XXIII ENABER – 2025

Reindustrialize to Preserve? Evidence on the Environmental Impacts of Structural Change in Brazil (1980 – 2023)

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Abstract: This paper examines the environmental impacts of structural change in Brazil from 1980 to 2023, with a particular focus on how industrialization and deindustrialization have shaped CO_2 emissions and the ecological footprint. We apply ARDL and NARDL models to capture both short- and long-run dynamics, as well as potential asymmetries in the structural transformation effects. The ARDL results indicate that a greater share of manufacturing in GDP is associated with a long-run environmental degradation reduction. The NARDL models reveal that positive shocks in industrial participation contribute more effectively to environmental mitigation than negative shocks. The results are robust across both environmental indicators considered. These findings underscore the potential of green reindustrialization as a more promising path to sustainability than deindustrialization. This study adds to the literature by highlighting the often-overlooked environmental costs of Brazil's premature deindustrialization and exploring how reindustrialization strategies could offer a way forward.

Keywords: environmental degradation; deindustrialization; green reindustrialization.

Reindustrializar para Preservar? Evidências dos Impactos Ambientais da Mudança Estrutural no Brasil (1980 – 2023)

Resumo: Este artigo analisa os impactos da mudança estrutural sobre a degradação ambiental no Brasil de 1980 a 2023, com foco particular em como a industrialização e a desindustrialização afetam as emissões de CO_2 e a pegada ecológica. São empregados modelos ARDL e NARDL para captar relações de curto e longo prazo, bem como possíveis assimetrias nos efeitos da transformação estrutural. Os resultados ARDL indicam que o aumento da participação da indústria manufatureira no PIB está associado à redução da degradação ambiental no longo prazo. Os modelos NARDL mostram que os choques positivos da participação industrial contribuem mais efetivamente na mitigação ambiental do que os choques negativos, com resultados consistentes em ambos os indicadores considerados. As evidências ressaltam o potencial da reindustrialização verde como um caminho mais promissor para a sustentabilidade do que a desindustrialização. Este estudo contribui para a literatura ao destacar os custos ambientais frequentemente negligenciados da desindustrialização prematura do Brasil e explorar como as estratégias de reindustrialização podem oferecer um caminho a seguir.

Palavras-chave: degradação ambiental; desindustrialização; reindustrialização verde.

Submission topic: 8. Meio ambiente, recursos naturais e sustentabilidade.
JEL Code: Q14; Q53; Q56.

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1. Introduction

The debate over how productive structures affect the environment has gained increasing prominence in light of the challenges posed by the ecological crisis and shifting development patterns in Brazil and around the world. The intensification of environmental problems – such as rising greenhouse gas emissions and growing pressure on ecosystems – has unfolded in a context marked by significant changes in the sectoral composition of economies, particularly the processes of deindustrialization and reprimarization in middle-income countries. In Brazil's case, these structural transformations have implications not only for economic performance but also for environmental sustainability, highlighting the need for analyses that integrate productive and ecological dimensions in a coherent framework.

After a period of industrial expansion driven by import substitution policies from the 1960s through the 1990s, several influential studies – including Bresser-Pereira and Marconi (2008), Oreiro and Feijó (2010), Cano (2012), and Nassif and Castilho (2020) – have noted that Brazil's economy has undergone an intensified process of deindustrialization since the early 2000s. This is evidenced by the declining share of manufacturing in GDP, employment, and exports. The deindustrialization process has occurred alongside the economy's reprimarization, marked by the growing prominence of primary and natural resource activities – intensive sectors fueled by rising international commodity prices and strong Chinese demand for these goods, which are critical to supporting China's own industrialization and urbanization. As a result, Brazil's manufacturing sector – especially its medium-high and high-tech industries, which tend to employ cleaner and more environmentally friendly technologies – has contributed progressively less to macroeconomic outcomes. Meanwhile, the expansion of the service sector has largely involved large-scale consumption activities with low technological sophistication, further exacerbating environmental degradation (Frey and Rosa, 2003).

