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Economic Growth and Environmental Degradation in South Africa: Environmental Kuznets Hypothesis and Sustainable Development

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ABSTRACT

This article tests the EKC hypothesis for South Africa from 1990 to 2023 using ecological footprint and biodiversity loss. The paper applies ARDL-ECM, threshold, and quantile regression to establish how green innovation and macroeconomic variables affect environmental sustainability. ARDL results confirm the EKC hypothesis, showing that economic growth initially declines but later improves the environment sustainability. Threshold regression establishes that this only holds when green innovation exceeds a specific threshold. Quantile regression finds that green innovation moderates the environmental effect of exchange rate and trade openness but not GDP, industrial development, or FDI. The paper stresses that environmental improvement is dependent on the size and direction of green innovation. The work calls for coordination between technological progress and macroeconomic policy and suggests investment in green technology, green trade reforms, and directional innovation systems. The study contributes conceptually and methodologically to EKC literature with policy relevance to the South Africa.

Keywords: Economic Growth, Environmental Degradation, Green Innovation, South Africa
JEL Classification: 047, Q56, 032, N77

1. INTRODUCTION

Environmental degradation is a key impasse to sustainable development in the developing world, particularly in countries that are battling high poverty, unemployment, and energy insecurity at the same time. South Africa exemplifies this paradox since it is still struggling with the contradiction between economic growth and environmental sustainability. Given its intensive capital-energy reliance on sectors such as mining, coal-fired power, and industry, South Africa has been subjected to increasing ecological burdens, ranging from severe loss of biodiversity and soil degradation to a persistent rise in ecological footprint (Wang and Ibrahim, 2024). These challenges necessitate more empirical and theoretical investigations of how growth patterns can be separated from environmental degradation—mainly through mechanisms such as technological innovation, institutional adaptability, and policy reform.

The Environmental Kuznets Curve (EKC) hypothesis is a useful, albeit controversial framework for challenging the dynamic relationship between economic growth and environmental degradation. The EKC theory posits that environmental damage increases first with incomes but then decreases as nations invest in cleaner technologies, have more effective institutions, and build service-oriented economies (Grossman and Krueger, 1991; Acheampong and Opoku, 2023). However, conventional applications of the theory have a propensity to ignore deeper structural causes such as environmental sustainability and technological advancement that are essential for the efficient use of resources, cleaner technologies, and sustainable practices in order to ensure rapid innovation potential. This theoretical paradigm has been widely tested across the world and within regional contexts, although with mixed empirical evidence, particularly in the developing economies of South Africa (Rafindadi and Usman, 2019; Usman et al., 2020; Güngör et al., 2021; Udeagha and Muchapondwa, 2022; Udeagha and Breitenbach, 2023; Wang and Ibrahim, 2024).

In South Africa, as in many parts of the world, empirical evidence has generally supported the presence of the EKC and indicated that economic growth initially worsens environmental degradation—most notably through increased carbon emissions and pollution—before eventually contributing positively to the environment as income levels rise and technological progress comes into effect (Udeagha and Muchapondwa, 2022; Adekunle, 2025). However, the point where this transition occurs is still open to debate, and the environmental recovery pace is a function of several variables that include the structure of the economy, the consumption pattern of energy, financial growth, trade openness, and the quality of institutions (Udeagha and Breitenbach, 2023; Wang and Ibrahim, 2024).

The South African situation is also made complex by the relationship between industrialization, globalization, and foreign direct investment (FDI), all of which have deep effects on economic growth and the environment. While trade openness and globalization can spur economic development, they contribute to environmental degradation if not complemented by institutional regulatory frameworks and investments in green technology (Usman et al., 2020; Güngör et al., 2021). Conversely, fiscal decentralization, technological innovation, and the use of renewable energy have been proved to render the environment sustainable with policy interventions that induce sustainable development orientations playing key roles (Rafindadi and Usman, 2019; Wang and Ibrahim, 2024).

In South Africa, the ecological footprint varied greatly between 1970 and 2023 (see Figure 1 below): from 3.57 global hectares per capita in 1970 to 4.22 in 1974 due to high industrial activity, then falling to 4.21 in 1975 despite the economic decline. It further decreased to 3.17 in 1983, driven by economic turmoil and reduced production, and further fell to 2.84 in 1992 amidst international sanctions and reduced resource consumption. It again peaked at 4.02 in 2008, reflecting economic recovery and increased consumption; afterwards, it dropped to 3.09 in 2020 following the global financial crisis. In 2023, it increased to 3.25, indicating continuous environmental pressures yet staying below the historic peaks due to better resource use (Global Footprint Network, 2025).

As shown in Figure 1, biodiversity has continuously fallen from 2.40 in 1970 to 2.11 in 1977 and 1.94 in 1979 because of habitat loss and alteration of land uses induced by economic growth. It then suffered the most dramatic decline during the 1980s and continued until it got to 1.26 in 1992. The declines were much more gradual during the 1990s and the 2000s, due to conservation efforts, generally stabilizing around 1.45 between 2000 and 2009 but reached a low of 1.20 in 2020. In 2023, after some slight improvements, it recorded 1.27 but was still critically low (Global Footprint Network, 2025). Moreover, South African economic growth was volatile in nature, touching its peak at 3.17% in 1974, retracting backward due to problems of a political and economic nature by −4.44% in 1983, and again rebounding to 3.20% in 2000. Sustained growth in the middle of the 2000s was disrupted by the crisis in 2008 which led to a contraction of −2.70% in 2009 and −7.11% in 2020 due to COVID-19, decelerating further to −0.27% in 2023 (World Bank, 2024).

A cautious approach that weighs between the trajectories of economic growth and the need for environmental conservation and rehabilitation is needed in order to achieve sustainable development in South Africa. This means not only utilizing the possibilities of green technology and renewable energy but also improving regulatory quality, fostering foreign investment, and guaranteeing that economic policy aligns with environmental objectives (Güngör et al., 2021; Udeagha and Muchapondwa, 2022). The United Nations Sustainable Development Goals (SDGs) promote a convergent approach to these efforts, emphasizing transparency between macroeconomic and environmental dimensions of development.

Although, there have been several policies introduced to ensure sustainable environment-growth practices—the Green Economy Accord, the National Development Plan (NDP), the Carbon Tax Act, the National Environmental Management Act, and the Renewable Energy Independent Power Producer Programme (REIPPPP)—the policies themselves have not been successful enough to produce consistent results. The key barriers are insufficient green investment, poor capacity for policy implementation, and poor collaboration among innovation institutions and environmental governance (Adebayo et al., 2023). Apart from the barriers stated above, environmental innovation remains underfinanced and poorly embedded in the national industrial plan. This presents a need for an empirical method that disentangles how green innovation thresholds and structural change collaborate to determine South Africa's environmental future.

