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Research article

Investigating the pollution haven hypothesis in the top-5 FDI recipient countries in Africa: Evidence from heterogeneous panel data with sharp and smooth transitions

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ABSTRACT

In recent decades, industrial expansion has become a priority for many African countries, often advancing under less stringent environmental regulations. This trend has exacerbated pollution levels and biodiversity loss, posing significant threats to the continent long-term sustainability. This study contributes to the discourse on environmental economics by examining the Pollution Haven Hypothesis (PHH) within Africa, using panel data from 1970 to 2022 for the five leading recipients of Foreign Direct Investment (FDI). Departing from previous methodologies, it adopts heterogeneous panel data modeling that integrate both sharp and gradual structural shifts through the recently developed Fourier Seemingly Unrelated Regressions Mean Group (F-SURMG) estimator. This refined approach effectively tackles heterogeneity, structural shift, and cross-sectional dependence, ensuring a more comprehensive and robust estimation of the relationship between FDI and environmental degradation, as measured by the ecological footprint (EFP). The results reveal that FDI inflows significantly contribute to environmental degradation in Africa, supporting the PHH. Specifically, the F-SURMG estimates indicate that a 1 % increase in FDI leads to a 1.2 % rise in EFP. However, country-specific effects vary widely. While Nigeria and Kenya exhibit a strong positive influence between FDI and EFP, Egypt, Morocco, and South Africa show no statistically significant impact, likely due to higher GDP per capita, renewable energy adoption, and increasingly stringent regulatory frameworks. To enhance environmental sustainability in FDI-driven African economies, policymakers must tighten industrial emission regulations to ensure foreign investors comply with environmental standards. Offering tax incentives for green investments can redirect FDI toward sustainable sectors, promoting eco-friendly industrial expansion.

1. Introduction

Foreign direct investment (FDI) has emerged as a key catalyst for global economic integration, with developing regions—particularly Africa—experiencing robust increases in inflows. Sub-Saharan Africa (SSA), for instance, saw FDI rise from $829 million in 1970 to $1.3 billion by 1987, driven in part by liberalization reforms of the 1980s (WDI, 2025). This trend continued, with inflows reaching $15.4 billion in 2001 and approximately $40.6 billion by 2023 (WDI, 2025). These capital movements have contributed to economic growth and fiscal stability (Solarin and Al-Mulali, 2017b; Adeel-Farooq et al., 2021; Oyadeyi et al., 2024).

Existing literature highlights the tendency of pollution-intensive industries to relocate from countries with stringent environmental regulations to those with more relaxed policies, thus increasing pollution levels (Ferrara et al., 2015; Adeel-Farooq et al., 2021; Chirilus and Costea, 2024). In many developing economies, particularly in Africa, the interplay of lower labor costs, abundant natural resources, and weak environmental oversight fosters increased production at reduced operational expenses (Solarin and Al-Mulali, 2017b; Apergis et al., 2022; Avazdahandeh, 2024; Oyadeyi and Oyadeyi, 2025a). These economies often attract FDI concentrated in resource-intensive sectors such as oil refining (Javorcik and Wei, 2004; Shofwan and Fong, 2011; Xie & Zhang, 2024) and mining (Oyadeyi and Oyadeyi, 2025b), which may

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exacerbate environmental degradation. This dynamic intensifies the debate between two competing hypotheses. The Pollution Haven Hypothesis (PHH) which argues that weak regulation effectively "invites" environmentally harmful investments, exacerbating local pollution. In contrast, the Pollution Halo Hypothesis (PHL) suggests that multinational firms may bring advanced technologies, higher environmental standards, and better practices, which could, in turn, reduce pollution over time (Solarin and Al-Mulali, 2017b; Murshed, 2023; Wen et al., 2022; Oyadeyi and Oyadeyi, 2025a, 2025b). Understanding which dynamic dominates in the African context remains a critical policy and research question.

Addressing this question, numerous studies have investigated the link between FDI and environmental degradation, primarily through the lens of the PHH (Dong et al., 2012; Dagar et al., 2022; Kisswani and Zaitouni, 2023). Empirical evidence at the global level suggests that foreign investments often contribute to increased pollution levels in host countries (Solarin and Al-Mulali, 2017b; Adeel-Farooq et al., 2021; Dagar et al., 2022; Kisswani and Zaitouni, 2023), with some researchers identifying the regulatory chill effect—where host governments avoid implementing stricter environmental policies to maintain their attractiveness to investors (Dong et al., 2012). Conversely, advocates of the PHL argue that FDI enhances environmental standards by facilitating technological advancements (Al-Mulali and Tang, 2013), improving productivity (Mert and Bölük, 2016), and fostering cleaner industrial practices (Zugravu-Soilita, 2017).

However, empirical evidence from African context tends to support the PHH, with a 1 % increase in FDI inflows linked to a 0.03 % (Abbas et al., 2023) and 0.21 % (Oumarou et al., 2024) rise in CO2 emissions, emphasizing FDI's environmental cost. Nevertheless, some research challenges these findings, arguing that FDI inflows in the region do not consistently align with either the pollution haven or pollution halo hypotheses, suggesting a more complex interaction between investment and environmental outcomes (Boamah et al., 2023). These divergent perspectives underscore the importance of re-evaluating the environmental consequences of FDI—particularly within Africa's five FDI recipients: Egypt, South Africa, Morocco, Nigeria, and Kenya.

These countries are selected based on two key arguments. First, they have experienced substantial FDI growth since 1970, with foreign investments increasing nearly tenfold in Nigeria and exceeding tenfold in Kenya, Egypt, Morocco, and South Africa (WDI, 2025). These expansions were essentially driven by deliberate policy efforts, including privatization programs and structural adjustments introduced in the 1980s under the IMF's framework to attract foreign investment and stimulate economic growth. Moreover, according to the African Development Bank AfDB (2021) report, these five countries collectively attracted approximately 80 % of Africa's total investments between 2011 and 2020. Meanwhile, they collectively account for approximately 70 % of Africa's total carbon dioxide (CO_2) emissions [measured in million tons of CO_2 equivalent (Mt CO_2e), excluding emissions and removals from Land Use, Land-Use Change, and Forestry (LULUCF)] since 1970 (WDI, 2025), underscoring their substantial environmental footprint. In response, they have enacted various climate policies to mitigate pollution and promote sustainability, such as Egypt's National Climate Change Strategy 2050 (Climate Change Laws of the World, 2022), Kenya's National Climate Change Framework Policy (2016) (Ministry of Environment and Natural Resources, 2016), Nigeria's National Climate Change Policy (2021–2030) (FAO, 2021), Morocco's National Plan Against Climate Change (2030) (Climate Change Laws of the World, 2022), and South Africa's Climate Change Act 22 (2024) (Centre for Environmental Rights, 2024). While these initiatives aim to foster sustainable practices, their effectiveness in mitigating the environmental impact of FDI remains uncertain, raising concerns about the balance between economic growth and ecological sustainability objectives.

Second, these countries hold significant regional influence and serve as key economic and investment hubs on the African continent. Beyond the continent growing environmental concerns, these nations shape Africa's trade policies and investment flows as pivotal economic powerhouses. South Africa, as the leading economy in the Southern African Development Community (SADC), directs industrial investments and economic policies that influence its neighboring nations. Egypt plays a central role in North Africa, dictating trade and industrial strategies that impact regional resource allocation. Nigeria, West Africa's dominant economy, drives oil-based trade policies that affect pollution-heavy industries across SSA. Kenya, a key economic gateway in East Africa, balances industrial expansion with environmental sustainability through its urban development policies. As trendsetters, their regional leadership dictates policy alignment, influencing FDI strategies and environmental regulations across Africa.

Given their economic significance and environmental footprint, the top five FDI-recipient countries in Africa provide a strategic vantage point for reevaluating the trade-offs embedded in FDI-driven sustainable development. As major recipients of foreign capital and key contributors to regional emissions, they raise two fundamental research questions: (1) Do capital inflows entrench environmentally harmful industrial practices, or do they support a transition toward greener, more resilient economies? and (2) Is the environmental impact of FDI uniform across these countries, or does it vary according to each nation's institutional context, policy landscape, and development capacity?

This study advances the literature by examining the environmental impact of FDI in Africa's top investment destinations—an area that remains notably understudied, despite the breadth of work on the FDI–pollution nexus. These countries, while central to the continent's economic growth, continue to grapple with severe environmental degradation, raising enduring concerns associated with the PHH. To the best of our knowledge, no prior research has directly investigated the environmental implications of FDI within this specific group of countries through the lens of the PHH. By filling this empirical gap, the study offers timely insights to inform more sustainable and context-sensitive investment strategies across Africa.

Moreover, most existing studies addressing the environmental effects of FDI in Africa rely on linear econometric models, which are often ill-suited to capture complex nonlinear dynamics. Structural changes—such as policy reforms, economic shocks, or technological progress—can alter model parameters over time, reducing the reliability and precision of traditional estimators. Yet, methods that explicitly accommodate such temporal shifts remain underdeveloped in panel data literature. To address this gap and respond to our two research questions, we apply a novel methodological framework not yet explored in the FDI–pollution literature: the Fourier Seemingly Unrelated Regressions (F-SUR) and Fourier Seemingly Unrelated Regressions Mean Group (F-SURMG) estimators, recently introduced by Guliyev (2023). These techniques enhance estimation by capturing heterogeneity, both gradual and abrupt structural changes, and cross-sectional dependence. By incorporating flexible Fourier terms, they offer a more dynamic and context-sensitive understanding of the relationship between FDI and environmental quality.

Finally, beyond its main objective, this study also contributes to the understanding of the income-environment relationship, commonly known as the Environmental Kuznets Curve (EKC) hypothesis. The EKC hypothesis describes an inverted U-shaped relationship between environmental pollution and economic growth. Initially, environmental quality deteriorates as economies expand, but it begins to improve once per capita income reaches a critical threshold. Numerous empirical studies have validated this pattern across different samples and pollution indicators (Apergis and Ozturk, 2015; Aslan et al., 2018; Chang, 2009; Destek et al., 2018; Yilanci et al., 2022). However, the relationship has rarely been examined through the lens of factor heterogeneity and structural changes—critical dimensions that remain largely unexplored in existing research. To sum up, the results confirm that FDI inflows significantly contribute to environmental degradation in Africa, supporting the PHH. However, further analysis reveals substantial country-specific variations, highlighting the need for context-specific sustainability policy responses.

The structure of this paper is as follows: **Section 2** presents the literature review, **Section 3** outlines data and methodology, **Section 4** discusses results and interpretations, and **Section 5** offers conclusions and policy recommendations.