In this context, the main objective of this paper is to examine the impact of structural change on environmental degradation in Brazil, using data from 1980 to 2023. The study seeks to address two key questions: (i) whether shocks in the manufacturing sector's share of GDP have distinct effects on environmental quality in the short and long term; and (ii) whether the results are nonlinear depending on whether the economy is experiencing episodes of industrialization or deindustrialization. To this end, the analysis employs CO_2 emissions and the ecological footprint as indicators of environmental degradation and estimates linear (ARDL) and nonlinear (NARDL) Autoregressive Distributed Lag models. In addition to the effects of structural change, the models consider the role of real per capita income, urbanization, and trade openness as conditioning variables in the process of environmental degradation in Brazil.

This study offers three key contributions to literature. It takes a broader view of environmental degradation by combining two complementary indicators – carbon emissions and the ecological footprint – to capture different dimensions of environmental pressure linked to structural change in Brazil. It also examines whether structural change generates distinct effects in the short and long run through ARDL models, an aspect rarely explored in existing research. Finally, it investigates potential nonlinearities in these effects by analyzing both industrialization and deindustrialization episodes using NARDL models, addressing a gap in the Environmental Kuznets Curve literature, which has traditionally focused on the environmental impacts of industrialization alone. Together, these contributions provide a stronger empirical basis for designing public policies aimed at addressing the country's environmental challenges.

The paper is structured into five sections, including this introduction. Section two reviews the theoretical and empirical foundations concerning the relationship between industrialization and environmental degradation. Section three outlines the methodology and data used in the estimations. Section four presents and discusses the main findings. Finally, section five offers the concluding remarks.

2. Theoretical framework and empirical evidence

Understanding the relationship between economic dynamics and the environment is essential for designing effective public policies aimed at mitigating environmental degradation. Among the many challenges facing the contemporary world, one of the most critical is ecological overshoot – a situation in which the resilience limits of ecosystems are exceeded. This meta-problem lies at the heart of the global ecological crisis and calls for approaches that integrate economic dynamics with the planet's biophysical boundaries. In this context, the urgency and severity of the issue were underscored by Richardson et al. (2023), who showed that six of the nine planetary boundaries have already been breached, including those related to climate change, biosphere integrity, and biogeochemical cycles. If these thresholds continue to be violated, they could undermine the stability of the Earth system and, with it, the ecological foundations of human development itself.

There is no universal economic "law" that defines a single, fixed relationship between economic growth and environmental quality. This relationship is highly context-dependent, shaped by factors such as a country's stage of development, productive structure, technological profile, natural resource base, and institutional framework. Mainstream economic theory has largely sought to address environmental challenges by incorporating negative externalities and restoring market allocative efficiency. While these tools have analytical value, their practical effectiveness has often fallen short in the face of the complexity and scale of contemporary ecological problems. This has prompted the emergence of alternative approaches that seek to integrate economic and ecological perspectives, expanding the debate beyond the narrow lens of market efficiency. Among these, the literature on the Environmental Kuznets Curve (EKC) stands out as a traditional attempt to explain the relationship between economic growth and the environment.

Inspired by Kuznets' (1955) original work, which described an inverted U-shaped relationship between income inequality and economic growth, the EKC proposes a similar pattern between environmental degradation and per capita income. According to this hypothesis, environmental impacts tend to rise during the early stages of development but decline once a certain income threshold is reached, as cleaner technologies are adopted, institutions improve, and demand for environmental quality grows (Grossman and Krueger, 1995).

Despite its intuitive appeal, the EKC remains a controversial hypothesis. Stern (2004) argues that the inverted U-shaped relationship is not robust across different econometric specifications and depends heavily on the type of pollutant or environmental indicator used. Other studies (Dasgupta et al., 2002; Dinda, 2004) have shown that empirical findings vary depending on the dataset, level of aggregation, and control variables included. Moreover, the EKC has been criticized by ecological economics for promoting an overly optimistic narrative about growth, while overlooking the ecological limits of the planet (Karsch, 2019). Daly (1996), for instance, coined the term "growthmania" to denounce this obsession with endless economic expansion.

In light of these limitations, more recent studies have aimed to refine the growth-environment relationship by replacing per capita income with structural measures such as the Economic Complexity Index (Hausmann et al., 2014). The central idea is that economies with more diverse and knowledge-intensive productive structures tend to perform better in environmental terms. As Neagu (2019) notes, complex economies are those that mobilize knowledge through wide networks of people and institutions to produce a varied mix of sophisticated, knowledge-driven goods that foster economic prosperity and increase the share of high-value-added exports. Economic complexity also helps explain trade patterns, as more developed countries typically hold comparative advantages in activities that depend on the coordination of highly skilled human capital.