This current paper differs from earlier literature on the subject in that it has a triple-novelty framework. First, the study is one of the few to test the EKC hypothesis on South Africa using a threshold regression model—a method seldom used for this purpose but one that is well-equipped to model nonlinear regime-switching dynamics. Second, it uses twin ecological indicators, that is, ecological footprint and loss of biodiversity—thus offering a more complete picture of environmental degradation than the usual CO_2 emissions. Third, it uniquely brings green innovation dynamics into the growth-environment nexus by linking environmental effects to macroeconomic drivers and environmental technology proxies (e.g., access to clean energy and technologies, greenhouse emissions, and renewable waste), which are typically ignored in conventional EKC applications.

Therefore, this article offers an empirical examination of how growth affects environmental sustainability in South Africa's innovative potential threshold regimes. It addresses the following essential questions:

1. Does South Africa's economic growth follow the Environmental Kuznets Curve pattern when measured through ecological footprint and biodiversity loss?
2. What role does the green innovation threshold play in conditioning the trajectory of ecological footprint and biodiversity loss in South Africa?
3. To what extent does the level of green innovation dynamically moderate the relationship between macroeconomic performance and ecological sustainability in South Africa?

The rest of the paper is structured as follows. Section 2 presents a discussion of the literature on EKC theory, innovation-environment linkages, and sectoral-level processes in South Africa. Section 3 outlines the theoretical framework, model specification, data sources, and estimation method. Section 4 explains and examines the empirical findings, while Section 5 concludes with policy recommendations for pushing forward innovation-driven sustainability.

2. LITERATURE REVIEW

The EKC hypothesis is one of the most debated and empirically tested paradigms in environmental economics. It forecasts an inverted U-shaped relationship between economic growth and environmental pollution, stating that environment quality deteriorates during the initial stages of economic growth but subsequently gets better as a country reaches a certain income level. This theoretical assumption, first developed by Grossman and Krueger (1991), relies upon the suppositions that as incomes grow, the structural composition of an economy shifts away from polluting industries to cleaner industries, in addition to greater public pressure for environmental quality and more stringent environmental policies. However, while the EKC presents an idealized version of environmental transition, real-world application of the EKC has produced uneven results, largely due to heterogeneity in country contexts, environmental measures, and methodology.

Empirical studies that have empirically examined the EKC have traditionally employed carbon dioxide (CO_2) emissions as the standard environmental measure, applying linear time series or panel data techniques. For example, Lean and Smyth (2010) conducted a big study of ASEAN countries using Vector Error Correction Models (VECM) to examine the long-run relationship between CO_2 emissions and income growth. They found evidence in favor of the EKC hypothesis as they illustrated income growth raising emissions at first before lowering them as soon as a certain income level is reached. Similarly, Pao and Tsai (2011) tested the EKC hypothesis of BRICS economies using VECM and established the inverted U-shaped relationship although with considerable variation in turning points and magnitudes across the countries that were investigated.

Wang (2012) applied the Fully Modified Ordinary Least Squares (FMOLS) estimator to a panel of 98 countries and further validated the EKC hypothesis by determining that there were significant long-run relationships between CO_2 emissions and GDP. However, the study noted that the point of inflection was very sensitive to income category classifications and industrialization phases, with advanced-income countries exhibiting clearer EKC patterns than their less-developed-income counterparts. In contrast to the above, Mert and Bozdag (2014), in their analysis of Bosnia-Herzegovina from 1992 to 2009, found that economic growth and emissions had no conformity to the EKC curve. Instead, their regression gave an "inverted N" shape, indicating that pollution rises and falls several times as income rises and falls. This conclusion highlighted the probability that in countries of post-conflict reconstruction or structural instability, the EKC pattern does not hold due to unstable policy regimes and dispersed industrial transitions.

Further evidence of the volatility of the EKC is presented in Sahli and Rejeb (2015), who investigated its viability in Middle East and North Africa (MENA) countries. Employing dynamic panel data techniques, their study established a long-run inverted U-shaped curve, and the authors cautioned that the institutional quality and governance ability played a fundamental role in determining the robustness of the EKC. Similarly, Apergis and Öztürk (2015) examined 14 ASEAN economies using FMOLS and Dynamic Ordinary Least Squares (DOLS) techniques. The findings verified the EKC hypothesis along with identifying feedback relationships between CO_2 emissions and GDP, hence implying bidirectional causality that renders the linear causality underlying EKC analysis questionable.

The strength of the EKC hypothesis has been disputed by some research, however, especially when broader indicators of environmental degradation are used. Charfeddine and Mrabet (2017) analyzed 15 MENA countries using FMOLS and DOLS to test whether the EKC hypothesis holds if ecological footprint and carbon footprint are used as a metric. They established the EKC for ecological footprint that, as development takes place, technological progress and regulatory institutions begin to counteract human impact on nature. Their paper did, however, note that energy structure, that is, the utilization of fossil fuels—can distort results of EKC. Bekun et al. (2021), in a study of 26 EU countries based on a Panel Smooth Transition Regression model, concluded that ecological footprint is not necessarily tracing the EKC trajectory, particularly in very trade-dependent and externally energy-reliant economies. They were of the opinion that trade openness, when environmental control is insufficient, has a tendency to increase ecological burden even at higher incomes.

For South Africa, the EKC hypothesis has received limited empirical testing and the existing literature contains distinct methodological and conceptual limitations. Menyah and Wolde-Rufael (2010) were some of the earliest to test the linkage between energy consumption, pollution emissions, and economic growth in South Africa. Their study utilized Granger causality and ARDL bounds tests for 1965-2006 and established that economic growth Granger-causes CO_2 emissions but not vice versa. This implies that environmental degradation would be an unconscious by-product of economic activity and would not be driven by growth in itself. They did not examine whether the dynamics change with different income levels, nor did they conduct tests for nonlinearities.

Ganda (2019) examined the relationship between energy use, renewable energy, and South African carbon emissions using the ARDL method for 1980-2014. His analysis confirmed that the consumption of coal, electricity, and hydrocarbon gas raised emissions significantly, while the use of petroleum and the aggregate usage of energy had a mitigating effect. Notably, the EKC hypothesis was only confirmed in the short term, thereby highlighting the fact that energy transitions are a gradual process that needs long-term institutional backing. The work highlighted the importance of breaking down the sources of energy when assessing environmental impacts, an aspect most EKC studies overlook.