2. Literature review

2.1. Theoretical literature

Theoretical literature suggests that FDI can exert both detrimental and beneficial effects on a host country's environment. Its influence on pollution operates primarily through three mechanisms: scale, composition, and technique effects. The scale effect arises when FDI-induced economic growth leads to increased industrial activity and, consequently, higher emissions (Grossman and Krueger, 1991). The composition effect reflects the nature of industries attracted by FDI—if capital flows target pollution-intensive sectors, environmental degradation may intensify (Zugravu-Soilita, 2017). Conversely, the technique effect posits that multinational corporations often transfer cleaner, more efficient technologies, thereby enhancing environmental performance in host countries (Shahbaz et al., 2016; Shahbaz et al., 2020).

On one hand, the scale and composition effects support the PHH, where firms relocate to nations with weaker environmental policies, leading to increased pollution (Solarin and Al-Mulali, 2017b; Wen et al., 2022). Regulatory frameworks drive this phenomenon, as countries with lax laws may lower standards to attract investment (Dong et al., 2012). This regulatory chill effect is particularly evident in Africa's where foreign investors, especially in resource-intensive sectors like oil refining and mining, exacerbate environmental degradation (Javorcik and Wei, 2004; Shofwan and Fong, 2011). On the other hand, the technique effect aligns with the PHL, which argues that FDI can drive cleaner technologies and better environmental practices (Al-Mulali and Tang, 2013). Foreign firms introduce eco-friendly innovations, improving environmental standards (Mert and Bölük, 2016). Thus, the environmental impact of FDI is shaped by several contextual factors, including the strength of environmental regulations and institutional frameworks, the nature of the industries involved (e.g., technology-intensive, extractive, manufacturing, or service-based), societal dynamics, and the overall level of development within host countries. Fig. 1 presents the conceptual framework illustrating the FDI–pollution nexus within the dual perspectives of the Pollution Haven and Pollution Halo Hypotheses.

2.2. Empirical literature

Extensive research has explored these theories (PHH and PHL) across various regions, countries, and economic contexts, predominantly employing panel data methods. Adeel-Farooq et al. (2021), Singhania and Saini (2021), Nguyen-Thanh et al. (2022), Avazdahandeh (2024), and Xie and Zhang (2024) examined the environmental consequences of FDI in developed and developing economies. Their findings support the PHH, indicating that FDI contributes to environmental degradation. Similarly, Duan and Jiang (2021) and Dagar et al. (2022) quantified FDI's environmental effects across income classifications—high-income, low-income, and middle-income economies—confirming the PHH. In country-specific studies, Solarin et al. (2017a) examined Ghana, while Temurlenk and Lögün (2022) assessed Turkey, both confirming PHH.

Other studies focused on specific regions. Wen et al. (2022) and Murshed (2023) analyzed BRICS nations, reaffirming PHH's applicability. Garsous and Kozluk (2017) conducted firm-level research across 23 OECD countries, finding evidence of PHH among listed companies. Kisswani and Zaitouni (2023) assessed South-East Asian nations (Philippines, Thailand, Malaysia, and Singapore), concluding that FDI has worsened environmental conditions, often leading to greenwashing. Beyond the PHH, some studies found support for both PHH and PHL hypotheses. Apergis et al. (2022) evaluated 11 OECD and BRICS countries, Wang et al. (2023) studied 67 nations globally, and Kutlu Furtuna and Atis (2024) examined the world's 20 highest emitters. These works concluded that FDI's effects are mixed, reinforcing both hypotheses. Ferrara et al. (2015) applied a two-country oligopoly model, finding simultaneous PHH and PHL dynamics. Meanwhile, Liu and Guo (2023) studied 283 cities in and Uche et al. (2024) analyzed Brazil, both confirming dual environmental outcomes.

A third body of literature favors the PHL hypothesis, suggesting FDI fosters environmental improvement. Shao (2018) and Abdelgany and Gad-Elhak (2022) used panel methods to confirm PHL's validity, while Yilanci et al. (2023) focused on Indonesia. Urban-level studies—Gao et al. (2022) on 19 Chinese cities, Li et al. (2023) on 110 cities along the Yangtze River Economic Belt, and Polloni-Silva et al. (2021) on São Paulo, Brazil—further support PHL. Meanwhile, some research found no correlation between FDI and environmental degradation. Javorcik and Wei (2004) examined 25 Eastern European countries, while Tenaw (2020) assessed 20 African nations, finding FDI had no measurable environmental impact. Country-specific studies by Shofwan and Fong (2011) (Indonesia) and Chirilus and Costea (2024) (Romania) yielded similar results. Dong et al. (2012) introduced the Regulatory Chill Hypothesis (RCH), arguing that governments may weaken environmental policies to retain foreign investors. In summary, the literature reveals varied environmental effects of FDI, largely dependent on country or regional context. While studies confirm PHH in Ghana, Turkey, and South-East Asia, others find positive environmental outcomes in Brazil, China, and Indonesia, supporting PHL. Some research, however, fails to find any connection between FDI and environmental degradation. The preceding discussion highlights the conflicting conclusions in both theoretical perspectives and empirical findings regarding the environmental impact of FDI, largely due to the reliance on traditional econometric methods. Notably, the existing literature lacks studies that simultaneously account for structural breaks, parameter heterogeneity, and cross-sectional dependence in examining the FDI–pollution relationship. This study addresses that gap by analyzing the environmental consequences of FDI in five of Africa's leading investment destinations—Egypt, South Africa, Morocco, Nigeria, and Kenya—using advanced econometric techniques capable of capturing these complex dynamics.

3. Data and methods

3.1. Exploratory data analysis

We assess the relevance of the PHH in the top five African countries receiving the highest FDI between 1970 and 2022. To achieve this objective, we use the Ecological Footprint (EFP) measured in per capita terms of final consumption as the dependent variable and the data come from the Global Footprint Network (GFN). FDI net inflows measured as a percentage of GDP serves as the key explanatory variable (Aminu et al., 2023). Additionally, we incorporate GDP per capita (USD, current prices), urban population percentage (URBAN), and the KOF trade globalization index (KOFTRGI) as control variables. GDP, FDI, and URBAN data are from the World Bank database. KOFTRGI data are sourced from KOF Swiss Economic Institute. Table A1 in Appendix A outlines the variables, including their description, measurement, and sources, while also presenting the descriptive statistics of the series.

By scrutinizing the key variables of interest (FDI and EFP) as reported in Table A1, the findings highlight significant disparities in FDI and EFP across the five selected countries. Specifically, Egypt stands out among the five selected countries in terms of FDI inflows, recording the highest mean value of 2.103 and a peak of 9.348 % of its GDP in 2006. This positions Egypt as the most attractive destination for foreign investments not only within the group but also across the entire continent. In contrast, South Africa leads in EFP, with the highest mean value of 2.37 and a maximum of 9.67 metric tons per capita, reflecting its strong

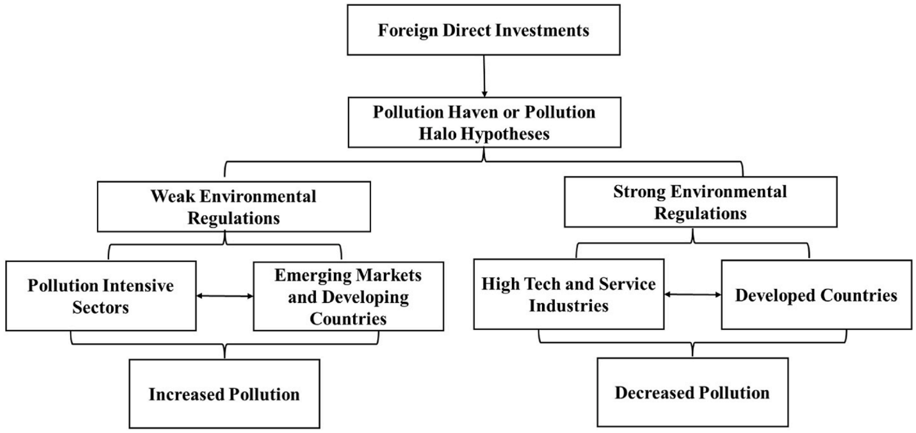

Fig. 1. Conceptual framework illustrating the FDI–pollution nexus under the Pollution Haven and Pollution Halo Hypotheses. Source: Authors' own elaboration.

industrial development. While these findings highlight Egypt's position as a leading investment hub on the continent, they also draw attention to South Africa's substantial environmental impact.

Beyond descriptive statistics, we examine the dynamic trends in EFP and FDI inflows across the five selected countries. We apply kernel density estimation, a method that generates a continuous density curve to represent the distribution and characteristics of random variables (Xia et al., 2024). This technique is particularly useful in examining the shifting patterns of EFP as demonstrated by Liu et al. (2021) .[1] Fig. 2 presents the results of this analysis. Egypt's EFP peaked in 1971–1972, then declined and stabilized post-1980, reaching 3.25 in 2022. The density center shifted leftward, reflecting a gradual reduction in environmental pressure over time.

FDI inflows showed extreme fluctuations, surging to 48.72 in 1973, then declining steadily and stabilizing below 1.0 after 2005. Post-2010, the wave width narrowed, suggesting a more concentrated flow of investment at reduced levels. These trends highlight Egypt's transition toward lower emissions alongside a constrained investment landscape. When looking at South Africa figures, EFP peaked in 1973, then declined sharply and stabilized through the 1980s and 1990s. From 2000 onward, it steadily decreased, reaching 0.38 in 2022. The density center shifted leftward, reflecting a concentrated distribution of lower EFP values post-2010. Meanwhile, FDI inflows exhibited sharp fluctuations, peaking at 1.55 in 1994, before gradually declining throughout the 2000s. The wave width of FDI density narrowed post-2010, signaling a stabilization of investment inflows at lower levels.

Morocco's EFP showed strong fluctuations, peaking in 1972 (33.55) and again in 2019 (7.02) before declining to 3.69 in 2022. The density center shifted downward post-2019, indicating a sustained reduction, while peak widening during high-EFP periods suggests varying environmental pressures over time. Meanwhile, FDI inflows were highly unstable, spiking at 18.08 in 1971, then exhibiting gradual decline after the 1980s, stabilizing at low levels post-2003, with a narrowing density after 2010. As far as Nigeria is concerned, Nigeria's EFP trended upward, peaking in 1971 (19.09), 1993 (13.93), and 2001 (16.18) before stabilizing. The density center shifted upward post-2000, reflecting sustained environmental pressure. The peak widened between 1990 and 2002, then narrowed post-2010, indicating concentrated higher EFP levels. By 2022, EFP reached 5.01, highlighting ongoing environmental challenges. At the same time, FDI inflows remained volatile, experiencing a significant rise after 2000, peaking at 1.37 in 1986 and 2021, before slightly declining in 2022 (1.31). The density width narrowed after 2010, suggesting a stabilization of investment inflows at higher levels.

