For Model 1, the Breusch-Pagan test ($\chi^2 = 308.13$, $p < 0.01$), Pearson LM (26.68, $p < 0.01$), and Pearson CD (-2.08, $p = 0.0368$) indicate significant cross-sectional dependence, whereas the Friedman ($p = 0.9993$) and Frees Q (2.45) statistics do not, likely due to their lower power in small panels.

For Model 2, the Breusch-Pagan test ($\chi^2 = 290.28$, $p < 0.01$) and Pearson LM (24.80, $p < 0.01$) also suggest cross-sectional dependence, while the Pearson CD (-1.44, $p = 0.1489$), Friedman ($p = 0.9907$), and Frees Q (1.92) are not significant. These results indicate that, despite some differences among the tests, there is moderate to significant correlation among countries in both models. Consequently, it is recommended to use second-generation unit root and cointegration tests (CIPS and CADF) prior to FMOLS estimation to ensure the robustness and validity of the econometric results. Given the presence of moderate to significant cross-sectional dependence in both models, it is necessary to adopt second-generation econometric tests to examine the stationarity of the time series and the existence of long-run relationships among the variables. Classical unit root and cointegration tests do not account for cross-sectional dependence and could yield biased results in this context.

Therefore, the panel series will be subjected to CIPS (Cross-sectionally Augmented IPS) and CADF (Cross-sectionally Augmented Dickey-Fuller) unit root tests, while long-term cointegration will be tested using Pedroni and Kao tests, which are specifically designed for panels with cross-sectional correlations. This approach ensures the robustness of the FMOLS estimates and allows for reliable interpretation of the determinants of CO2 emissions.

The presence of cross-sectional dependence indicates the profound economic integration of the world's major emitters. These countries are closely interconnected through global value chains, highly interdependent energy markets and shared processes of technological diffusion (World Trade Organization, 2023). This interdependence means that a macroeconomic shock, technological innovation or climate policy implemented in one of these countries could significantly impact the emission trajectories of others, primarily via trade, energy and technology (IEA, 2021; IRENA, 2023). Consequently, national decarbonisation strategies based on reducing brown lock-in (BLI) or activating green complexity potential (GCP) cannot be designed in isolation. These strategies would be more effective if they were coordinated internationally, particularly with regard to the harmonisation of industrial standards, energy policies, and the joint financing of critical green technologies. This would help to mitigate the effects of carbon leakage and maximise the positive outcomes of cross-border spillovers.

3.5. Panel unit root test

Table 6 presents the results of the second-generation panel unit root tests, including both CIPS and CADF statistics, provide a comprehensive assessment of the stationarity properties of the series while accounting for cross-sectional dependence among the countries. The results indicate that none of the variables is stationary in levels, whether considering an intercept only or both intercept and trend, as the test statistics are not significant and the associated p-values exceed conventional thresholds. However, after first differencing, all variables except for the urbanization variable (LNURB) become stationary, with CIPS and CADF statistics highly significant at the 1% level. Specifically, LNCO2, LNGDP, LNRE, LNNRE, LNBLI, and LNGCP are integrated of order one, I(1), meaning that they achieve stationarity only after first differencing. In contrast, LNURB is stationary in levels, I(0), indicating that urbanization exhibits a stable pattern without stochastic trend.