A growing body of research (; Neagu, 2019; Neagu and Teodoru, 2019; Chu, 2021; Romero and Gramkow, 2021; Boleti et al., 2021; Mealy and Teytelboym, 2022) has examined the links between economic complexity, economic development, and environmental degradation, with particular emphasis on output-side flows, especially greenhouse gas emissions. These studies broadly agree that as productive structures become more complex, countries experience changes in their energy and material profiles, which in turn shape their patterns of pollution and waste generation.

Building on this line of inquiry, a study by Andrade and Simões (2022) offered further insight into the relationship between economic complexity and environmental performance. Their findings showed that greater complexity tends to promote impact decoupling (such as decarbonization) at a faster pace than resource decoupling (such as material footprint). This occurs because resource decoupling often depends on deeper transformations in consumption patterns, whereas impact decoupling can be more readily achieved through the adoption of cleaner, more efficient technologies. This distinction highlights the importance of considering both dimensions of decoupling when assessing the environmental benefits of structural change.

Recent contributions have further refined the understanding of how economic complexity interacts with environmental outcomes by adopting a sectoral lens. Montagna et al. (2025) propose a sectoral economic complexity index, allowing for a more granular analysis of how sophistication within specific industries correlates with environmental performance. Their findings reveal that sectors with higher complexity levels, particularly those that are energy-intensive, tend to achieve greater reductions in emissions when they advance in technological sophistication. This sectoral approach highlights that broad strategies aimed at increasing economic complexity may fall short unless accompanied by targeted industrial policies that prioritize greener trajectories in key sectors.

Although much of the literature on economic complexity and the environment points to a negative relationship between complexity and environmental degradation, not all studies support this view in a simple inverted U-shaped pattern. Cantero-Galiano et al. (2025), for instance, analyzed the five most economically complex countries in the European Union and identified an N-shaped relationship between economic complexity and ecological footprint. Their findings suggest that while initial gains in environmental performance may accompany technological progress and greater productive diversification, further rounds of increasing complexity can bring renewed environmental pressures. The study underscores that complexity alone does not ensure sustainable outcomes; rather, institutional quality and targeted public policies are essential to guide complexity in ways that support an ecological transition.

Research linking the sophistication of a country's productive structure with its environmental performance has added valuable nuance to the debate, but it also highlights risks that policymakers must consider. Two are particularly noteworthy. First, there is the risk of merely repackaging the logic of “growthmania” by assuming that more complex forms of growth are inherently beneficial for the environment. Second, there is the danger of promoting an overly optimistic view that greater productive sophistication on its own will suffice to address environmental challenges. As Cimoli, Dosi, and Stiglitz (2010) argue, building more complex productive structures is far from automatic; it requires deliberate industrial strategies and institutional frameworks capable of supporting capability accumulation and managing the political economy challenges that come with structural transformation.

The economic and political agenda that connects economic dynamics to sustainability has paved the way for national and regional strategies aimed at combining reindustrialization and ecological transition through integrated public policies. In this context, Guarini and Oreiro (2023) provide an analysis that links ecological transition with structural change in developing countries, drawing on the new developmentalist framework. They show that the shift to a low-carbon economy – understood as an ecological structural transformation – is compatible with the reindustrialization of middle-income countries, as long as this transformation is supported by a coordinated set of macroeconomic, industrial, and institutional policies.

Guarini and Oreiro (2023) argue that expanding the role of green industries within the productive structure can help foster a virtuous cycle between industrial development and environmental sustainability. That said, this transformation must be anchored in the principles of a just transition, especially as industrial sectors move toward decarbonization. As Upham, Sovacool, and Ghosh (2022) emphasize, the shift from environmentally harmful sectors to greener industries must be guided by a framework that integrates social justice, innovation, and community participation, with key priorities including participatory planning, addressing regional inequalities, and ensuring a fair distribution of economic benefits and costs.