Kenya's EFP exhibited sharp fluctuations, peaking in 1982 (14.00), 1984 (13.91), and 2014–2015 (10.92) before stabilizing. The density center initially shifted downward, indicating a decline in environmental pressure, but expanded post-2015, reflecting renewed variability. By 2022, EFP reached 4.14, suggesting lingering environmental concerns despite earlier stabilization. In contrast, FDI inflows remained subdued, peaking briefly in 2010 (2.26), before declining and stabilizing at lower levels. The wave width narrowed after 2015, suggesting more concentrated investment trends. In sum, our exploratory data analysis reveals distinct structural breaks in EFP and FDI inflows, shifting from early volatility to stabilization post-2010, reflecting declining emissions and more concentrated investment inflows amid evolving economic policies. This highlights the importance of accounting for structural breaks when modeling the impact of FDI on environmental sustainability in this study.

3.2. Model specification

The model employed in this study represents the stochastic adaptation of the Impact, Population, Affluence, and Technology (IPAT) model, commonly known as the STIRPAT model (Espoir et al., 2024). According to the STIRPAT framework, a country's environmental pollution at time t is predominantly influenced by economic, demographic, and technological factors, expressed as:

$$\mathrm{I}_{i,t} = \varphi_0 + \mathrm{P}_{i,t}^{\gamma_1} + \mathrm{A}_{i,t}^{\gamma_2} + \mathrm{T}_{i,t}^{\gamma_3} + \omega_{i,t} \tag{1}$$

where I represents environmental pollution, while P, A, and T denote population, affluence, and technology, respectively. φ, $\gamma_1 - \gamma_3$ represent the constant term and the exponentials of the pollution influencing factors, and ω is the stochastic error term.

In Eq. (1), I is represented by EFP, P is captured by urban population, A is represented by GDP per capita (Onifade et al., 2021; Espoir and Sunge, 2021), and T is captured by the trade globalization index (Nikou and Sardianou, 2025). While this formulation aligns with the conventional STIRPAT model, we enhance its specification by incorporating FDI, not only to evaluate its impact on pollution but also to assess the validity of the PHH. This extension results in an augmented STIRPAT model, offering a more comprehensive analytical framework. The augmentation of the STIRPAT model with the FDI variable is justified on both theoretical and empirical grounds (Nosheen et al., 2020; Balsalobre-Lorente et al., 2021). The traditional STIRPAT model examines the

[1] For Example, the kernel density estimation function for lnEFP is defined as follows: $f(x) = \frac{1}{nh}\sum_{I=1}^{N} K\left(\frac{lnEFP_i - \overline{lnEFP}}{h}\right)$. In this context, $f(x)$ is the kernel density estimation function, where $K(.)$ is the kernel Gaussian function, h is the bandwidth parameter which controls the smoothness of the density estimation, and n is the sample size. $\overline{lnEFP}$ represents the average EFP per capita, with $lnEFP_1$, $ElnFP_2$, ..., $lnEFP_i$ denoting values for each region.

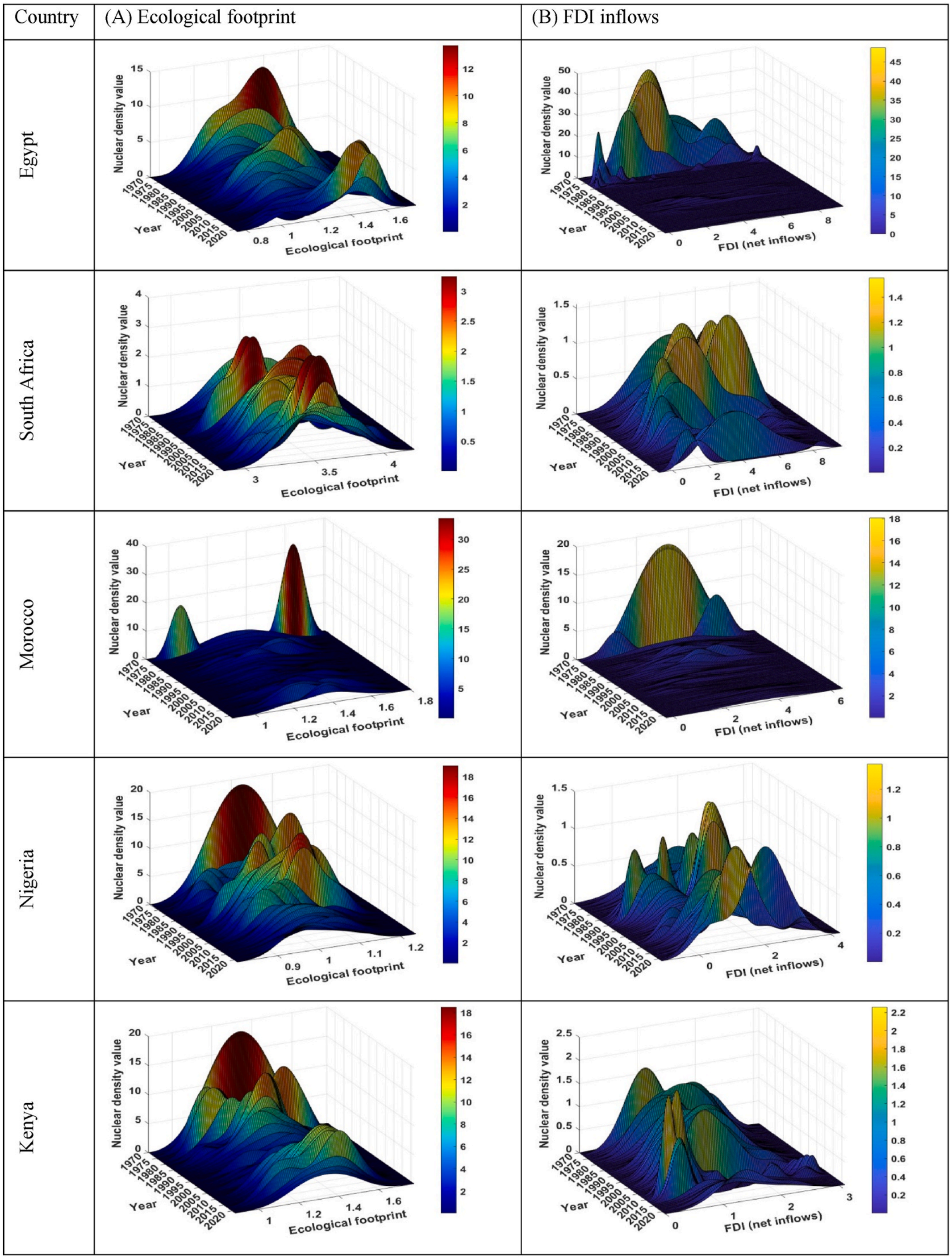

Fig. 2. Kernel density curves of EFP and FDI net inflows in top-5 African FDI recipient countries.

impact of population, affluence, and technology on environmental pressure. However, integrating FDI enhances the model's explanatory power by addressing a crucial dimension of globalization—capital flows—which may significantly influence pollution levels. Given that foreign investments may shift pollution-intensive industries to African countries with weaker environmental regulations, incorporating FDI allows us to examine whether capital mobility exacerbates or mitigates environmental degradation, making this extension essential for a robust analysis. Thus, the two key hypotheses emerging in the context of Africa's top five FDI-recipient economies are.

H1. (Pollution Haven Hypothesis - PHH): FDI inflows exacerbate environmental degradation by enabling firms to relocate polluting activities to countries with relatively weaker environmental regulations.

H2. **(Pollution Halo Hypothesis - PHL):** FDI promotes the adoption of cleaner technologies and sustainable practices, thereby contributing to improved environmental outcomes in host countries.

To assess these hypotheses, we align our model to the EKC hypothesis testing framework by introducing a quadratic term for GDP per capita, following the methodology of Espoir and Sunge (2021) and Leitão et al. (2023). Accordingly, our final econometric model is reorganized and expressed in log-linearized form as presented in Eq. (2):

$$\ln EFP_{i,t} = \varphi_0 + \gamma_1 FDI_{i,t} + \gamma_2 \ln GDP_{i,t} + \gamma_3 \ln GDPSQ_{i,t} + \gamma_4 URBAN_{i,t} + \gamma_5 \ln KOFTRGI_{i,t} + \omega_{i,t} \tag{2}$$

As can be seen, the first regressor in Eq. (2) is FDI, which is related to EFP. We expect its estimated coefficient to be positive and significant. Specifically, if $\gamma_1 > 0$ and statistically significant, it confirms the presence of the PHH, indicating that FDI contributes to increased environmental degradation. Conversely, if $\gamma_1 < 0$ and statistically significant, it supports the PHL, suggesting that FDI enhances environmental sustainability through technology transfer and improved practices. The expected signs of the GDP and GDPSQ coefficients are positive and negative, respectively. Precisely, if $\gamma_2 > 0$ and $\gamma_3 < 0$, it confirms the presence of the EKC, indicating that economic growth initially increases pollution, but at higher income levels, environmental degradation declines as cleaner technologies and sustainable practices emerge. The impact of urbanization on EFP is uncertain, with mixed findings in the literature. Charfeddine et al. (2018), Ozturk et al. (2016), and Danish et al. (2020) suggest a negative coefficient, indicating reduced pollution due to improved efficiency. Conversely, Danish and Wang (2019) and Wang et al. (2016) argue that urbanization increases emissions through industrialization and high urban population density. Thus, the expected coefficient (γ_4) may be positive or negative, depending on each country specific economic and agglomeration orientation. Finally, the environmental impact of trade globalization remains uncertain, especially in understudied African countries. Pata et al. (2024) highlight both growth-driven pollution and sustainability potential through innovation in BRICS states. Nikou and Sardianou (2025) found that higher trade globalization index (TGI) increases economic activity, resource use, and ecological deficits, emphasizing the complex trade-offs of globalization. Hence, the expected coefficient (γ_5) may also be positive or negative.

3.3. *Panel specification tests*

3.3.1. *Testing cross-sectional dependence and slope heterogeneity*

Estimating Eq. (2) requires a thorough analysis of the panel dataset's properties, moving beyond descriptive statistics to consider cross-sectional dependence (CD) and slope homogeneity. These factors ensure robust estimation, minimizing bias and enhancing the reliability of results in heterogeneous panel settings (Tato ğ lu, 2020). Testing for cross-sectional dependence and slope heterogeneity facilitates the selection of an appropriate panel data estimator, effectively capturing all underlying structural properties and dynamics of the model. We start by analyzing the presence or not of CD in the data. The Pesaran CD test (2015, 2021) is widely used for this purpose, relying on the following formulation:

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \widehat{\rho}_{i,j} \tag{3}$$

where $\widehat{\rho}_{i,j}$ is an average parameter denoting the correlation between the regression errors. Juodis and Reese (2022) note that the Pesaran CD test can lead to over-rejection with semi-strong or strong latent factors, misidentifying dependence structures. To address this, they introduce CD_w, which randomizes residual weights to control false rejection rates, though it has limited statistical power. Their refined CD_w+ , incorporating a screening method from Fan et al. (2015), enhances reliability by tending to zero under the null hypothesis and diverging under the alternative. Xie and Pesaran (2022) further show that while the standard CD test remains valid for weak latent factors, it becomes biased when factors are stronger. They propose CD^*, a bias-corrected version of Pesaran's test, following a N(0,1) asymptotic distribution, ensuring robustness across different latent factor strengths. However, all these CD test batteries may not yield reliable results when the time dimension (T) exceeds the number of cross-sections (N). In such cases, the Lagrange Multiplier (LM) procedure developed by Breusch and Pagan (1980) is often preferred. This method has been shown to provide valid and robust results for relatively small N and sufficiently large T (Chang et al., 2015), making it a suitable alternative for panel datasets with unbalanced dimensions. Therefore, our final analysis is based on the Lagrange Multiplier (LM) test results, where the test statistic is given by:

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T\widehat{\rho}_{i,j}^{2} \tag{4}$$

where $\widehat{\rho}_{i,j}^{2}$ represents the pairwise correlation of residuals, N denotes the number of cross-sections, and T is the number of time observations.