Table 6
CIPS and CADF panel unit root test results

Variable	CIPS		CADF		Variable	CIPS		CADF	
	Intercept	trend	Intercept	trend		Intercept	trend	Intercept	Trend
LNCO2	-0.828	-2.270	- 1.015 (0.992)	-2.416 (0.359)	DLNCO2	-3.897***	-4.168***	-3.447*** (0.000)	-3.793*** (0.000)
LNGDP	-1.914	-2.161	-1.768 (0.489)	-1.998 (0.855)	DLNGDP	-3.076***	-3.144***	- 2.122 (0.119)	-2.250 (0.581)
LNURB	-2.244***	-2.136	-2.598*** (0.003)	-2.402 (0.377)	DLURB	-2.777***	-2.948***	-1.974 (0.234)	-1.849 (0.941)
LNRE	-1.254	-2.581	- 0.769 (0.999)	-1.816 (0.954)	DLNRE	-4.879***	-4.977***	-2.864*** (0.000)	-3.071*** (0.005)
LNNRE	-2.278	-2.725	-1.451 (0.844)	-2.500 (0.260)	DLNNRE	-4.163***	-4.415***	-3.465*** (0.000)	- 3.616*** (0.000)
LNBL	-1.357	-1.845	-1.008 (0.993)	-1.698 (0.981)	DLNBL	-4.106***	-4.550***	-2.724*** (0.001)	-3.165*** (0.002)
LNGCP	-1.697	-2.040	-1.206 (0.965)	-1.897 (0.920)	DLNGCP	-4.056***	-4.406***	-2.772*** (0.000)	-3.141*** (0.002)

Note: ***, and * are statistical significance at the 1%, and 10% levels, respectively. The critical values associated with the 1% and 10% thresholds for the CIPS statistics without trend are -2.21, -2.33, -2.57 respectively, while the critical values for the specification with trend are -2.73, -2.86, -3.1. For the CADF test, we use the T-bar statistic, and the associated p-values are indicated in parentheses.

Table 7
Panel Cointegration tests results

	Model 1				Model 2			
Pedroni tests								
Within dimension					**Within dimension**			
	Panel Statistic	Prob.	Weighted Statistic	Prob.	Panel Statistic	Prob.	Weighted Statistic	Prob.
V	1.269	0.102	-1.702	0.955	1.217	0.111	-1.422	0.922
Rho	0.632	0.736	0.768	0.779	0.407	0.658	0.751	0.773
PP	-2.425***	0.007	-3.827***	0.000	-2.755***	0.002	-4.423***	0.000
ADF	-2.510***	0.006	-4.279***	0.000	-2.876***	0.002	-3.363***	0.000
Between dimension					**Between dimension**			
	Groupe Statistic	Prob.			Groupe Statistic	Prob.		
Rho	2.199	0.986			1.866	0.969		
PP	-2.585***	0.004			-4.157***	0.000		
ADF	-2.552***	0.005			-4.468***	0.000		
Kao Test	t-Statistic	Prob.			t-Statistic	Prob.		
ADF	-3.336***	0.000			3.163***	0.000		
Westerlund Test								
Variance ratio	-1.621	0.052			-2.102**	0.017		

These findings confirm the appropriateness of applying panel cointegration tests to examine long-run relationships between CO2 emissions and their economic, energy, and environmental determinants, including economic growth, urbanization, renewable and non-renewable energy consumption, carbon-intensive economic structures, and green complexity, thereby ensuring the validity of subsequent FMOLS estimations.

Given that the majority of the variables are integrated of order one, I(1), while urbanization is stationary in levels, I(0), it is appropriate to proceed with panel cointegration analysis to investigate the existence of long-run equilibrium relationships among the variables. Establishing cointegration is essential because it ensures that the estimated relationships between CO2 emissions and their economic, energy, and environmental determinants are not spurious and that the long-term coefficients obtained from subsequent FMOLS estimations are reliable. Therefore, the next step involves applying Pedroni, Kao, and Westerlund (2007) cointegration tests to determine whether a stable long-run relationship exists across the panel of countries under study.

The second-generation unit root tests (Table 6) further confirm that urbanization (LNURB) is stationary in levels [I(0)], while the remaining variables are integrated of order one [I(1)]. Within the FMOLS panel framework, the inclusion of this I(0) variable does not affect the validity of the estimations, provided that cointegration among the I(1) variables is confirmed, which is the case in our models (Table 7).