Saint Akadiri et al. (2019) made further observations by examining the interaction between energy consumption, income, and environmental quality using the ARDL and Toda-Yamamoto causality tests for the example of South Africa. Their findings had revealed that while higher income levels improve environmental quality in the long run, energy use continued to be the main reason for environmental deterioration. Their findings also validated the EKC hypothesis to some degree, suggesting that the relationship between income and environmental quality is conditioned by the energy intensity and efficiency of production structure.

Adebayo et al. (2023) provided a timely and technically appropriate contribution employing a time-varying causality model and ARDL estimates to investigate the relationship between CO_2 emissions, financial development, renewable energy usage, economic growth, and environmental technology in South Africa. The study found that environmental technology and financial development always had lasting negative impacts on CO_2 emissions, whereas economic growth continued to enhance them. Renewable energy had little effect, and causality patterns shifted over time. This dynamic relationship also supports using nonlinear and time-varying methods when testing the EKC, especially for structurally changing economies.

On a global front, studies integrating innovation and environmental sustainability have provided more nuanced results. Wen et al. (2021), during their study of South Asian countries, found that globalization and utilization of renewable energy play significant roles in reducing CO_2 emissions. Their study utilized panel data methods and found that innovation-driven globalization helped to de-link income growth from emissions, and therefore suggests that technology change must be controlled for in EKC testing. Acheampong and Opoku (2023) also employed a dynamic system-generalized method of moments on 140 countries over the period 1980-2021. They established that environmental degradation, as represented by emissions and ecological footprint, decelerates economic growth unless offset by innovation, foreign direct investment, and human capital accumulation. The authors argued that the EKC should rather be described as an "innovation-mediated curve" rather than being any function of income.

Zhang et al. (2021), through their Pakistan study using the dynamic ARDL method, demonstrated that human capital, technological innovation, and natural resource management collectively determine the level of environmental degradation. They revealed that enhanced capacity of innovation leads to cleaner production practices that make environmental performance better at lower income levels. Their research presents a vital lesson for nations like South Africa, where the green economy transition is largely reliant on the innovation capacities of dominant sectors like mining, manufacturing, and energy.

Cumulatively, the available literature has made useful contributions to the topic under research but also un-fills major gaps that must be attended to. Firstly, they largely focus on CO_2 emissions, which capture only one side of environmental pollution. There is also a very severe lack of empirical examination of ecological footprint and loss of biodiversity which are indicators that enable one to perceive the larger environmental impact of economic activities. Secondly, there are very few studies employing nonlinear or threshold models that one would need to identify regime shifts in the economic–environmental relationship, particularly for economies with high inflation volatility, exchange rate shocks, and demographic shift like South Africa. Thirdly, the literature hardly captures innovation system indicators such as green R&D, renewable energy investment, or patent activity—when the former has a proven track record of limiting environmental degradation. However, global literature still embraces the use of innovation systems theory and threshold modeling within the EKC framework, namely in countries undergoing economic and energy transitions.

3. METHODOLOGY

3.1. Theoretical Framework

The study relies on the Environmental Kuznets Curve (EKC) theory, a major economic-environmental hypothesis, which is propounded by Grossman and Krueger (1991). According to this theory, there occurs an inverted-U curve relationship between environmental degradation and economic growth, such that in the early stages of development, economic growth results in environmental harm but after a threshold level of income, environmental quality improves due to cleaner technologies and regulatory instruments becoming accessible. Theoretical explanation is based on three cumulative effects: scale, composition, and technique effects. Algebraically, the EKC is formulated as a quadratic function in income, meaning that the environmental outcome Et is a function of per capita GDP and its square:

$$e_t = \phi_0 + \phi_1 gdp_t + \phi_2 gdp_t^2 + \varepsilon_t \tag{1}$$

Where $\phi_1 > 0$ and $\phi_2 < 0$ represent the inverted-U shape. However, the conventional EKC model lacks mechanisms to incorporate technological dynamics and environmental governance structures, which are particularly crucial in post-industrial economies such as South Africa. To improve the theoretical framework and encompass recent environmental policy discourses, the model is enhanced by green innovation and a set of macroeconomic indicators. Specifically, the study draws on the Innovation-Augmented EKC model (Zhang et al., 2021; Adebayo et al., 2023), which holds that innovation—and green technology innovation, in particular—can shift the EKC below by favoring the pattern towards clean production and consumption. Green innovation is not only a direct determinant of environmental quality but also a potential threshold and interaction variable, which is captured as augmented:

$$e_t = \phi_0 + \phi_1 gdp_t + \phi_2 gdp_t^2 + \phi_3 gii_t + \phi_4 (gdp_t * gii_t) + \varepsilon_t \quad (2)$$

In this case, gii_t is the green innovation index, and the interaction term (gdp_t*gii_t) captures the mechanism by which the threshold for innovation facilitates the environmental impact of income. To improve robustness, the study employs twin environmental indicators: ecological footprint (ef_t) and loss of biodiversity (bio_t), both reflecting different dimensions of ecological deterioration.

The model is further enriched with the addition of the following macroeconomic variables: trade openness (to account for the impact of globalization on the environment), foreign direct investment (as a form of technology and capital transfer), industrial development (as an indicator of sectoral structure), exchange rate (to account for external competitiveness as well as import-export behavior), and price level of inflation (to account for economic instability and consumption behavior). These variables rely on the theoretical assumptions of ecological modernization theory and structuralist development models that hypothesize that macroeconomic forces underlie the scale, composition, and technique impacts of environmental change (Huber, 2000). The augmented theoretical model is therefore:

$$e_t = \phi_0 + \phi_1 gdp_t + \phi_2 gdp_t^2 + \phi_3 gii_t + \phi_4 (gdp_t * gii_t) + \phi_5 top_t + \phi_6 fdi_t$$
$$+ \phi_7 ind_t + \phi_8 exr_t + \phi_9 price_t + \varepsilon_t \quad (3)$$

Where the additional variables—top_t (trade openness), fdi_t (foreign direct investment), ind_t (industrial development), exr_t (exchange rate), and $price_t$ (price level)—are hypothesized to conditionally or directly affect environmental quality.