In panel data analysis, determining whether slope coefficients of Eq. (2) are homogeneous across units is crucial for selecting the appropriate estimation technique. If slope homogeneity holds, pooled estimators may be valid; however, if heterogeneity exists, ignoring it could lead to biased and inconsistent results (Espoir et al., 2022). To address this, we employ the Pesaran and Yamagata (2008) delta test ($\widetilde{\Delta}_{CSA}$), a standardized refinement of Swamy (1970) test. While Swamy's test was designed for small-N, large-T panels, the Pesaran-Yamagata test accommodates large panels, ensuring robustness when both N and T approach infinity. Their methodology involves a two-step procedure to obtain the test statistics. First, the authors suggested computing the modified version of Swamy's test as:

$$\widetilde{S} = \sum_{i=1}^{N} \left(\left(\widehat{\gamma}_i - \widetilde{\gamma}_{WFE}\right)' \frac{X_i' IM_\tau X_i}{\widetilde{\sigma}_i^2} \widehat{\gamma}_i - \widetilde{\gamma}_{WFE} \right) \Bigg) \tag{5}$$

where $\widehat{\gamma}_i$ and $\widetilde{\gamma}_{WFE}$ represent coefficient vectors from pooled OLS and weighted fixed effects estimators, respectively. $\widetilde{\sigma}_i^2$ is the estimator of σ_i^2, and IM_τ is an identity matrix. Based on Swamy's statistic from Eq. (5), the standard delta statistic is calculated as:

$$\widetilde{\Delta}_{CSA} = \sqrt{N}\left(\frac{N^{-1}\widetilde{S} - K}{\sqrt{2K}}\right) \tag{6}$$

Under the null hypothesis of slope homogeneity, given condition (N, T) → ∞ with $\sqrt{N}/T$, the $\widetilde{\Delta}_{CSA}$ test follows an asymptotic standard normal distribution ($\omega \sim N(0, \sigma^2)$). Furthermore, in small samples—as in this study—the test's properties can be improved under the same assumption of normally distributed errors using a bias-adjusted version as:

$$\widetilde{\Delta}_{CSA-adj} = \sqrt{N}\left(\frac{N^{-1}\widetilde{S} - E\left(\widetilde{Q}_{i,t}\right)}{\sqrt{var\left(\widetilde{Q}_{i,t}\right)}}\right) \tag{7}$$

where the mean $E\left(\widetilde{Q}_{i,t}\right) = k$ and the variance $var\left(\widetilde{Q}_{i,t}\right) = \frac{2K(T-k-1)}{T+1}$.

3.3.2. *Testing for structural break*

Another frequently overlooked issue in panel data analysis is the presence of structural breaks, which often arise due to policy shifts, economic crises, technological advancements, or external shocks (Karavias, 2021). According to Levendis (2023), structural breaks disrupt the stability of relationships among variables, leading to biased estimations if not properly accounted for. A simple way to initially detect structural breaks in a time series is through visual inspection via plotting, as illustrated in Figure A in the Appendix. However, this approach may not capture all underlying structural shifts, especially when breaks are subtle or masked by fluctuations (Hansen, 2012). More rigorous statistical tests are often required to validate and quantify these breaks, ensuring accurate modeling and interpretation. Thus, we apply the test for a structural break with an unknown break date, as developed by Davies (1987), Andrews (1993), and Bai and Perron (1998).[2] Given the challenges posed by cross-sectional dependence, slope heterogeneity, and structural breaks, econometric methods that enforce homogeneity restrictions while disregarding spatial dependence and structural break effects may lead to misleading results. To address these concerns, this study employs the SB-SURMG and F-SURMG estimators, which have been recently developed to accommodate these three technical issues, as outlined in the preceding subsections.

3.4. Heterogeneous parameter estimations

3.4.1. Sharp changes in heterogenous panel

Existing literature highlights two key approaches for modeling structural changes in heterogeneous panel data models. The first approach assumes that structural shifts are uniform across all units, while the second recognizes that these changes may vary by unit. A widely applied method for the first approach is the Common Correlated Effects (CCE) estimator by Pesaran (2006). However, this estimator is most effective when both the cross-sectional dimension (N) and the time dimension (T) are sufficiently large. Given the structure of this study—where N = 5 and T = 53, with N < T—this requirement is not met. Furthermore, considering the diverse economic trajectories of the top-5 African FDI recipient countries, it is improbable that structural changes would occur simultaneously across all units. For the second approach, which allows structural changes to vary across units, Guliye, (2023) introduced SB-SURMG estimator. This method is specifically designed to capture highly heterogeneous structural shifts within panel data, ensuring robustness in scenarios where individual units experience distinct break patterns rather than uniform changes.

Considering n panel units, the SB-SUR model with a structural break in both intercept and slope can be expressed in a generalized form as follows:

$$y_{i,t} = \alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij,t} + 1(t \geq b_i)\left(\delta_i + \sum_{j=1}^{k} \gamma_{ij} X_{ij,t}\right) + \omega_{i,t} \tag{8}$$

and applying the expression of eq. (8) to our specification in (2) yields:

$$\begin{aligned} \ln EFP_{i,t} = {} & \varphi_{i0} + \gamma_{i1} FDI_{i,t} + \gamma_{i2} \ln GDP_{i,t} + \gamma_{i3} \ln GDPSQ_{i,t} + \gamma_{i4} URBAN_{i,t} \\ & + \gamma_{i5} \ln KOFTRGI_{i,t} + 1(t \geq b_i)\left(\delta_i + \sum_{j=1}^{k} \gamma_{ij} X_{ij,t}\right) + \omega_{i,t} \end{aligned} \tag{9}$$

where α_i is the baseline intercept for unit i, β_{ij} are the coefficients associated with explanatory variables $X_{ij,t}$, $1(t \geq b_i)$ is an indicator function that equals 1 when the break occurs, allowing a shift in parameters. Moreover, δ_i captures the shift in intercept due to the regime change, γ_{ij} accounts for changes in the slope coefficients for each explanatory variable after the break, and $\omega_{i,t}$ is the error term. An important assumption of the SB-SUR model is that $\omega_{i,t}$ is serially correlated across panel units. Applying OLS regression technique will not yield unbiased estimates Guliyev, 2023. Consequently, SB-SUR is typically estimated using Generalized Least Squares (GLS), which accounts for cross-unit correlations. The GLS estimates parameters are obtained as:

$$\widehat{\beta}^{SB-SUR} = \left(X'\Omega^{-1}X\right)^{-1} X'\Omega^{-1} Y \tag{10}$$

We apply the GLS regression and obtained the estimates for each country of our panel. To obtain a general estimator for the panel, the mean of these individual coefficients is calculated, yielding the SB-SURMG estimator, defined as:

$$\widehat{\beta}^{SB-SURMG} = \frac{1}{N} \sum_{i=1}^{N} \widehat{\beta}^{SB-SUR} \tag{11}$$

where $\widehat{\beta}^{SB-SUR}$ represents the estimated independent variable coefficients obtained from the SB-SUR model using GLS (Eq. (10)) and N denotes the total number of panel units included in the analysis.

3.4.2. Smooth changes in heterogenous panel

When structural change is known, dummy variables are commonly used to capture breaks. However, relying on them can be problematic when the exact timing, form, or number of breaks is unknown (Enders and Lee, 2012). Fourier series offer a flexible alternative for modeling structural changes in heterogeneous panel data. Unlike dummy-variable methods, they do not require prior knowledge of breakpoints and can capture both sharp and smooth transitions, addressing parameter instability effectively. This adaptability makes them particularly valuable for detecting gradual structural shifts often missed by conventional approaches. Guliyev (2025) introduced the single-frequency F-SUR (Fourier Seemingly Unrelated Regressions) model, incorporating Fourier terms to capture structural changes. The model for panel unit i is expressed as:

$$y_{i,t} = \alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij,t} + \gamma_i sine\left(\frac{2\pi kt}{T}\right) + \lambda_i cosine\left(\frac{2\pi kt}{T}\right) + \omega_{i,t} \tag{12}$$

where i represents panel units, with α_i as the intercept. $X_{ij,t}$ are independent variables with coefficients β_{ij}. Fourier components $\gamma_i sine\left(\frac{2\pi kt}{T}\right)$ and $\lambda_i cosine\left(\frac{2\pi kt}{T}\right)$ introduce flexibility in detecting cyclical patterns. The coefficients γ_i and λ_i quantify the effects of the Fourier series, varying across the five countries. They capture smooth structural changes over time, enabling a more nuanced examination of the link between FDI and EFP. k is the frequency. Becker et al. (2006) and Enders and Lee (2012a, 2012b) suggest setting k = 1, as it is generally sufficient to capture structural breaks effectively. t represents the trend, and T the time dimension, ensuring smooth transitions. The constant π is 3.1416.

To fully leverage the strengths of the F-SUR model, the econometric specification in Eq. (2) is augmented with Fourier terms. This enhancement allows the model to account for smooth structural shifts, thereby improving its flexibility and robustness. Based on the second research question, this extension also enables the formulation of a third hypothesis.

H3. The environmental impact of FDI is uniform across the top five recipient countries.

Despite their diversity, the top five African FDI destinations—Egypt, South Africa, Morocco, Nigeria, and Kenya—share structural similarities that support the plausibility of a uniform environmental impact from FDI. Common drivers such as industrialization, urbanization, and resource-based sectors (Awudu Sare et al., 2025), coupled with similar regulatory challenges (Dupasquier and Osakwe, 2005; N.C. Leitão, 2024) and multinational corporate practices (Gilroy et al., 2005), suggest aligned environmental outcomes. Regional policy initiatives like the African Continental Free Trade Area (AfCFTA) further reinforce this convergence by promoting harmonized investment and environmental frameworks (UNECA, 2024). Hence, our F-SUR model is specified as follows:

[2] In heterogeneous panel data models, Supremum, Average, and Exponential Wald tests detect structural breaks at the unit level rather than across the entire panel. We focus on Model 3, which captures a break in both the intercept and slope, signaling a regime shift in data structure.