3.6. Cointegration tests

The cointegration test results (Pedroni, Kao, and Westerlund) for both models, as presented in Table 7, confirm the existence of a stable long-run relationship between CO2 emissions and the explanatory variables. For Model 1, both the PP and ADF statistics are significant in the "within" and "between" dimensions, and the Kao test further supports the presence of cointegration, while the Westerlund test provides additional, albeit marginal, evidence. Similarly, for Model 2, the PP and ADF statistics are strongly significant, and the Kao and Westerlund tests jointly confirm robust cointegration across the panel, indicating that the variables move together in the long run and justifying the application of FMOLS to estimate reliable long-term coefficients.

4. Results and Discussion

4.1. FMOLS Estimation Results

This section presents and discusses the long-term effects of economic, energy, and environmental determinants on CO2 emissions, estimated using the Fully Modified Ordinary Least Squares (FMOLS) method. It highlights the roles of economic growth, energy consumption, and environmental innovation in shaping CO2 emission trends across the countries studied.

The results of the cointegration tests confirm the existence of a stable long-run relationship between CO2 emissions and the explanatory variables, thereby justifying the use of the FMOLS method. FMOLS accounts for potential endogeneity and serial correlation in panel data, providing robust and unbiased estimates of the long-term coefficients. Table 8 reports the FMOLS estimation results for both models. Model 1 focuses on the role of the carbon-intensive economic structure (BLI), while Model 2 incorporates the green complexity dimension (GCP) to capture the potential for ecological transition. In addition to BLI and GCP, both models include gross domestic product (GDP), urbanization (URB), renewable energy (RE), and non-renewable energy (NRE) as explanatory variables.

The table presents the estimated coefficients, standard errors, t-statistics, and significance levels, offering a comprehensive overview of the relationships between CO2 emissions and their economic, energy, and environmental determinants over the period 1999–2023.

The FMOLS estimation results, reveal the long-term effects of economic growth, energy, and environmental factors on CO2 emissions for both models. In Model 1, GDP has a positive and significant coefficient of 0.037, indicating that a 1% increase in GDP is associated with a 0.037% increase in CO2

Table 8
FMOLS Estimations

Model 1 : $CO2_{it} = f(GDP_{it}, URB_{it}, RE_{it}, NRE_{it}, BLI_{it})$					**Model 2**: $CO2_{it} = f(GDP_{it}, URB_{it}, RE_{it}, NRE_{it}, GCP_{it})$				
Variable	Coeff.	Std. Error	t-Stat.	Prob.	Variable	Coeff.	Std. Error	t-Stat.	Prob.
LNGDP	0.037***	0.013	2.728	0.006	LNGDP	0.074***	0.013	5.698	0.000
LNURB	0.069***	0.003	18.220	0.000	LNURB	0.085***	0.003	25.991	0.000
LNRE	-0.175***	0.010	-16.481	0.000	LNRE1	-0.201***	0.010	-18.346	0.000
LNNR	0.976***	0.012	80.593	0.000	LNNRE	0.955***	0.010	87.616	0.000
LNBLI	0.012***	0.004	2.806	0.005	LNGCP	-0.062***	0.010	-5.991	0.000
R^2	0.997				R^2	0.997			
$\bar{R}^2$	0.996				$\bar{R}^2$	0.997			