3.2. Model Specification

The theoretical models (1) and (3) are econometrically used to test the three objectives of the study, whose functional form is specified as:

$$ef_t|bio_t = f(gdp_t, gdp_t^2, gii_t, top_t, fdi_t, ind_t, exr_t, price_t) \quad (4)$$

The mathematical equation becomes:

$$ef_t \mid bio_t = \beta_0 + \beta_1 gdp_t + \beta_2 gdp_t^2 + \beta_3 gii_t + \beta_4 top_t + \beta_5 fdi_t$$
$$+ \beta_6 ind_t + \beta_7 exr_t + \beta_8 price_t \quad (5)$$

This is restated in its econometric form for empirical estimation as:

$$ef_t \mid bio_t = \beta_0 + \beta_1 gdp_t + \beta_2 gdp_t^2 + \beta_3 gii_t + \beta_4 top_t + \beta_5 fdi_t$$
$$+ \beta_6 ind_t + \beta_7 exr_t + \beta_8 price_t + \mu_t \quad (6)$$

To capture the effect of the green innovation threshold, the model is also specified using a regime-based framework:

$$ef \mid bio_t = \{\delta_0 + \delta_1 gdp_t + \delta_2 gdp_t^2 + \delta_3 z_t + \eta_t, if\ gii_t \le \gamma\}$$
$$\{\theta_0 + \theta_1 gdp_t + \theta_2 gdp_t^2 + \theta_3 z_t + \nu_t, if\ gii_t > \gamma\} \quad (7)$$

In equation (7), γ is the estimated green innovation threshold and z_t denotes the macroeconomic control variables. Lastly, in order to assess the conditional impacts at quantiles of environmental degradation, the model is specified for quantile $\tau \in (0,1)$ as:

$$Q_\tau(ef_t) = \lambda_{o\tau} + \lambda_{1\tau} gdp_t + \lambda_{2\tau} gii_t + \lambda_{3\tau}(gdp_t * gii_t) + \lambda_{4\tau} z_t$$
$$+ \lambda_{5\tau}(z_t * gii_t) \quad (8)$$

3.3. Estimation Strategy

The study employs four complementary estimation techniques: PCA for index construction, Autoregressive Distributed Lag (ARDL) bounds testing for long- and short-run relationships, threshold regression to capture green innovation regime shift, and quantile regression to capture distributional heterogeneity. The PCA technique is employed to construct the green innovation index between three standardized variables: combustible renewables and waste (ren_wst_t), access to clean fuels and technologies ($clean_t$), and per capita GHG emissions (ghg_t). The general PCA model is as follows:

$$gii_t = \varpi_1 ren\_wst_t + \varpi_2 clean_t + \varpi_3 ghg_t, where \sum_{i=1}^{3} \varpi_i^2 = 1 \quad (9)$$

The largest eigenvalue first principal component is kept as gii_t, which gives the strongest variation in green technological capacity.

For the first objective of this study, Pesaran et al. (2001) ARDL bounds testing procedure is used to examine cointegration between environmental indicators and macroeconomic variables. The method applies to small samples as well as mixed orders of integration, as verified by the estimates of stationarity. The ARDL specification for each of the dependent variables is as follows:

$$\Delta ef_t \mid bio_t = \psi_0 + \sum_{i=1}^{p} \psi_1 \Delta \mathrm{ef} \mid \mathrm{bio}_{t-i} + \sum_{j=0}^{q} \psi_2 \Delta X_{t-j} + \pi_1 ef \mid bio_{t-1}$$
$$+ \pi_2 X_{t-1} + \varepsilon_t \quad (10)$$

Where X_{it} includes the entire set of regressors. The joint significance of the level lag variables is used by the F-bound and t-bound tests to determine if there is a long-run relationship. Following cointegration detection, long-run and short-run elasticities are estimated using Error Correction Models (ECM), with the sign and magnitude of the error correction term indicating the speed of adjustment.

$$\Delta ef_t \mid bio_t = \theta_0 + \sum_{i=1}^{p} \theta_1 \Delta ef \mid bio_{t-i} + \sum_{j=0}^{q} \theta_2 \Delta X_{t-j} + \varphi ecm_{t-1} + \nu_t \quad (11)$$

To obtain the second objective, Hansen (1999) threshold regression methodology is applied to determine structural breakpoints in terms of green innovation thresholds. The method is not subject to endogenous regime switches and allows for estimation of different slope parameters across low and high innovation regimes identified.

$$ef_t \mid bio_t = \alpha + \beta_1 gdp_t * I\left(gii_t \le \gamma\right) + \beta_2 gdp_t * I\left(gii_t > \gamma\right) + \delta z_t + \varepsilon_t \quad (12)$$

The choice of γ is made using grid search minimum sum of squared residuals, and statistical inference is provided using a bootstrap approach.

The third objective is addressed using the quantile regression approach of Koenker and Bassett (1978), which provides the conditional distribution of the dependent variable beyond the mean. This approach identifies heterogeneous regressor effects at various levels of environmental degradation, as is consistent with asymmetric green innovation responses (see equation 8 for the specification). Standard errors are obtained via bootstrap replications to allow robust inference.

This sequential estimation method ensures model stability and discloses the conditional and nonlinear ways through which growth, innovation, and macroeconomic dynamics influence environmental sustainability in South Africa.

3.4. Data and Scope

The dataset comprises annual time series for South Africa between 1990 and 2023, spanning the long-run relationships between macroeconomic variables and environmental outcomes through a period that has been marked by fundamental structural change, energy reforms, and strategy of innovation-led development. The dependent variables are ecological footprint (per capita global hectares) and biodiversity loss index; both obtained from the Global Footprint Network. The primary independent variables are per capita GDP growth and the square of per capita GDP growth, trade openness measured as exports plus imports/GDP, foreign direct investment as net external resource flows, industrialization taken as industry's share of GDP, exchange rate as South Africa ZAR per one unit of USD, and inflation as recorded through the GDP deflator, with all variables drawn from World Bank's World Development Indicator (WDI) database. Moreover, green innovation index is developed using PCA of three environmental technology indicators: combustible renewables and waste (% of energy use), access to clean fuels and technologies (% of population), and green gas emissions per capita. The indicators are collected from the WDI and standardized prior to using PCA. The first principal component is kept to capture the index of innovation as it accounts for the highest percentage of variance among the three measures.