Table 1
Cross-sectional dependence and slope homogeneity test results.

Variables	CD	CD_w	CD_{w+}	CD^*	LM
Panel A: Cross-sectional dependence tests					
EFP	−1.75*	5.81 ***	34.81***	0.45	84.173***
	$\alpha = -0.074$	(0.000)	(0.000)	(0.692)	(0.000)
FDI	2.49***	0.43	9.78***	9.29***	18.003**
	$\alpha = 0.108$	(0.178)	(0.000)	(0.000)	(0.054)
GDP	20.62***	−4.45***	60.77***	0.87	426.503***
	$\alpha = 0.871$	(0.000)	(0.000)	(0.602)	(0.000)
URBAN	22.69***	−4.52***	67.25***	4.94***	515.059***
	$\alpha = 0.986$	(0.000)	(0.000)	(0.000)	(0.000)
KOFTRGI	6.56***	2.86***	27.73***	1.76*	86.473***
	$\alpha = 0.294$	(0.000)	(0.000)	(0.092)	(0.000)
FE model errors	−2.59 ***	0.37	39.26***	2.89***	171.643***
	$\alpha = -0.113$	(0.708)	(0.000)	(0.004)	(0.000)
Panel B: Slope homogeneity tests					
Test			Statistics	p-value	
$\widetilde{\Delta}_{CSA}$			22.739***	0.000	
$\widetilde{\Delta}_{CSA-adj}$			24.408***	0.000	

Notes: p-values in parenthesis, ***, **, and * denote statistical significance at p-value <0.01, <0.05, and <0.1 respectively. CD: Pesaran (2015, 2021) CD test, CD_w: Juodis and Reese (2021) CD_w test, CD_{w+}: CD_w with power enhancement from Fan et al. (2015), and CD^*: Pesaran and Xie (2021) CD test with 4 factors.

$$\ln EFP_{i,t} = \varphi_{i0} + \gamma_{i1} FDI_{i,t} + \gamma_{i2} \ln GDP_{i,t} + \gamma_{i3} \ln GDPSQ_{i,t} + \gamma_{i4} URBAN_{i,t} + \gamma_{i5} \ln KOFTRGI_{i,t} + \gamma_i sine\left(\frac{2\pi kt}{T}\right) + \lambda_i cosine\left(\frac{2\pi kt}{T}\right) + + \omega_{i,t} \tag{13}$$

The significance of the Fourier series is tested to identify nonlinear trends or smooth structural changes. If at least one term is statistically significant, it signals transitions or breaks, warranting inclusion (Guliyev, 2025). Since their asymptotic distributions are unknown, bootstrap resampling (Efron, 1979) is employed to generate bootstrapped distributions for significance testing. Consistent with asymptotic inferences (Nazlioglu et al., 2016), this study applies bootstrap standard errors in the F-SUR estimator. Moreover, we follow Guliyev (2025) and derived the F-SURMG (Fourier Seemingly Unrelated Regressions Mean Group) estimator as follows:

$$\widehat{\beta}^{F-SURMG} = \frac{1}{N} \sum_{i=1}^{N} \widehat{\beta}^{F-SUR} \tag{14}$$

where $\widehat{\beta}^{F-SUR}$ in Eq. (13) represents the estimated coefficients of the independent variables from the F-SUR model, while N denotes the total number of panel units. Our main analysis of the PHH test on FDI's impact on CO_2 emissions in the top five selected countries is based on the F-SURMG technique. As a point of comparison, we consider the SB-SURMG estimator, which accounts for sharp structural changes in a heterogeneous panel. This dual approach provides a comprehensive assessment of FDI–pollution dynamics, capturing both smooth and sharp structural shifts in the data.

4. Empirical results and discussions

4.1. Results of cross-sectional dependence and slope heterogeneity

Our empirical analysis begins by evaluating cross-sectional dependence and slope homogeneity within the panel data. To ensure robustness, we assess dependence at both the individual variable level and within the residuals of the Fixed Effects estimation of Eq. (2). The findings are summarized in Table 1. The test results demonstrate strong evidence of cross-sectional dependence across all variables, particularly based on the Breusch and Pagan (1980) LM test, where the null hypothesis of weak dependence fails at the 5 % significance level. The Pesaran (2015) CD test further supports this conclusion, indicating strong cross-sectional dependence for GDP per capita and the urban population rate, as their α values approach 1. In contrast, EFP, FDI inflows, and the trade globalization index exhibit weaker dependence, with α values below 0.5. Despite this variation, the robust versions of the Pesaran (2015) test (CD_w, CD_{w+}, and CD^*) confirm the presence of cross-sectional dependence across all examined variables. To further verify these findings, we perform the test on the residuals from the fixed effects (FE) model. Particularly, the Breusch and Pagan LM test on residuals similarly rejects the null hypothesis of weak dependence at the 5 % significance level, indicating substantial cross-sectional interactions within the residual structure.

Next, we examine the presence of slope heterogeneity across the five countries in our panel. Alongside the cross-sectional dependence (CD) test, this assessment is crucial for determining whether pooled regression methods or heterogeneous econometric techniques are more appropriate for subsequent analyses. The results of the slope heterogeneity test, presented in Table 1, indicate that for regression Eq. (2), the statistics from both tests ($\widetilde{\Delta}_{CSA}$ and $\widetilde{\Delta}_{CSA-adj}$) reject the null hypothesis of slope homogeneity at the 1 % significance level across all panel units. This finding highlights the risk of inaccurate inferences and misleading results if the FDI-CO_2 emissions regression analysis is conducted under the assumption of slope homogeneity restrictions.

4.2. Results of structural breaks

We finalize our analysis of the time-series properties by conducting structural break tests, limiting the investigation to a single break point due to the length of the time dimension. The results of the Supremum, Average, and Exponential Wald tests are computed individually for each country and reported in Table 2. The structural break tests confirm

Table 3
Results of multicollinearity test.

Variables	VIF	1/VIF
URBAN	1.90	0.526
lnGDP	1.46	0.685
lnKOFTRGI	1.34	0.748
FDI	1.13	0.887
Mean VIF	1.45	

Source: Authors' own computation

Table 2
Panel unit-specific break Identification results.

Test	Egypt	South Africa	Morocco	Nigeria	Kenya
Supremum Wald	28.389*** (0.002)	60.730*** (0.000)	13.357 (0.361)	99.158*** (0.000)	87.462*** (0.000)
Average Wald	11.487*** (0.023)	26.949*** (0.000)	7.653 (0.203)	60.471*** (0.000)	46.632*** (0.000)
Exponential Wald	11.642*** (0.0009)	28.009*** (0.000)	4.557 (0.280)	46.488*** (0.000)	40.165*** (0.000)
Break point	2011	1986	1995	1989	1988

Notes: Huber-White (1980) robust standard errors are applied to individual regression models to ensure reliable inference. The trimming parameter is set to 0.15. The null hypothesis is rejected at significance levels of *10 %, **5 %, and ***1 %, respectively.

Table 4
SB-SURMG estimation results.

Variables	Coefficient	Standard errors	z-statistics	p-values
FDI	0.0181***	0.007	2.452	0.014
lnGDP	0.127	0.553	0.231	0.817
lnGDPSQ	−0.0009	0.036	−0.026	0.980
URBAN	−0.020***	0.008	−2.425	0.015
lnKOFTRGI	0.117	0.139	0.840	0.401
CONSTANT	−0.024	2.017	−0.012	0.990

Note: *, **, *** denote significance at 10, 5, and 1 %, respectively.

statistically significant break points at the 5 % level for Egypt, South Africa, Nigeria, and Kenya, indicating distinct but sharp shifts rather than slow transitions. Morocco, however, exhibits weaker evidence of structural change, with higher p-values above 10 % level suggesting less pronounced break and indicating the possibility of a more gradual adjustment rather than a sudden break. The identified break dates are Egypt (2011), South Africa (1986), Morocco (1995), Nigeria (1989), and Kenya (1988). To account for these shifts, dummy variables are introduced for each country, ensuring that the heterogeneous panel model accurately captures these structural changes.

Lastly, to ensure robustness and avoid inconsistencies in the estimates, we performed a multicollinearity analysis alongside a correlation matrix. The results are presented in Table 3 and Table A2 of the Appendix, respectively. As shown in Table A2, we excluded lnGDPSQ from the analysis due to perfect multicollinearity with lnGDP, given that this variable is derived directly from lnGDP. The Variance Inflation Factor (VIF) results confirm the absence of multicollinearity, as all independent variables have VIF values below the threshold of 5. Moreover, the correlation coefficients for most variables fall below the commonly accepted multicollinearity threshold of 0.8 (Opoku et al., 2022). The lnGDP and its squared term exhibit a near-perfect correlation (0.9974), indicating potential multicollinearity concerns. However, income is a key variable in the STIRPAT (Li and Lin, 2015) and EKC (Grossman and Krueger, 1991) models, which underpin the methodological framework of this paper. Thus, omitting lnGDPSQ could lead to model misspecification bias in our estimations.

4.3. Results of sharp transitions in heterogenous panel

Given the significant structural break, cross-sectional dependence, and slope heterogeneity across panel units, the SB-SURMG estimator is employed to account for these complexities. The results of the estimation are presented in Table 4. As detailed in the methodology section, this estimation combines the SB-SUR results from Table B1 in Appendix B with the Mean Group (MG) estimator developed by Pesaran and Smith (1995). The findings in Table 4 reveal that, with all other factors remaining constant, a 1 % surge in FDI net inflows results in a 1.81 % increase in the ecological footprint. This relationship is highly significant, with a confidence level of 99 %. Consequently, the SB-SURMG estimation confirms the PHH, showing that FDI inflows contribute to environmental degradation in the analyzed African panel.

Furthermore, the results in Table 4 indicate that GDP has a positive effect (0.127) but lacks statistical significance, while GDPSQ exhibits a marginal negative impact (−0.0009) and is also statistically insignificant. These findings suggest a weak EKC effect, implying that economic growth alone does not meaningfully contribute to pollution reduction in the context of our panel. The coefficient of URBAN (−0.020) is negative and statistically significant at 99 % confidence level, indicating that urbanization reduces EFP. Specifically, a 1 % increase in urbanization leads to a 2 % decline in EFP. Finally, the estimated coefficient for KOFTRGI (trade globalization) is positive (0.117) but statistically insignificant, indicating that trade openness has no influence on EFP.

We additionally present individual regression results in Table B1 of Appendix B, providing deeper insights into country-specific estimations and variations across panel. The dummy variables for structural breaks are statistically significant at the 1 % and 10 % levels for Egypt and Kenya, respectively, confirming the importance of the identified break dates in the SB-SUR model. Specifically, following these breaks—2021 for Egypt and 1988 for Kenya—there has been a statistically significant rise in ecological footprint, suggesting notable environmental shifts. Conversely, the dummy variables for South Africa, Morocco, and Nigeria are not statistically significant, indicating that while structural breaks exist, they do not correspond with impactful changes in EFP within the model. This suggests that other underlying factors may be driving environmental trends in these countries.