emissions, reflecting the carbon-intensive nature of economic growth. This finding is consistent with the broader literature, confirming that economic growth is a primary driver of pollution (Daghbagi *et a*l., 2025a; Hamrouni, 2025; Zohra, K. 2025; Chen *et al*, 2024; Devianto *et al*, 2025, Zohra *et al*, 2025). The positive relationship between GDP growth and CO_2 emissions underscores the established idea that addressing global climate change and environmental degradation requires a decisive transition toward sustainable economic development (Wang, 2025). Urbanization has a positive and significant effect of 0.069, suggesting that, in the countries studied, Higher urban population shares are associated with higher emissions due to concentrated economic activity. Cities bring together a massive number of people, industries, cars, and construction projects in one place. All this concentrated activity requires huge amounts of energy, which mostly comes from burning fossil fuels like coal, oil, and gas, releasing large amounts of greenhouse gases. The positive relationship between urban population and CO2 emissions aligns with established literature, confirming that population growth is a significant driver of environmental pollution (Thi Mai *et al.,* 2024; Xuan, 2024; Hoa *et al.,* 2024). Renewable energy exhibits a strong negative effect of -0.175, confirming its role in reducing emissions, while non-renewable energy has a strong positive coefficient of 0.976, highlighting the continued reliance on fossil fuels. This finding reinforces the established consensus that increasing the use of renewable energy reduces CO2 emissions (Daghbagi *et al.*, 2025; Ehigiamusoe and Dogan, 2022; Li and Haneklaus, 2022; Mohsin *et al.*, 2021; Kahouli *et al*, 2025). The carbon-intensive economic structure (BLI) positively affects emissions with a coefficient of 0.012, indicating that economies with higher carbon intensity produce more CO2.

In Model 2, the results are broadly consistent, with GDP positively influencing emissions (0.074), urbanization remaining positive (0.085), renewable energy reducing emissions (-0.201), and non-renewable energy strongly increasing emissions (0.955). Importantly, the green complexity potential (GCP) shows a significant negative coefficient of - 0.062, suggesting that countries with higher green technological capacity tend to reduce CO2 emissions, highlighting the importance of ecological transition and innovation in mitigating environmental impacts.

Although FMOLS corrects for endogeneity in cointegrated panels, we note that reverse causality between CO_2 emissions and Green Complexity Potential (GCP) may exist; hence, the estimated coefficients should be interpreted as long-run associations rather than strictly causal effects. Overall, the FMOLS results confirm that while economic growth, urban population and fossil fuel consumption drive CO2 emissions, renewable energy and green complexity play a crucial role in curbing environmental degradation, and these findings are robust given the high R^2 values of 0.997 in both models.
Overall, these results underscore the importance of economic, energy, and environmental factors in determining CO2 emissions and demonstrate that the transition toward a greener economy, captured by GCP, can play a significant role in reducing the carbon footprint of the studied countries.

4.2. Robustness test

To ensure the robustness of the long-run relationships previously estimated, the study applies the Panel-Corrected Standard Errors (PCSE) method, which accounts for cross-sectional dependence and heteroskedasticity across countries. This approach provides efficient and unbiased standard errors, allowing for more reliable inference in panel data models.

The robustness analysis using the Panel-Corrected Standard Errors (PCSE) estimator confirms the stability of the relationships identified in the FMOLS models. The results, reported in Table 9, show that all coefficients remain significant at the 1% level and maintain the expected theoretical signs, supporting the reliability of the long-run relationships previously established.

In Model 1, GDP continues to exert a positive and significant influence on CO2 emissions, with a coefficient of 0.031, indicating that economic growth remains a key driver of environmental degradation. Urbanization (0.122) also has a positive and highly significant effect, confirming the FMOLS. Renewable energy exhibits the expected negative and significant effect on CO2 emissions (–0.141), confirming its mitigating role in CO2 reduction. Conversely, the coefficient of non-renewable energy (1.008) show that it remains the strongest positive contributor, underscoring the continued dependence on fossil fuels. The positive and statistically significant coefficient of the Brown Lock-In Index (BLI) (1.002) confirms that economies that are specialised in carbon-intensive activities have persistently higher levels of CO_2 emissions. This finding is consistent with that of Andres *et al.* (2023), who identified BLI as a major structural determinant of emissions and a key indicator of transition risk, particularly in economies that are highly dependent on brown exports. Similar evidence is also observed at subnational and sectoral levels, where productive structures far removed from green products generate persistent carbon lock-in trajectories (Pérez-Hernández *et al.*, 2021; Qayyum *et al.,* 2021; Tian *et al.*, 2023).