4. EMPIRICAL RESULTS AND DISCUSSION

4.1. Preliminary Result

The PCA result in Table A1 confirms that the first principal component with an eigenvalue of 1.986 and accounting for 66.2% of the cumulative variance describes the dominant relationship between renewable waste, clean energy, and greenhouse gas emissions. Component 1 is defined by renewable waste and clean energy with strong opposing loadings, indicating a latent index of environmental sustainability. Therefore, the PCA is warranted in dimension reduction and necessitates the application of a composite indicator for robustness. Additionally, the descriptive statistics are exhibited in Table A2, noting a moderately high ecological footprint and low biodiversity loss, with extreme dispersion in GDP and industrial development. The structural heterogeneity in the macroeconomic indicators in South Africa is evidenced by the large standard deviation in GDP, trade openness, industrial development, exchange rate, and price level, which necessitates further nonlinear modeling techniques. Likewise, the correlation matrix shown in Table A3 shows that ecological footprint positively correlates with all the independent variables and is inversely correlated with squared GDP as well as inflation price level. Notably, green innovation positively correlates highly with ecological footprint and negatively correlates highly with biodiversity loss, pointing to its conditional significance in explaining environmental outcomes. Moreover, the positive correlation between industrial growth and GDP, in addition to their weak association with loss of biodiversity, justifies the employment of dynamic interaction models. Lastly, the BDS test in Table A4 indicates the presence of significant nonlinearity for all variables except FDI. The non-rejection of the null of I.I.D. across dimensions for ecological footprint, biodiversity loss, GDP, and green innovation indicates the presence of sophisticate nonlinear dynamics in the environmental-growth nexus, warranting the methodological application of linear and nonlinear estimation methods throughout subsequent sections. Finally, Table A5 also shows that most of the variables are integrated of order one (I (1)), with the only exceptions being GDP, its square, FDI, industrial development, and price level that are stationary at level (I (0)), and that the green innovation index does not have a definite order of integration. The mixed integration orders affirm the suitability of employing the linear ARDL technique that accommodates such a mixed integration order.

4.2. Main Results

Table 1 establishes significant evidence of cointegration in both

Table 1: T-bound and F-bound cointegration tests result for model 1 and 2

Model	F-statistic	t-statistic	Decision rule (F)	Conclusion (F)	Decision rule (t)	Conclusion (t)
ef_t model	8.284***	−6.659	F>I (1) upper bound⇒reject H_0	Cointegration	t < I (1) lower bound⇒reject H_0	Cointegration
bio_t model	7.74***	−5.83	F>I (1) upper bound⇒reject H_0	Cointegration	t < I (1) lower bound⇒reject H_0	Cointegration
	Significance level	**F-statistic I (0)**	**F-statistic I (1)**	**t-statistic I (0)**	**t-statistic I (1)**	
	10%	1.95	3.06	−2.57	−4.4	
	5%	2.22	3.39	−2.86	−4.72	
	2.50%	2.48	3.7	−3.13	−5.02	
	1%	2.79	4.1	−3.43	−5.37	

Source: Authors' Computations, 2025. 1% (***), 5% (**), and 10% (*) significance level

models since F-statistics according to ecological footprint and biodiversity loss significantly exceed the upper bound critical values at the 1% significance level, while the corresponding t-statistics are well below the lower bound thresholds. This mutual rejection of the null hypothesis under both bounds confirms the existence of a long-run equilibrium relationship between biodiversity loss, ecological footprint, and their macroeconomic as well as innovation-driven determinants. The models are therefore statistically justified for long-run analysis within the EKC framework, warranting the incorporation of green innovation, economic growth, and structural variables in explaining environmental degradation in South Africa.

Table 2 presents the ARDL estimates verifying the EKC hypothesis in South Africa for ecological footprint and biodiversity loss models. In the long run, GDP has a positive and statistically significant effect on ecological footprint and biodiversity loss, and the squared term of GDP is negative and significant, thus verifying the inverted U-shaped EKC relationship where economic growth gains pace for environmental degradation; however, it later curbs it following a turning point. Green innovation has a strong long-term positive effect on ecological footprint, indicating that while technological advancement is rising, its application can remain inefficient or directed in the wrong direction; nevertheless, its effect on biodiversity is positive but insignificant. FDI is positively and significantly associated with long-term biodiversity loss, thereby reflecting the introduction of environmentally harmful capital or technology, while industrial development negatively and significantly affects biodiversity loss, meaning industrial progress in South Africa can be offset by conservation efforts. Exchange rate depreciation significantly reduces both ecological footprint and loss of biodiversity, reflecting that an undervalued local currency might help stem environmentally harmful imports or reduce pressure driven by consumption. Inflation price level significantly increases biodiversity loss in the long run but has no effect on the ecological footprint.

Both ecological footprint and biodiversity loss mostly depend on their lagged values in the short run, indicating environmental inertia. The coefficients of GDP and its square in the short run with respect to biodiversity loss are significant and of the same sign as the long-run EKC relationship. Green innovation exerts a large and significant short-run effect to increase both ecological footprint and biodiversity loss, thus affirming its short-run expansionary environmental impact. Trade openness comes with a small but statistically significant short-run positive coefficient for both measures, suggesting exposure to environmentally intensive trade. Short-run FDI negatively and significantly affects environmental degradation, specifically biodiversity loss, and its lag is also highly negative. Industrial growth has a negative lag effect on ecological footprint, supplementing its short-run negative impacts. Short-run exchange rate impacts are mostly insignificant, though a lagged exchange rate appreciation reduces biodiversity loss marginally, while the inflation of the price level does not exert any significant short-run impacts. Lastly, the models have high explanatory power with $R^2 > 0.93$ and low RMSE, indicating good fit and predictive capacity. In conclusion, the empirical results provide strong evidence supporting the EKC hypothesis but also reveal the changing roles of innovation, trade, capital inflow, and macroeconomic factors in shaping South Africa's environment.