Ullah et al. (2020) offer some evidence from Pakistan's experience between 1980 and 2018, focusing on the asymmetric impacts of industrialization and deindustrialization on CO_2 emissions. Their findings indicate that while industrialization is linked to rising emissions, periods of deindustrialization coincide with reductions. However, the authors are clear in cautioning against viewing deindustrialization as a viable environmental strategy. Instead, they stress the importance of industrialization pathways anchored in ecological principles, cleaner technologies, and eco-friendly industries as the foundation for sustainable development.

Building on these insights, Destek (2021) analyzes Turkey's structural transformations – spanning initial industrialization, deindustrialization, and reindustrialization – and their environmental consequences between 1970 and 2017. The study highlights how these phases produced distinct outcomes, with reindustrialization delivering the most favorable results by containing increases in CO_2 emissions and the ecological footprint. Notably, while deindustrialization contributed to lower emissions, it was also associated with a rise in ecological footprint, underscoring how a shift toward consumption-driven services or primary activities can sustain or even intensify environmental pressures.

Extending this discussion to a broader comparative context, Destek et al. (2024) provide new evidence on the environmental impacts of industrialization and deindustrialization across developed and developing countries. They find that positive shocks to industrial activity tend to exacerbate environmental degradation in both groups. Yet, the environmental effects of deindustrialization vary significantly: while it is linked to improvements in developed economies, it tends to accelerate environmental harm in developing countries, where it often takes the form of premature deindustrialization. The authors, therefore, call for industrialization strategies in developing contexts that are explicitly guided by ecological principles and supported by policies that foster clean technologies and sustainable industrial practices.

In line with these findings, Oreiro and Guarini (2025) and Isabella et al. (2024) emphasize the need to integrate structural change, ecological transition, and industrial policy in addressing environmental degradation. Their work helps consolidate a research and policy agenda that aligns with the challenges discussed in this paper, making clear that structural change must not be seen as neutral in environmental terms. Rather, it should be conceived as a lever for driving ecological transition and promoting social inclusion.

3. Methods and data

Building on the theoretical and empirical foundations reviewed earlier, this paper aims to empirically examine the effects of structural change on environmental degradation in Brazil, focusing on distinct temporal dynamics (short- versus long-run) and potential asymmetric effects of industrialization and deindustrialization. The goal is to generate evidence that reinforces the importance of a green reindustrialization process for the Brazilian economy. To this end, the study applies linear and nonlinear Autoregressive Distributed Lag (ARDL and NARDL) models for cointegration, as proposed by Pesaran and Shin (1999), Pesaran et al. (2001), and Shin et al. (2014).

The ARDL methodology offers several advantages over traditional vector autoregression (VAR) models and standard cointegration tests and error correction models (such as Engle-Granger or Johansen). It provides more efficient properties for capturing long-run relationships, particularly in studies with relatively small data samples. ARDL models can also accommodate variables with different integration orders (I(0) or I(1)) and allow for the selection of optimal lag structures to improve model fit. The method involves testing for the existence of long-run relationships among a set of variables. To do so, the ARDL model is estimated in its error correction form (ARDL-ECM), which can be specified as shown in Equation (1):

$$\Delta y_t = \alpha_0 + \alpha_1 T + \beta_1 y_{t-1} + \beta_2 x_{t-1} + \sum_{i=0}^{n} \Phi_{1i} \Delta y_{t-i} + \sum_{i=0}^{p} \Phi_{2i} \Delta \mathrm{x}_{t-i} + \mathcal{E}_t \qquad (1)$$

where y_t is the dependent variable, α_0 is the intercept, $\alpha_1 T$ represents the trend term, x denotes the independent variables, β_i are the long-run parameters, Φ_i are the short-run parameters, and E_t is the white-noise error term.

To test cointegration between the dependent variable and the explanatory variables, Pesaran et al. (2001) propose the use of a Wald (F-test) to assess the joint significance of the long-run parameters in the models. This approach helps address issues of endogeneity and serial correlation, and it remains valid regardless of whether the series are stationary. However, under the null hypothesis of no cointegration, the test statistics follow non-standard asymptotic distributions. To address this, Pesaran et al. (2001) developed a set of critical values (bounds limits), where the regressors are assumed to be either all I(0) (lower bound) or all I(1) (upper bound). The test involves comparing the computed F-statistic to these bounds. If the F-statistic exceeds the upper I(1) bound, cointegration is confirmed among the variables.