FDI has a positive and statistically significant effect on EFP in Egypt, Morocco, and Nigeria. Specifically, a 1 % increase in FDI inflows raises EFP by 0.9 % in Egypt, 1.7 % in Morocco, and 4.5 % in Nigeria. These results suggest that FDI intensifies environmental pressures, underpinning the PHH in these countries. In Egypt and Nigeria, the results of GDP show a positive and significant impact, while GDPSQ is negative and significant, supporting an inverted U-shaped EKC, where pollution rises with economic growth before declining at higher income levels. In South Africa, lnGDP has a negative and significant effect, while lnGDPSQ is positive and significant, confirming a U-shaped EKC pattern. This suggests that initial economic growth reduces environmental impact, but at higher income levels, pollution intensifies, potentially due to industrial expansion and resource-intensive activities. In Morocco, the estimated coefficient for lnGDP (−0.489) is negative but insignificant, while lnGDPSQ (0.050) is positive and statistically significant. This suggests that in early-development stage, economic growth does not harm the environment, but as GDP per capita gradually increases, its environmental impact becomes detrimental. As for Kenya, the coefficient on lnGDP and lnGDPSQ are both insignificant.

Furthermore, our estimation indicates that URBAN has a negative and statistically significant impact on EFP in Egypt (−0.030), Nigeria (−0.012), and South Africa (−0.019), suggesting that urbanization worsens environmental quality in these countries. In Kenya (−0.047), the impact is negative but statistically insignificant, while in Morocco (0.004), the coefficient is positive but insignificant as well. Finally, the results for lnKOFTRGI indicate a positive and statistically significant effect on EFP in Egypt (0.341), South Africa (0.527), and Nigeria (0.056), suggesting that trade globalization contributes to environmental pressures in these countries. Conversely, in Morocco (−0.137) and Kenya (−0.202), the coefficients are negative but statistically insignificant, indicating no measurable impact on environmental quality.

4.4. Results of smooth transitions in heterogenous panel

Although the results of the SB-SURMG (Table 4) and SB-SUR (Table B1) provide valuable insights, they rely on the assumption that the identified breaks are sharp rather than smooth. However, in reality, shifts in macroeconomic factors, often driven by policy changes, trade liberalization, or economic structural adjustments, tend to occur gradually rather than instantaneously. To address this limitation, we relax the sharp-break assumption of the SB-SURMG model and conduct the F-SURMG regression, as specified in Eq. (14). As previously explained, the hypothesized smooth transition effect is captured through Fourier series (sine and cosine), which vary for each country of our panel. Fig. 3 illustrates the time-fluctuations of the sine and cosine series, key components of the Fourier series for $k = 1$. The sine series depicts a gradual evolution in the dependent variable (EFP), starting with an upward trend, dipping downward, and then rising again. Conversely, the cosine series follows an opposite trajectory, initiating with a decline before shifting into an upward movement.

The results of the F-SURMG, which capture a more flexible representation of transition dynamics, are reported in Table 5. As for the SB-

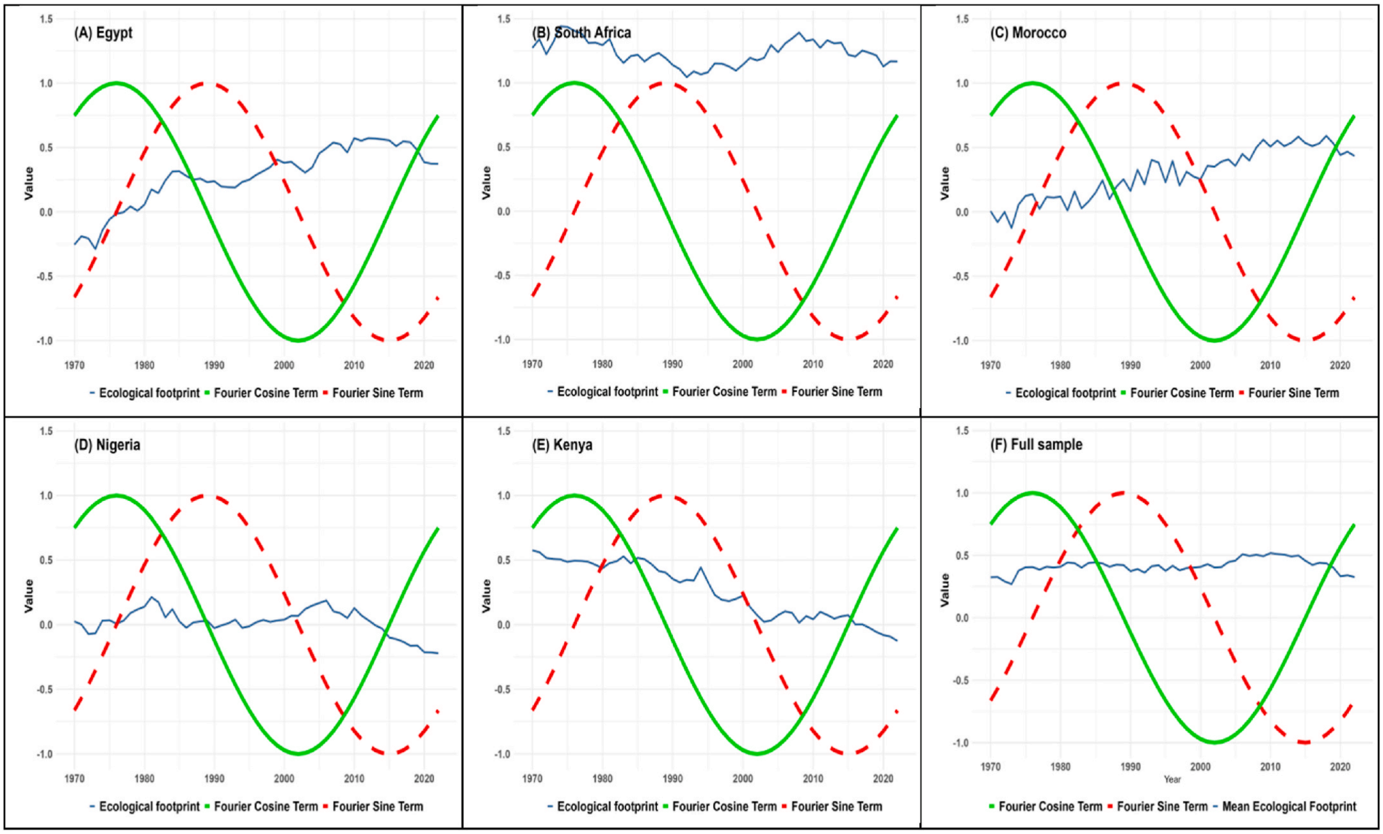

Fig. 3. Cross-country EFP with Fourier sine and cosine terms over the 1970–2022 period.

Table 5
F-SURMG estimation results.

Variables	Coefficient	Standard errors	z-statistics	p-values
FDI	0.012***	0.005	2.328	0.020
lnGDP	0.564	0.482	1.170	0.242
lnGDPSQ	−0.027	0.033	−0.833	0.405
URBAN	−0.022***	0.007	−2.885	0.004
lnKOFTRGI	0.128*	0.074	1.732	0.083
CONSTANT	−1.748	1.672	−1.045	0.296

Note: *, **, *** denote significance at 10, 5, and 1 %, respectively.

SURMG estimator, the F-SURMG combines the F-SUR estimation results with the MG estimator, as provided in Appendix B. The results reveal that a 1 % rise in FDI inflows leads to a 1.2 % increase in EFP, with the effect being statistically significant at the 99 % confidence level. This effect on the FDI is estimated at much lower magnitude compared to what we reported in the SB-SURMG regression. We find that the coefficient magnitude for FDI is considerably lower than in the SB-SURMG regression, underscoring the differences in assumptions between the two estimators. Moreover, the positive and statistically significant coefficient provides strong validation for the PHH. While recent studies have reached similar conclusions, they often rely on econometric techniques that do not fully capture the complexities addressed in our study. For example, Aminu et al. (2023) applied the fully modified ordinary least squares (FM-OLS) method to a panel of 13 sub-Saharan African countries covering the period 1995–2019, while Boubacar et al. (2023) employed an expanded two-step generalized method of moments (GMM) on a broader sample of 54 African countries spanning 2004–2020. Both studies provide empirical support for the pollution haven hypothesis.

However, the negative environmental impact of FDI inflows in Africa is unsurprising. First, foreign investment is concentrated in resource-intensive industries like mining and oil extraction, leading to deforestation and pollution (Ahmed et al., 2022). Second, lax environmental regulations allow foreign firms to operate with minimal oversight, worsening degradation (Nguyen and Vo, 2021). Third, industrial expansion increases fossil fuel consumption and carbon emissions (Boubacar et al., 2023); while urban growth accelerates waste generation and air pollution through infrastructure projects (Mensah and Adu, 2020). Together, these factors strengthen the PHH, highlighting the environmental risks of FDI in African economies (Khan et al., 2021a,b).

Regarding the impact of lnGDP and lnGDPSQ, the results indicate that lnGDP has a positive coefficient (0.564), while lnGDPSQ exhibits a negative coefficient (−0.027). However, neither demonstrates statistical significance, suggesting that their impact on EFP remains minimal. As far as urbanization is concerned, the results indicate that URBAN has a negative and statistically significant coefficient (−0.022) at 99 % confidence level. This outcome indicates that a 1 % increase in the urbanization rate results in a 2.2 % reduction in the EFP. This result aligns with Danish et al. (2020), who identified a 2.4 % negative impact of urbanization on EFP within BRICS countries. Similarly, Mignamissi & Djeufack (2021), using data from 48 African countries between 1980 and 2016, identified a U-shaped relationship, where urbanization initially reduces EFP at lower development levels but increases it as development progresses. A major factor in the decline of EFP with urban expansion in Africa is the transition toward less land-intensive economic activities. Urban areas are increasingly shifting toward service-based sectors such as finance, digital industries, and trade, which require fewer natural resources compared to traditional land-dependent industries such as subsistence agriculture or deforestation-driven livelihoods. This structural shift alleviates pressure on ecosystems, reducing the overall per capita footprint. Finally, the coefficient of lnKOFTRGI (0.128) is positive and significant at the 90 % confidence level. This suggests that openness to international trade rise EFP.

The results presented in Table 5 reflect MG panel estimations. We now shift our focus to the F-SUR estimates to examine country-specific effects. Table B2 in Appendix B presents the F-SUR estimation results. The first section of the table reports key model evaluation metrics, including RMSE, R-squared values, and χ^2 statistics for each country's regression equation. The R-squared values exceed 78 % in all cases, with some surpassing 95 %, indicating a strong explanatory power of the independent variables in capturing EFP dynamics. On the other hand, the sine and cosine coefficients of the Fourier series are statistically significant at the 99 % confidence level for most countries in the panel, except for Morocco. This aligns with the structural break test results reported for Morocco in Table 2, further confirming its distinct trend. The significance of the Fourier series indicates the presence of smooth structural shifts or nonlinear patterns in four of the five countries analyzed.