Table 2: ARDL result for EKC hypothesis in South Africa

Long run estimate			Short run estimate		
Variable	**ef_t**	**bio_t**	**Variable**	**eco_t**	**bio_t**
gdp_t	0.042* (0.093)	0.022** (0.026)	ef_{t-1}	−0.968*** (0.000)	
gdp^2_{it}	−0.005* (0.065)	−0.004** (0.002)	bio_{t-1}		−2.466*** (0.000)
gii_t	0.346*** (0.000)	0.027 (0.118)	bio_{t-1}		1.173** (0.005)
top_t	−0.006 (0.644)	−0.005 (0.148)	Δgdp_t		0.002 (0.863)
fdi_t	0.050 (0.128)	0.041*** (0.000)	Δgdp_{t-1}		−0.014* (0.062)
ind_t	−0.023 (0.309)	−0.019** (0.022)	Δgdp^2_t		0.008** (0.018)
exr_t	−0.067*** (0.000)	−0.015*** (0.000)	Δgdp^2_{t-1}		0.006** (0.054)
$price_t$	0.017 (0.112)	0.012** (0.022)	Δgii_t	0.213** (0.026)	0.134** (0.045)
			Δgii_{t-1}	0.279** (0.006)	0.107 (0.238)
			Δtop_t	0.017* (0.098)	0.014* (0.072)
			Δfdi_t	−0.044** (0.045)	−0.091** (0.007)
			Δfdi_{t-1}	−0.017 (0.221)	−0.047** (0.015)
			Δind_t	−0.019 (0.154)	
			Δind_{t-1}	−0.029** (0.001)	
			Δexr_t	0.003 (0.874)	0.022 (0.198)
			Δexr_{t-1}		−0.038* (0.099)
			$\Delta price_t$		0.008 (0.586)
			$\Delta price_{t-1}$		0.015 (0.208)
$constant_t$	3.873*** (0.000)	4.007** (0.001)	$constant_t$	3.873*** (0.000)	4.007*** (0.001)
R^2	0.935		R^2	0.940	
RMSE	0.064		*RMSE*	0.040	
$B\text{-}P_{Heteroscedastic}$	0.910 (0.341)		$B\text{-}P_{Heteroscedastic}$	3.990* (0.046)	
$B\text{-}G_{Autocorrelation}$	0.294 (0.588)		$B\text{-}G_{Autocorrelation}$	0.237 (0.626)	
N	32		*N*	32	

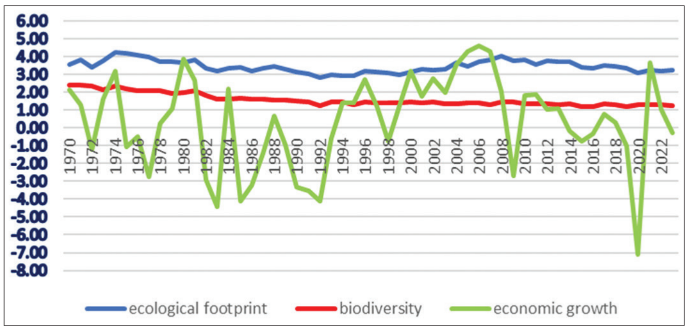
Source: Authors' Computations, 2025. 1% (***), 5% (**), and 10% (*) significance level

Table 3: Threshold regression result for the role of green innovation threshold in conditioning the trajectory of environmental sustainability

Variable	ef_t		bio_t	
	Low GII	High GII	Low GII	High GII
gdp_t	−0.011 (0.857)	−0.037 (0.627)	0.044 (0.106)	−0.038 (0.260)
gdp_{it}^2	0.015** (0.030)	−0.018** (0.031)	0.001 (0.894)	0.001 (0.937)
top_t	0.012 (0.377)	0.011 (0.286)	0.001 (0.872)	0.002 (0.635)
fdi_t	−0.004 (0.909)	−0.003 (0.936)	0.009 (0.523)	0.002 (0.897)
ind_t	0.012 (0.790)	0.006 (0.903)	−0.026 (0.189)	0.012 (0.582)
exr_t	0.006 (0.862)	−0.074* (0.074)	−0.013 (0.416)	−0.003 (0.854)
$price_t$	−0.033 (0.107)	0.078** (0.046)	0.015* (0.087)	−0.011 (0.504)
$constant_t$	2.836*** (0.000)		1.284*** (0.000)	
R^2	0.889		0.698	
RMSE	0.137		0.060	
N	34		34	

Source: Authors' Computations, 2025. 1% (***), 5% (**), and 10% (*) significance level

Figure 1: Ecological footprint, biodiversity, and economic growth in South Africa (1970-2023)

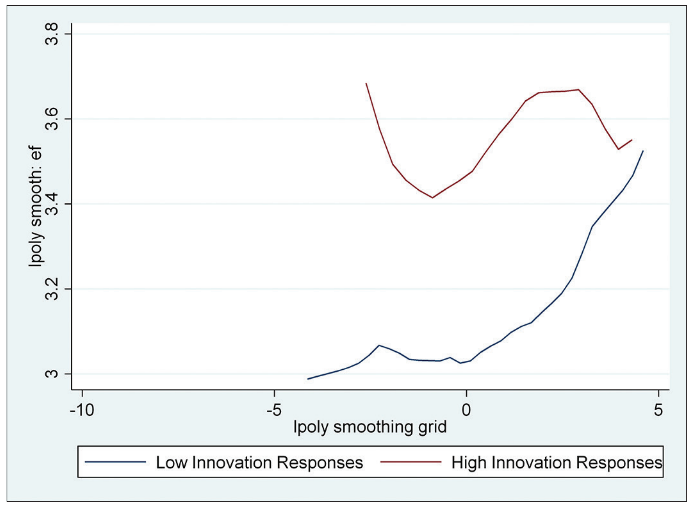


Source: Global Footprint Network (2025); World Bank (2024)

Table 3 confirms the existence of a threshold effect of green innovation in determining the impact of macroeconomic variables on environmental sustainability in South Africa. When green innovation is low or high, ecological footprint has no effect, while its square term is positive and significant in the case of low levels of green innovation and becomes negative in the case of high levels of green innovation, thus proving the presence of an EKC only for the case of green innovation—meaning that bigger responses to innovation enable countries to reach a turning point where growth begins reducing the pressures imposed on the environment. Exchange rate becomes greatly negative as levels of green innovation are high, so currency depreciation can assist in reducing ecological deterioration when there is high green innovation. Price level is significantly positive when levels of green innovation are high, quite possibly indicating higher environmental expenses from clean technologies. For loss of biodiversity, none of the economic variables are statistically significant across thresholds except for the price level of inflation, which is weakly significant and positive under low levels of green innovation, which means that biodiversity is more vulnerable and less responsive to macroeconomic fluctuations regardless of green innovation thresholds.

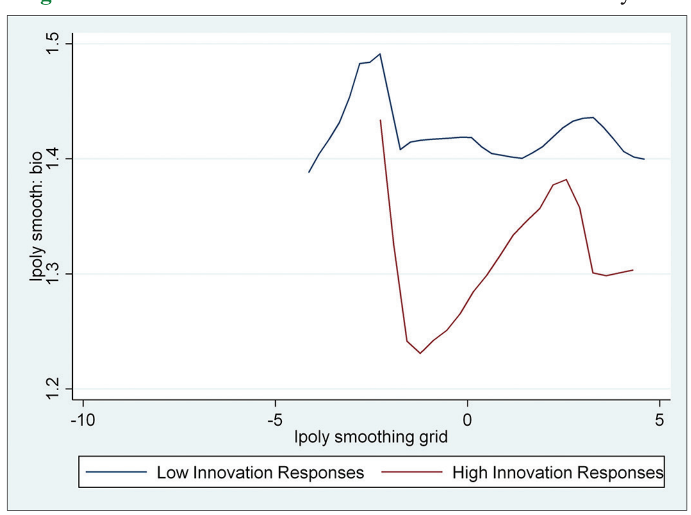
Figure 2 corroborates this result by illustrating a higher and steeper curve of ecological footprint with high innovation responses, which shows that current levels of innovation are still resource-intensive rather than resource-efficient. Conversely, low innovation responses illustrate a flat curve with rising pressure only at later stages, reflecting diminishing environmental degradation.