Once a long-run relationship is confirmed, the short- and long-run coefficients of the models can be estimated, along with the speed of adjustment toward long-run equilibrium in response to short-run shocks in the variables. In addition, diagnostic tests should be conducted to check for serial autocorrelation (LM test) and to assess parameter stability—using the cumulative sum of residuals (CUSUM) and cumulative sum of squared residuals (CUSUMSQ) tests as proposed by Brown et al. (1975) to ensure the robustness and validity of the estimated models.

To capture potential asymmetries in the effects of explanatory variables on the dependent variables, Shin et al. (2014) introduced a nonlinear version of the ARDL model, known as the NARDL. The purpose of this approach is to test whether the estimated relationships are symmetric – that is, whether the magnitude of an increase in a variable reflects (in absolute terms but opposite direction) the magnitude of a decrease in that same variable.

$$y_t = \beta^{+} x_t^{+} + \beta^{-} x_t^{-} + \mu_t \qquad (2)$$

where β^+ and β^- are the long-run parameters associated with the $k \times 1$ vectors of regressors x_t, decomposed as shown in Equation (3):

$$x_t = x_0 + x_t^+ + x_t^- \tag{3}$$

where x_t^+ and x_t^- represent the partial sums of the positive and negative decompositions of x_t, as defined in Equations (4) and (5) below:

$$x_t^+ = \Sigma_{i=1}^{t} \Delta x_i^+ = \Sigma_{i=1}^{t} \max\,(\Delta x_i, 0) \tag{4}$$

$$x_t^- = \Sigma_{i=1}^{t} \Delta x_i^- = \Sigma_{i=1}^{t} \min\,(0, \Delta x_i) \tag{5}$$

After substituting the NARDL (p, q) form from Equation (3), Equation (6) can be specified as the asymmetric error correction model (AECM):

$$\Delta y_t = \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \varphi_j \Delta y_{t-j} + \sum_{j=0}^{q} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \varepsilon_t \tag{6}$$

where $\theta^+ = -\rho\beta^+$ e $\theta^- = -\rho\beta^-$.

The first two testing steps for the linear (ARDL) and nonlinear (NARDL) models are similar: the bounds test is first applied to determine whether cointegration exists among the variables, followed by a joint test of the null hypothesis that $\rho = \theta^+ = \theta^- = 0$. In the next step, the Wald (F-statistic) test is used in the NARDL models to assess whether long-run ($\theta^+ = \theta^-$) and short-run ($\pi^+ = \pi^-$) relationships between the variables are symmetric.

Based on this methodology, Equations (7) and (8) are estimated to test the linear effects of structural change on environmental degradation in Brazil:

ARDL Model 1 – Dependent variable: CO_2 emissions.

$$\Delta CO_2 = \alpha_0 + \alpha_1 T + \beta_1 VAmanuf_{t-1} + \beta_2 GDPpercapita_{t-1} + \beta_3 URB_{t-1} + \beta_4 OPEN_{t-1} + \sum_{i=0}^{n} \phi_1 \Delta CO_{2\,t-i} + \sum_{i=0}^{p} \phi_2 VAmanuf_{t-i} + \sum_{i=0}^{q} \phi_3 \Delta GDPpercapita_{t-i} + \sum_{i=0}^{r} \phi_4 \Delta URB_{t-i} + \sum_{i=0}^{v} \phi_4 \Delta OPEN_{t-i} + \varepsilon_t \tag{7}$$

Model ARDL 2 – Dependent variable: ecological footprint.

$$\Delta EF = \alpha_0 + \alpha_1 T + \beta_1 VAmanuf_{t-1} + \beta_2 GDPpercapita_{t-1} + \beta_3 URB_{t-1} + \beta_4 OPEN_{t-1} + \sum_{i=0}^{n} \phi_1 PE_{t-i} + \sum_{i=0}^{p} \phi_2 VAmanuf_{t-i} + \sum_{i=0}^{q} \phi_3 \Delta GDPpercapita_{t-i} + \sum_{i=0}^{r} \phi_4 \Delta URB_{t-i} + \sum_{i=0}^{v} \phi_4 \Delta OPEN_{t-i} + \varepsilon_t \tag{8}$$

The aim of these two ARDL models is to capture possible diferences – in both sign and magnitude – in the effects of industrialization shocks (*VAmanuf*) on CO_2 emissions and the ecological footprint, from both short- and long-run perspectives.