The results in Table B2 shows that the impact of FDI on EFP differs across the five countries but also deviates from the estimates obtained using the SB-SUR model (Table B1), reflecting differences in their underlying assumptions regarding the timing and nature of structural breaks in the data. These discrepancies highlight the importance of incorporating both sharp and gradual structural transitions to ensure an unbiased estimation. In Egypt, South Africa, and Morocco, FDI inflows does not exhibit a statistically significant effect on EFP. This lack of significance is likely due to several structural factors. First, these countries have higher GDP per capita (IMF, 2024) and greater renewable energy adoption (Oyewo et al., 2023), reducing FDI's direct influence on environmental degradation. Second, the enforcement of institutional frameworks, regulatory quality, and sustainability policies help balance FDI's environmental impact, mitigating pollution-intensive effects predicted by the PHH. Third, FDI in these economies is largely directed toward service-oriented industries, technology, and renewable energy projects, rather than pollution-heavy sectors, further limiting its environmental footprint. By contrast, Nigeria and Kenya exhibit a significant positive relationship between FDI and EFP, reinforcing the idea that FDI's environmental impact is highly context-dependent, shaped by economic structure, regulatory frameworks, and energy transitions. This finding contradicts Odugbesan and Adebayo (2020), who employed (non)linear ARDL estimations and identified a negative relationship for Nigeria.

Regarding the EKC hypothesis, when both sharp and smooth transitions are accounted for, the results validate it only for Nigeria and Egypt, as evidenced by the positive and significant lnGDP coefficients (0.736 and 2.305) and the negative and significant lnGDPSQ coefficients (−0.045 and −0.143). Urbanization has a negative and significant impact across all countries except Morocco. Furthermore, trade globalization exhibits a positive and statistically significant effect at the 99 % confidence level for Egypt, South Africa, and Nigeria.

4.5. Robustness check

One critical econometric issue that may compromise the reliability of our estimates is endogeneity in the FDI-pollution relationship (Demena and Afesorgbor, 2020). This issue stems from simultaneous causation, omitted variable bias, and measurement errors. FDI contributes to environmental degradation through industrial expansion, yet pollution levels can also influence investment decisions, as firms seek locations with lax environmental regulations—a central tenet of the PHH. Additionally, unobserved factors such as regulatory stringency, institutional quality, and technological advancements may affect both FDI and pollution, leading to omitted variable bias. For instance, economies with stronger environmental policies may attract cleaner investments, reinforcing the PHL. To mitigate endogeneity, we conducted a robustness check using the instrumental variable seemingly unrelated regression mean group (IVSURMG) estimator (Sevinç and Tatoğlu, 2023). This method effectively addressed simultaneity-induced endogeneity between FDI and EFP, ensuring more reliable and consistent estimates. The results of this estimation are presented in Table 6. As shown in this table, the FDI coefficient (0.046) is positive and statistically significant at the 99 % confidence level, reinforcing the validity of the PHH in Africa. This finding suggests that higher FDI inflows are associated with increased pollution levels, supporting the argument that foreign investments tend to concentrate in regions with more lenient environmental regulations.

5. Conclusion and policy implication

This study examined the environmental impact of Foreign Direct Investment (FDI) in Africa's top five FDI recipient countries—Egypt, South Africa, Morocco, Nigeria, and Kenya—using the F-SURMG estimator from 1970 to 2022. These nations serve as key economic hubs, attracting significant foreign investment while playing a major role in environmental changes across the continent. Unlike conventional FDI-environment studies that rely on nonlinear econometric models, this research leveraged the F-SURMG estimator to account for structural shifts, heterogeneity, and cross-sectional dependence. Findings support the Pollution Haven Hypothesis (PHH), indicating that FDI has contributed to environmental degradation, particularly in Kenya and Nigeria, while no significant relationship was observed in Egypt, Morocco, and South Africa.

The implications of these findings extend beyond environmental concerns, influencing economic policies and societal well-being. Policymakers must implement stricter environmental regulations while embedding sustainability provisions in investment agreements to mitigate pollution risks associated with foreign investments. Governments should encourage eco-friendly investment by offering tax incentives for green technologies and sustainable business practices. Strengthening environmental governance will ensure adherence to regulatory policies, preventing firms from exploiting weak environmental laws.

From a societal perspective, unchecked FDI-driven industrial expansion can lead to air and water pollution, exacerbating health issues such as respiratory diseases and waterborne illnesses (Shah et al., 2021). Vulnerable communities—often residing near industrial zones—bear the greatest burden, highlighting the need for equitable environmental policies. Investments in clean energy infrastructure, such as renewable energy projects, can align economic growth with sustainability, ensuring

Table 6
IVSURMG estimation results.

Variables	Coefficient	Standard errors	z-statistics	p-values
FDI	0.046***	0.021	2.191	0.028
lnGDP	−0.057	0.636	0.090	0.928
lnGDPSQ	0.012	0.040	0.307	0.759
URBAN	−0.025***	0.011	−2.252	0.024
lnKOFTRGI	−0.003	0.153	−0.025	0.980
CONSTANT	1.360	2.341	0.581	0.561

Note: *, **, *** denote significance at 10, 5, and 1 %, respectively. We used ΔFDI_{t-2} as instrument for the first-stage instrumental variable estimation (2SLS). We did not report country-specific results (IVSUR), but we can provide them upon request.

that FDI contributes to long-term development without environmental degradation. Additionally, routine environmental impact assessments should be institutionalized to monitor compliance, fostering accountability among foreign investors.

In contrast, Egypt, Morocco, and South Africa—where FDI's environmental impact remains negligible—should capitalize on their relatively cleaner industrial environment by promoting green infrastructure development and incentivizing sustainable foreign investments. By embedding environmental sustainability into investment contracts, governments can attract high-value FDI without compromising ecological integrity. A well-regulated investment landscape will enable these nations to position themselves as leaders in responsible and sustainable economic development. Ultimately, balancing economic growth with environmental preservation requires a comprehensive policy approach. Governments must not only regulate polluting industries but also proactively shape investment strategies that integrate environmental protection as a fundamental component of economic planning. Without such interventions, the adverse societal and ecological consequences of FDI-driven pollution may undermine long-term development goals, perpetuating environmental degradation and health disparities.

This study has two key limitations that can be explored by future research. First, it focuses exclusively on the top five FDI-recipient countries in Africa. While the findings are robust within this context, future research could expand the scope to include countries with lower levels of FDI and emissions. Such comparisons would help validate the generalizability of our results and provide a more comprehensive understanding of FDI's environmental effects across the continent. Second, the analysis remains at the national level. Future studies could explore the sectoral impacts of FDI across different industries, as well as conduct firm-level or sub-national analyses to capture spatial and organizational variations in environmental outcomes. These extensions would offer deeper insight into the mechanisms through which FDI influences environmental performance within diverse African contexts.

CRediT authorship contribution statement

Delphin Kamanda Espoir: Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Olajide O. Oyadeyi:** Writing – review & editing, Writing – original draft, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1
Summary Statistics

Country	Variables	Description	Source	Mean	Std. dev	Min	Max
Egypt	EFP	The Ecological Footprint per capita of final consumption	GFN (2025)	1.352	0.289	0.749	1.773
	FDI	Foreign Direct Investment Inflows (% of GDP)	WB (2025)	2.103	2.052	−0.204	9.348
	GDP	Gross Domestic Product per capita (current US$)	WB (2025)	1372.04	1098.44	232.272	4233.31
	GDPSQ	Gross Domestic Product per capita Squared (current US$)	WB (2025)	3066300	4341808	53950.29	1.79e+07
	URBAN	Urban population (% of total population)	WB (2025)	72.269	3.029	66.731	77.714
	KOFTRGI	KOF Trade Globalization Index	KSEI (2025)	47.972	5.614	37.062	60.956
South Africa	EFP	The Ecological Footprint per capita of final consumption	GFN (2025)	3.457	0.342	2.842	4.222
	FDI	Foreign Direct Investment Inflows (% of GDP)	WB (2025)	0.956	1.613	−0.768	9.660
	GDP	Gross Domestic Product per capita (current US$)	WB (2025)	4043.172	2136.605	952.352	8646.06
	GDPSQ	Gross Domestic Product per capita Squared (current US$)	WB (2025)	2.08e+07	1.97e+07	906974.3	7.48e+07
	URBAN	Urban population (% of total population)	WB (2025)	55.866	6.798	47.809	68.335
	KOFTRGI	KOF Trade Globalization Index	KSEI (2025)	50.160	7.126	38.286	61.681
Morocco	EFP	The Ecological Footprint per capita of final consumption	GFN (2025)	1.361	0.260	0.882	1.805
	FDI	Foreign Direct Investment Inflows (% of GDP)	WB (2025)	1.370	1.285	−0.265	6.444
	GDP	Gross Domestic Product per capita (current US$)	WB (2025)	1773.696	1113.459	260.265	3785.94
	GDPSQ	Gross Domestic Product per capita Squared (current US$)	WB (2025)	4362397	4532294	67737.88	1.43e+07
	URBAN	Urban population (% of total population)	WB (2025)	50.532	8.776	34.477	64.596
	KOFTRGI	KOF Trade Globalization Index	KSEI (2025)	47.701	10.843	35.208	69.378
Nigeria	EFP	The Ecological Footprint per capita of final consumption	GFN (2025)	1.023	0.100	0.801	1.237
	FDI	Foreign Direct Investment Inflows (% of GDP)	WB (2025)	1.257	0.986	−1.150	4.282
	GDP	Gross Domestic Product per capita (current US$)	WB (2025)	1250.632	813.875	160.479	3088.72
	GDPSQ	Gross Domestic Product per capita Squared (current US$)	WB (2025)	2213975	2404651	25753.51	9540191
	URBAN	Urban population (% of total population)	WB (2025)	33.725	10.860	17.76	53.521
	KOFTRGI	KOF Trade Globalization Index	KSEI (2025)	21.051	7.221	8.956	32.227
Kenya	EFP	The Ecological Footprint per capita of final consumption	GFN (2025)	1.322	0.281	0.881	1.776
	FDI	Foreign Direct Investment Inflows (% of GDP)	WB (2025)	0.717	0.682	−0.005	3.094
	GDP	Gross Domestic Product per capita (current US$)	WB (2025)	698.495	574.623	141.039	2109.56
	GDPSQ	Gross Domestic Product per capita Squared (current US$)	WB (2025)	811857	1230455	19892	4450244
	URBAN	Urban population (% of total population)	WB (2025)	19.323	5.001	10.295	29.002
	KOFTRGI	KOF Trade Globalization Index	KSEI (2025)	39.490	4.531	30.906	49.468
Full sample	EFP	The Ecological Footprint per capita of final consumption	GFN (2025)	1.703	0.926	0.749	4.222
	FDI	Foreign Direct Investment Inflows (% of GDP)	WB (2025)	1.281	1.474	−1.150	9.660
	GDP	Gross Domestic Product per capita (current US$)	WB (2025)	1827.607	1710.86	141.039	8646.06
	GDPSQ	Gross Domestic Product per capita Squared (current US$)	WB (2025)	6256144	1.18e+07	19892	7.48e+07
	URBAN	Urban population (% of total population)	WB (2025)	46.343	19.734	10.295	77.714
	KOFTRGI	KOF Trade Globalization Index	KSEI (2025)	41.275	13.022	8.956	69.378