Figure 2: Green innovation threshold condition for ecological footprint



Source: Authors' computations, 2025

Figure 3: Green innovation threshold condition for biodiversity loss



Source: Authors' computations, 2025

Table 4: Quantile regression result for the extent green innovation dynamically moderate the relationship between macroeconomic performance and environmental sustainability

Dependent variable: ef_t			
Variable	$q_{0.25}$	$q_{0.50}$	$q_{0.75}$
gdp_t	−0.010 (0.755)	0.058* (0.062)	0.012 (0.598)
top_t	0.002 (0.841)	0.016* (0.064)	0.011 (0.108)
fdi_t	0.010 (0.622)	0.015 (0.401)	−0.001 (0.922)
ind_t	0.001 (0.979)	−0.041* (0.066)	−0.006 (0.711)
exr_t	−0.028 (0.154)	−0.064** (0.001)	−0.051** (0.001)
gdp_t*gii_t	−0.025 (0.178)	−0.003 (0.881)	−0.011 (0.396)
top_t*gii_t	0.010*** (0.000)	0.006** (0.006)	0.010*** (0.000)
fdi_t*gii_t	−0.019 (0.251)	−0.021 (0.179)	−0.010 (0.410)
ind_t*gii_t	0.022 (0.166)	0.005 (0.720)	0.003 (0.758)
exr_t*gii_t	−0.031** (0.030)	−0.007 (0.605)	−0.027** (0.009)
$constant_t$	3.519*** (0.000)	3.076*** (0.000)	3.365*** (0.000)
N	34	34	34

Figure 3 illustrates an inverted loss pattern of biodiversity whereby low innovation levels correlate with more degradation of biodiversity and the higher the level of innovation response, the greater the loss of biodiversity beyond a certain point, illustrating that biodiversity protection is more moderated by the magnitude of innovation than ecological footprint.

Table 4 presents the quantile regression estimates to estimate how green innovation dynamically engages with macroeconomic performance and ecological footprint at different conditional distributions (25th, 50th, and 75th percentiles). With the median quantile (50th percentile), GDP and trade openness are positively and statistically significant with ecological footprint, implying that in levels of environmental pressure that are typical, economic growth and trade openness increase environmental degradation. Conversely, industrial growth suggests a negative and significant relationship at this percentile, and it implies that greater industrial efficiency or adoption of cleaner production techniques can work to reduce the environmental pressure. The exchange rate is negative and significant at both the 50th and 75th percentiles, suggesting that a devaluation of currency reduces the environmental strain—potentially by reducing the availability of imported environmentally harmful products or increasing the competitiveness of clean exports.

Moreover, the interaction terms reflect significant information regarding how green innovation shifts these relationships. The trade openness-green innovation interaction is positive and highly significant in all quantiles, suggesting that as countries are more open to trade, having green innovation increases environmental impacts—perhaps because increasing trade in energy-intensive sectors takes place even as green technology spreads. However, that of exchange rate and green innovation is negative and statistically significant at both the 25th and the 75th percentiles, indicating that green innovation acts as a buffer to the environmental effect of exchange rate volatility, particularly when ecological stress is either low or high. Nonetheless, the statistical nexus between GDP and green innovation, FDI and green innovation, and industrial growth and green innovation is insignificant at all quantiles. This implies that green technology does not play a significant role in influencing the contribution of economic growth, investment flows, or industrialization towards environmental sustainability in this context.

4.3. Discussion of Result

The findings of this paper present strong empirical evidence in favor of the EKC hypothesis for South Africa, subject to important qualifications along the lines of innovation thresholds and macroeconomic dynamics. The ARDL estimates offer confirmation of the presence of an inverted-U curve between economic growth and environmental degradation, both in ecological footprint and biodiversity loss. This confirms earlier findings by Ganda (2019) and Saint Akadiri et al. (2019) that while South African early-stage growth accelerates environmental degradation, beyond a given income level, the country begins to offset this effect—presumably via industrial structural change and technology adoption. However, all this hinges on the catalyzing role of green innovation. The estimates of the EKC from the threshold regression show that it is only when green innovation is at higher stages that economic growth contributes towards environmental improvement, thus operationalizing the EKC trajectory. At lower ranges of innovation, the squared GDP is positive and significant, indicating environmental deterioration even at higher income levels. This is in agreement with Zhang et al. (2021) and Acheampong and Opoku (2023) in that they point out innovation intensity mediates the pollution-income relationship. Thus, innovation is not only a control variable but also a regime-switching determinant that alters the environmental effect of growth.

Furthermore, the results underscore the heterogeneous environmental response to other macroeconomic proxies in different regimes of innovation. Exchange rate depreciation under high levels of innovation always restricts ecological footprint, confirming that currency devaluation can potentially constrain import-based environmental degradation, particularly when coupled with domestic green technological capability. Conversely, the relationship between green innovation and trade openness consistently exacerbates ecological footprint for all quantiles. The finding suggests that the pattern of South Africa's trade remains environmentally intensive despite having green innovation, possibly due to the dominance of the extractive industry and energy-intensive production. These findings are in line with Aydın et al. (2019) and Caviglia-Harris et al. (2009), who stated that openness to trade can exacerbate environmental pressures if robust environmental governance is not put in place. The low connection between green innovation and FDI or industrial growth also implies decoupling of capital flows and green economy transformation—a weakness previously noted by Adebayo et al. (2023) on underfinancing and a lack of proper integration of environmental technology in the industrial sector of South Africa. Overall, the results suggest that while innovation is necessary, its effect is subject to threshold levels and sectoral coordination and therefore requires a coordinated policy response that focuses innovation towards green sectors and interlinks macroeconomic arrangements with sustainability objectives.