To explore the short- and long-run nonlinearities of structural change, this variable is replaced by its positive and negative partial decompositions. Accordingly, Equations (9) and (10) are estimated as follows:

Model NARDL 3 – Dependent variable: CO_2 emissions.

$$\Delta CO_2 = \alpha_0 + \beta_1 VAmanuf_{t-1}^{+} + \beta_2 VAmanuf_{t-1}^{-} + \beta_3 GDPpercapita_{\,t-1} + \beta_4 URB_{\,t-1} + \beta_5 OPEN_{t-1} + \sum_{i=0}^{m} \phi_1\, \Delta CO_2{}_{\,t-i} + \sum_{i=0}^{n} \phi_2\, \Delta VAmanuf_{t-i}^{+} + \sum_{i=0}^{p} \phi_3\, \Delta VAmanuf_{t-i}^{-} + \sum_{i=0}^{q} \phi_3\, \Delta GDPpercapita_{\,t-i} + \sum_{i=0}^{r} \phi_4\, \Delta URB_{\,t-i} + \sum_{i=0}^{v} \phi_4\, \Delta OPEN_{\,t-i} + \varepsilon_t \tag{9}$$

Model NARDL 4 – Dependent variable: ecological footprint.

$$\Delta EF = \alpha_0 + \beta_1 VAmanuf_{t-1}^{+} + \beta_2 VAmanuf_{t-1}^{-} + \beta_3 GDPpercapita_{\,t-1} + \beta_4 URB_{\,t-1} + \beta_5 OPEN_{t-1} + \sum_{i=0}^{m} \phi_1\, \Delta EF_{\,t-i} + \sum_{i=0}^{n} \phi_2\, \Delta VAmanuf_{t-i}^{+} + \sum_{i=0}^{p} \phi_3\, \Delta VAmanuf_{t-i}^{-} + \sum_{i=0}^{q} \phi_3\, \Delta GDPpercapita_{\,t-i} + \sum_{i=0}^{r} \phi_4\, \Delta URB_{\,t-i} + \sum_{i=0}^{v} \phi_4\, \Delta OPEN_{\,t-i} + \varepsilon_t \tag{10}$$

The NARDL models' goal is to assess whether asymmetries exist between the effects of positive shocks (industrialization) and negative shocks (deindustrialization) in structural change on environmental quality indicators.

The estimated models use annual data for the Brazilian economy covering the period from 1980 to 2023. All variables are expressed in natural logarithms to capture elasticities. Table 1 defines the variables used in the estimations.

Table 1 – Variables and sources

Variable	Definition	Source	Expected sign
CO_2	Per capita carbon dioxide emissions excluding LULUCF* (in metric tons of CO_2 per capita)	WDI	*
EF	Per capita ecological footprint (in global hectares – gha)	Global Footprint Network	*
VAmanuf	Value added by manufacturing in GDP (as % of GDP)	WDI	Positive in the short run and negative in the long run
GDPpercapita	Per capita GDP (in constant 2015 US dollars)	WDI	Positive
URB	Urbanization rate (as % of total population)	WDI	Positive
OPEN	Trade openness (sum of exports and imports as % of GDP)	WDI	Negative

Source: Authors' own elaboration.

* LULUCF stands for Land Use, Land-Use Change and Forestry. This category refers to greenhouse gas emissions and removals resulting from activities such as deforestation, reforestation, forest management, and the conversion of natural ecosystems into agricultural or urban areas.

The dependent variables in the models consist of the two measures used to capture environmental degradation in Brazil: CO_2 emissions and the ecological footprint (EF), sourced from the World Bank's World Development Indicators (WDI) and the Global Footprint Network, respectively. CO_2 emissions represent per capita carbon dioxide emissions excluding LULUCF and serve as a traditional indicator of environmental degradation. The ecological footprint reflects the impact of human activities on the environment by estimating the area of biologically productive ecosystems needed to provide the natural resources consumed and to absorb the waste generated relative to the planet's capacity for regeneration.