Table 9
PCSE Estimations

Model 1 : $CO2_{it} = f(GDP_{it}, URB_{it}, RE_{it}, NRE_{it}, BLI_{it})$					***Model 2***: $CO2_{it}(GDP_{it}, URB_{it}, RE_{it}, NRE_{it}, GCP_{it})$				
Variable	Coeff.	Std. Error	t-Stat.	Prob.	Variable	Coeff.	Std. Error	t-Stat.	Prob.
LNGDP	0.031***	0.008	3.96	0.000	LNGDP	0.016***	0.007	2.23	0.000
LNURB	0.122***	0.006	19.95	0.000	LNURB	0.113***	0.005	19.23	0.000
LNRE	-0.141***	0.012	-11.12	0.000	LNRE1	-0.141***	0.011	-11.99	0.000
LNNR	1.008***	0.010	98.50	0.000	LNNRE	1.0175***	0.009	105.69	0.000
LNBLI	0.224***	0.003	6.47	0.000	LNGCP	-0.030***	0.003	-9.26	0.000
c	1.002	0.204	4.90	0.000	C	1.758	0.205	8.56	0.000
R^2	0.997				R^2	0.997			
$\bar{R}^2$	0.996				$\bar{R}^2$	0.996			

**** indicate significance at 1%*

In Model 2, the coefficients follow a similar pattern. GDP (0.016) remains positively related to emissions but with a smaller magnitude, while urbanization (0.113) continues to increase CO2 emissions significantly. Renewable energy maintains a negative and significant effect (–0.141), while non-renewable energy (1.0175) again demonstrates a strong and positive impact. Most importantly, the negative and highly significant Green Complexity Potential coefficient of (–0.030) emphasises the pivotal role of latent green productive capabilities in reducing emissions. This finding is consistent with the work of Mealy and Teytelboym (2022), who demonstrate that proximity to complex green products is a viable means of decarbonisation through structural change. It is also consistent with the findings of Stojkoski *et al.* (2023) and Lee *et al.* (2023), who emphasise that export diversification only becomes environmentally beneficial when it builds on existing adjacent capabilities. Accordingly, our findings complement studies focusing on renewable energy and green innovation (Mohsin *et al.*, 2021; Ehigiamusoe & Dogan, 2022; Li & Haneklaus, 2022) by demonstrating that green complexity potential is a key structural driver of emissions reduction.

The main contribution of this study is the joint analysis of Brown Lock-In (BLI) and Green Complexity Potential (GCP) within a unified empirical framework. Unlike the existing literature, which typically examines these dimensions separately, our results demonstrate that they coexist and have opposing effects on CO_2 emissions, particularly in the world's top ten emitting countries. This distinction enables us to move beyond the limitations of aggregate measures of economic complexity, providing an explanation as to why advanced economies can simultaneously possess a high potential for green technological capabilities while remaining durably anchored in carbon-intensive productive structures.

5. Conclusion and policy recommendations

This study aimed to analyse the paradox that characterises the world's ten largest CO2emitters: despite high economic complexity and growing commitments to green transition, these economies remain among the main contributors to global emissions. By using two complementary indicators from the economic complexity framework, the Brown Lock-In Index (BLI) and Green Complexity Potential (GCP), this research provides a more accurate reading of the structural determinants underlying their environmental performance. This approach goes beyond traditional measures of complexity by distinguishing between 'brown' sophistication, which is highly emitting, and the true potential for green transition within the same productive system. Methodologically, the use of the FMOLS and PCSE estimators, has made it possible to establish robust long-term relationships between productive structure, green potential and CO2emissions over the period 1999-2023. The inclusion of GDP, renewable and non-renewable energy consumption, and urbanisation as control variables reinforced the empirical robustness of the results.