5. CONCLUSION AND POLICY IMPLICATIONS

This paper empirically examined the relationship between economic growth and environmental degradation in South Africa between 1990 and 2023 using ecological footprint and loss of biodiversity as measures of the environment within the EKC framework. Following a rigorous empirical methodology that includes the ARDL bounds test error correction model, threshold regression, and quantile regression techniques, this study confirmed the presence of a nonlinear inverted-U relationship between economic growth and environmental degradation, though conditional on specific innovation regimes. The EKC hypothesis holds true in both ecological variables, where GDP and its square both have hypothesized signs and are statistically significant. However, the presence and direction of such a relationship are heavily dependent on the level of green innovation, thereby emphasizing innovation's pivotal role in ensuring sustainable growth.

Furthermore, threshold regression analysis revealed that it is only when green innovation exceeds a critical threshold that economic growth begins to reduce environmental degradation, thus proving the presence of an EKC only for the case of green innovation. Under low innovation levels, the growth fails to slow down environmental degradation, thereby rendering the EKC hypothesis incorrect. The quantile regression results also reveal heterogeneous impacts of macroeconomic variables in the ecological footprint distribution. Trade openness, exchange rate, and industrial growth impact differently based on the rate of innovation intensity and environmental pressure. The nexus of green innovation and trade openness, though consistently significant, has the tendency to support environmental degradation, and hence, the diffusion of innovation is found not yet effectively embedded within green industries of clean trade. This points to deep structural issues in South Africa's green economy transition and brings forth new insight into innovation thresholds dynamically organizing environment trajectories. More generally, the paper makes a theoretical contribution to the EKC literature in demonstrating that green innovation is not merely a control variable but also a fundamental determinant of environmental sustainability.

Based on the findings of this study, South African policymakers must center on scaling up environmental innovation beyond critical threshold points by increasing investment in clean technologies, targeted subsidies for eco-efficient industries, and intensive linking of industrial policy and trade policy with green targets. This means increasing environmental R&D, encouraging cleaner exports, managing pollution-intensive imports, and integrating systems of green innovation into national development plans for equitability and sustainability of the growth trajectory.

Future studies should explore sectoral green innovation thresholds using disaggregated industry-level data and analyze how institutional quality, environmental regulation, and public environmental awareness influence the growth-environment relationship. Increasing the scope to natural resource depletion, energy intensity, or climate resilience indicators may also provide a better overall environmental sustainability outlook for developing economies like South Africa.

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APPENDICES

Table A1: PCA result

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.986	1.022	0.662	0.662
Comp2	0.964	0.914	0.321	0.983
Comp3	0.050		0.017	1.000
PCA eigenvectors				
Variable	**Comp1**	**Comp2**	**Comp3**	**Unexplained**
ren_wst_t	−0.699	0.056	0.713	0.000
$clean_t$	0.672	−0.287	0.683	0.000
ghg_t	0.243	0.956	0.163	0.000

Source: Authors' Computations, 2025

Table A2: Descriptive statistics

Variable	Description	Obs.	Mean	Standard deviation	Min	Max
ef_t	Ecological Footprint	34	3.353	0.311	2.843	4.024
bio_t	Biodiversity Loss	34	1.362	0.082	1.200	1.491
gdp_t	Gross Domestic Product	34	0.693	2.603	−7.107	4.591
gdp_{it}^2	Squared Gross Domestic Product	34	7.055	9.925	0.030	50.504
gii_t	Green Innovation Index	34	0.000	1.409	−2.163	1.581
top_t	Trade Openness	34	49.873	8.811	34.321	65.975
fdi_t	Foreign Direct Investment	34	1.397	1.826	−0.060	9.678
ind_t	Industrial Growth	34	0.728	3.495	−12.050	6.181
exr_t	Exchange Rate	34	8.648	4.454	2.587	18.450
$price_t$	Price Level of Inflation	34	7.780	3.223	3.993	15.655

Source: Authors' Computations, 2025

Table A3: Correlation matrix

Variable	ef_t	bio_t	gdp_t	gdp^2_{it}	*giit*	*topt*	*fdit*	*indt*	*exrt*	*pricet*
ef_t	1.000									
bio_t	−0.095	1.000								
gdp_t	0.359	0.163	1.000							
gdp^2_{it}	−0.073	0.046	−0.265	1.000						
gii_t	0.700	−0.618	0.071	0.009	1.000					
top_t	0.657	−0.498	0.248	−0.130	0.864	1.000				
fdi_t	0.157	−0.112	0.288	0.031	0.286	0.350	1.000			
ind_t	0.214	0.139	0.888	−0.310	−0.092	0.025	0.240	1.000		
exr_t	0.214	−0.677	−0.099	0.024	0.796	0.784	0.324	−0.280	1.000	
$price_t$	−0.507	0.508	−0.311	0.097	−0.768	−0.704	−0.226	−0.062	−0.665	1.000

Source: Authors' Computations, 2025

Table A4: BDS nonlinearity test

Variable	Dimension 2		Dimension 3		Remark
	BDS statistics	Z-value	BDS statistics	Z-value	
ef_t	15.078***	0.000	17.134***	0.000	Nonlinear
bio_t	2.892**	0.004	4.634***	0.000	Nonlinear
gdp_t	4.799***	0.000	4.163***	0.000	Nonlinear
gdp^2_{it}	4.176***	0.000	4.252***	0.000	Nonlinear
gii_t	22.370***	0.000	24.130***	0.000	Nonlinear
top_t	14.556***	0.000	14.570***	0.000	Nonlinear
fdi_t	−0.346	0.729	−1.061	0.289	Linear
ind_t	2.311**	0.021	2.548**	0.011	Nonlinear
exr_t	12.991***	0.000	12.934***	0.000	Nonlinear
$price_t$	7.175***	0.000	7.544***	0.000	Nonlinear

Source: Authors' Computations, 2025. 1% (***), 5% (**), and 10% (*) significance level

Table A5: ADF stationarity test

Variable	ADF-level		ADF-first difference		Remark
	Statistics	Probability	Statistics	Probability	
ef_t	−1.724	0.419	−3.723**	0.004	I (1)
bio_t	−0.485	0.895	−4.679***	0.000	I (1)
gdp_t	−3.101**	0.027	−4.353***	0.000	I (0)
gdp^2_{it}	−3.392**	0.011	−4.695***	0.000	I (0)
gii_t	−1.719	0.422	−2.116	0.238	Nil
top_t	−1.393	0.586	−4.600***	0.000	I (1)
fdi_t	−2.661*	0.081	−5.682***	0.000	I (0)
ind_t	−2.668*	0.080	−4.541***	0.000	I (0)
exr_t	0.380	0.981	−3.398**	0.011	I (1)
$price_t$	−3.055**	0.030	−3.716**	0.004	I (0)

Source: Authors' Computations, 2025. 1% (***), 5% (**), and 10% (*) significance level