Table A2
Correlation matrix

Variables	lnEFP	FDI	lnGDP	lnGDPSQ	URBAN	lnKOFTRGI
lnEFP	1.0000					
FDI	0.0175	1.0000				
lnGDP	0.5696	0.1563	1.0000			
lnGDPSQ	0.5926	0.1555	0.9974	1.0000		
URBAN	0.3016	0.3311	0.5595	0.5553	1.0000	
lnKOFTRGI	0.5059	0.1966	0.2951	0.3118	0.5001	1.0000

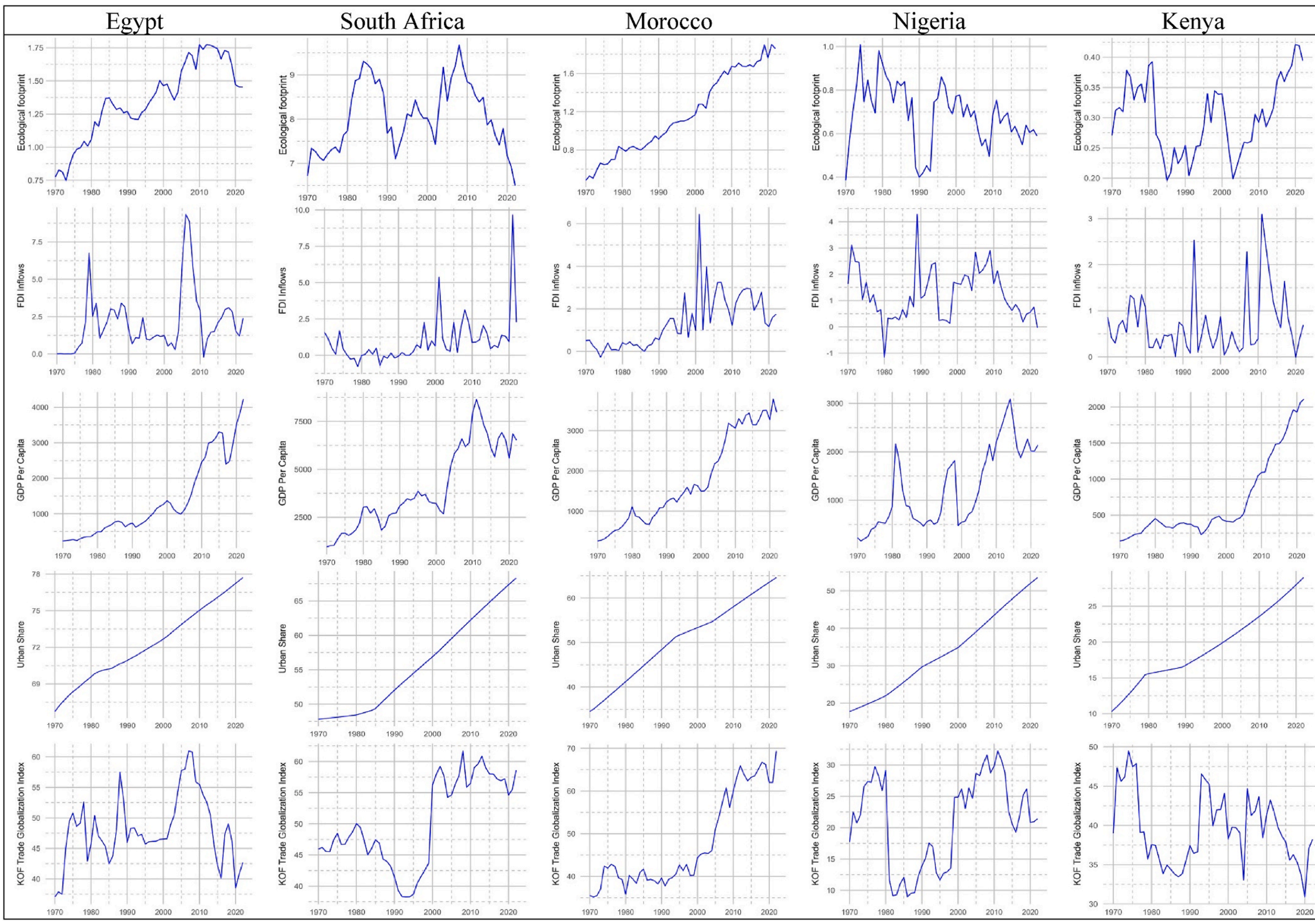

Fig. A1. Time-series trends across selected countries for the period spanning 1970–2022.

Appendix B

Table B1
SB-SUR Estimation Results

Equation	RMSE	R-squared	χ^2 statistic	p-value
Egypt	0.043	0.963	1438.93	0.000
South Africa	0.055	0.678	126.02	0.000
Morocco	0.062	0.894	470.78	0.000
Nigeria	0.057	0.663	123.50	0.000
Kenya	0.055	0.933	755.96	0.000
Variables	Coefficient	Bootstrap Std. Err.	z-statistics	p-value
Egypt				
FDI	0.009***	0.003	2.90	0.004
lnGDP	1.632***	0.170	9.60	0.000
lnGDPSQ	−0.095***	0.012	−7.47	0.000

(*continued on next page*)

Table B1 (*continued*)

Variables	Coefficient	Bootstrap Std. Err.	z-statistics	p-value
URBAN	−0.030***	0.010	−2.98	0.003
lnKOFTRGI	0.341***	0.063	5.38	0.000
D2011	0.112***	0.032	3.51	0.000
CONSTANT	−5.531***	0.731	−7.56	0.000
South Africa				
FDI	0.002	0.004	0.48	0.633
lnGDP	−1.570***	0.389	−4.03	0.000
lnGDPSQ	0.105***	0.024	4.27	0.000
URBAN	−0.019***	0.003	−5.67	0.000
lnKOFTRGI	0.527***	0.078	6.69	0.000
D1986	−0.033	0.028	−1.15	0.249
CONSTANT	6.029***	1.644	3.67	0.000
Morocco				
FDI	0.017***	0.008	2.00	0.046
lnGDP	−0.489	0.312	−1.57	0.117
lnGDPSQ	0.050***	0.024	2.11	0.035
URBAN	0.004	0.004	1.07	0.287
lnKOFTRGI	−0.137	0.117	−1.17	0.242
D1995	−0.042	0.033	−1.25	0.213
CONSTANT	1.424	1.358	1.05	0.294
Nigeria				
FDI	0.045***	0.009	4.98	0.000
lnGDP	0.904***	0.183	4.91	0.000
lnGDPSQ	−0.056***	0.013	−4.20	0.000
URBAN	−0.012***	0.001	−7.89	0.000
lnKOFTRGI	0.056***	0.019	2.84	0.005
D1989	0.031	0.029	1.09	0.275
CONSTANT	−3.292***	0.638	−5.15	0.000
Kenya				
FDI	0.015	0.011	1.40	0.162
lnGDP	0.162	0.198	0.82	0.413
lnGDPSQ	−0.008	0.015	−0.55	0.581
URBAN	−0.047***	0.007	−6.21	0.000
lnKOFTRGI	−0.202***	0.075	−2.66	0.008
D1988	−0.051*	0.031	−1.64	0.101
CONSTANT	1.246*	0.766	1.63	0.104

Table B2
F-SUR Estimation Results

Equation	RMSE	R-squared	χ^2 statistic	p-value
Egypt	0.042	0.965	1523.60	0.000
South Africa	0.045	0.783	218.28	0.000
Morocco	0.061	0.899	493.87	0.000
Nigeria	0.046	0.784	204.87	0.000
Kenya	0.043	0.958	1223.88	0.000
Variables	Coefficient	Bootstrap Std. Err.	z-statistics	p-value
Egypt				
FDI	0.001	0.003	0.37	0.710
lnGDP	2.305***	0.488	4.72	0.000
lnGDPSQ	−0.143***	0.034	−4.20	0.000
URBAN	−0.026*	0.013	−1.91	0.056
lnKOFTRGI	0.257***	0.064	4.00	0.000
sine	−0.032*	0.018	−1.70	0.090
cosine	0.068***	0.028	2.36	0.018
CONSTANT	−7.792***	1.363	−5.72	0.000
South Africa				
FDI	0.003	0.006	0.61	0.544
lnGDP	0.408	0.818	0.50	0.618
lnGDPSQ	−0.015	0.049	−0.32	0.747
URBAN	−0.028***	0.004	−7.02	0.000
lnKOFTRGI	0.348***	0.077	4.53	0.000
sine	−0.088***	0.025	−3.53	0.000
cosine	0.107***	0.026	4.05	0.000
CONSTANT	−0.808	3.228	−0.25	0.802
Morocco				
FDI	0.008	0.010	0.73	0.463
lnGDP	−0.443	0.589	−0.75	0.452
lnGDPSQ	0.046	0.044	1.04	0.297
URBAN	0.001	0.005	0.28	0.782
lnKOFTRGI	−0.024	0.170	−0.14	0.887
sine	−0.021	0.033	−0.64	0.520

(*continued on next page*)

Table B2 (*continued*)

Variables	Coefficient	Bootstrap Std. Err.	z-statistics	p-value
cosine	−0.018	0.035	−0.50	0.614
CONSTANT	1.063	2.147	0.50	0.620
Nigeria				
FDI	0.028***	0.011	2.50	0.012
lnGDP	0.736***	0.310	2.37	0.018
lnGDPSQ	−0.045***	0.022	−2.01	0.044
URBAN	−0.014***	0.001	−9.71	0.000
lnKOFTRGI	0.058**	0.030	1.95	0.051
sine	−0.067***	0.023	−2.80	0.005
cosine	−0.031	0.019	−1.62	0.105
CONSTANT	−2.598***	1.032	−2.52	0.012
Kenya				
FDI	0.017*	0.010	1.65	0.099
lnGDP	−0.182	0.302	−0.60	0.547
lnGDPSQ	0.021	0.024	0.90	0.368
URBAN	−0.045***	0.011	−3.95	0.000
lnKOFTRGI	0.0007	0.106	0.01	0.994
sine	0.090***	0.028	3.12	0.002
cosine	−0.028	0.023	−1.24	0.215
CONSTANT	1.395***	0.833	1.67	0.094

Appendix C. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2025.126536.

Data availability

Data will be made available on request.

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