The findings of this study are clear. On the one hand, economies that are heavily locked into carbon-intensive production structures, characterised by high BLI, are experiencing a significant increase in emissions, confirming the existence of structural lock-in that limits environmental progress. On the other hand, a high GCP contributes to reducing emissions, highlighting that countries with close access to complex green technologies can mobilize their productive capacities to mitigate carbon pressure. Our quantified result establishing GCP as a decarbonization lever necessitates a strategic overhaul of industrial policies. Rather than supporting green technologies indiscriminately, policymakers should focus on "adjacent green branches" the complex green products closest to a country's existing productive capabilities, identifiable through Product Space-type analytical tools. By targeting these niches, countries can maximize the impact of their green potential. Policies should prioritize innovation funding, including collaborative R&D and demonstration projects, and create pioneering markets through instruments such as public procurement and regulatory standards tailored to these high-potential products. Furthermore, dynamic monitoring of GCP should serve as a policy compass, enabling authorities to adjust measures continuously and evaluate their effectiveness in strengthening green productive capabilities. In this way, GCP moves from being a potential indicator to an operational tool for guiding emission reductions, providing concrete insight into how much mitigation is feasible through green diversification. These results outline a dual-lever strategy for overcoming the 'Polluters' Paradox': reducing dependence on carbon-intensive activities while activating the potential for green diversification. For countries with high brown lock-in, particularly some fossil fuel exporters, the priority is to manage the transition away from carbon-intensive sectors and diversify the productive base. This involves targeted 'de-lock-in' measures, such as phasing out fossil fuel subsidies, introducing a carbon price to finance a just transition, and enforcing strict energy efficiency and eco-design standards. At the same time, the GCP must guide the strategic development of green industries that are closely linked to existing skills, for example by redirecting petrochemical expertise towards green hydrogen or carbon capture and storage. For technologically advanced economies with high green potential, the challenge is to accelerate the activation of this potential by promoting the creation of markets for green technologies, supporting collaborative R&D, and strengthening innovation ecosystems. Investment in critical infrastructure, smart grids, charging stations and energy storage devices, is also essential to enable the large-scale deployment of these new technologies. In short, the success of the low-carbon transition depends on an integrated approach combining proactive industrial policy, informed by the BLI and GCP, with energy and fiscal policies that provide incentives to overcome the Polluters' Paradox of the top ten emitters.

While our findings provide novel insights into the role of BLI and GCP in major emitters, several limitations should be noted and suggest avenues for future research. Our analysis focuses on the ten largest CO_2 emitters, which together account for almost 70% of global emissions. While this focus is justified by the relevance of the 'polluter's paradox,' it introduces a selection limitation: the results may not be directly generalizable to smaller or developing economies, which could exhibit different structural characteristics, energy dependencies, and stages of transition. Moreover, given the diversity among the top emitters, it is plausible that the magnitude and even the direction of BLI and GCP effects differ across countries. While our estimates reflect average long-term relationships, future studies could explore country-specific dynamics using methods allowing for heterogeneous effects, such as random coefficient models, subgroup analyses, or comparative case studies. Accounting for such heterogeneity will further clarify how structural lock-in and green potential shape decarbonization pathways in diverse national contexts. Extending the BLI and GCP framework to a broader and more heterogeneous set of countries would also enable testing the robustness of our findings and examining how contextual factors such as development level, resource endowments, and trade openness moderate the influence of brown lock-in and green potential on emissions. In addition, a promising area for future research is the dynamic interaction between BLI and GCP. Introducing an interaction term into a unified model would allow testing whether strong green potential can offset the negative effects of carbon lock-in. This could reveal whether economies that are heavily dependent on carbon-intensive activities, yet possess high green potential, are better able to overcome structural lock-in and accelerate their energy transition. Such analyses would provide more nuanced insights into decarbonization pathways by linking structural risk with transformation opportunities, thereby guiding more targeted and effective policy interventions.

Data availability: The datasets used during the current study are available from the corresponding author on reasonable request.

Compliance with ethical standards

Ethics approval and consent to participate Not applicable.

Consent to publish Not applicable.

Competing interests the authors declare that they have no competing interests.

Acknowledgment: This research was funded by the General Directorate of Scientific Research & Innovation, Dar Al Uloom University, through the Scientific Publishing Funding Program.

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