The main explanatory variable is the manufacturing value added (VAmanuf) as a percentage of GDP. This variable is widely used in the economic literature as a proxy for industrialization degree (Rowthorn and Ramaswamy, 1997; Tregenna, 2009; Oreiro and Feijó, 2010). In line with the evidence from the Environmental Kuznets Curve (EKC), positive linear shocks to VAmanuf are expected to lead to greater environmental degradation in the short run due to pollution and inefficient use of productive resources during the early stages of industrial expansion. Over the long run, however, a negative sign is anticipated for the linear effects, as industrial growth may occur through the adoption of more advanced, cleaner, and environmentally friendly technologies that contribute to improved environmental quality. For the nonlinear effects, we expect to find evidence of asymmetries (in both magnitude and sign) between positive shocks (industrialization) and negative shocks (deindustrialization) in VAmanuf on the indicators of environmental degradation (CO_2 emissions and ecological footprint).

The other control variables used were drawn from the World Bank's World Development Indicators (WDI) and follow the specification adopted by Destek (2021) in his analysis of Turkey. These include per capita GDP (GDPpercapita), measured in constant 2015 US dollars, as an indicator of economic growth; the urbanization rate (URB), measured as the share of the urban population in total population; and trade openness (OPEN), defined as the sum of exports and imports as a percentage of Brazil's GDP. The latter is used as a proxy for productivity gains and enhanced domestic competitiveness through the import of capital goods and technologies that can boost productive efficiency (Feijó and Carvalho, 1994). The expected signs for per capita GDP and urbanization are positive, as both economic growth and rapid urbanization tend to lead to inefficient resource use and a deterioration of environmental quality. By contrast, the expected sign for trade openness is negative, since technological improvements associated with greater openness are generally resource-saving, helping to reduce CO_2 emissions and the ecological footprint.

4. Results and discussion

Before discussing the econometric findings, it is useful to briefly describe the behavior of the variables used in the estimations. Table 2 presents the descriptive statistics for the series analyzed, while Figure 1 illustrates the trends in the study's three main variables of interest – CO_2 emissions, ecological footprint, and VAmanuf – over the period from 1980 to 2023.

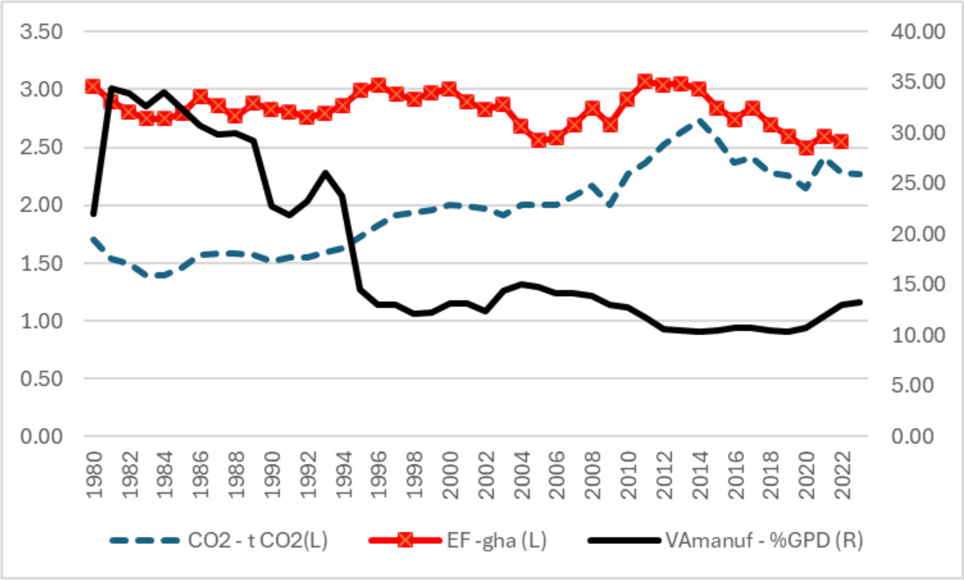
Table 2 – Descriptive Statistics

	CO_2 emisions	Ecological Footprint	VAmanuf	Per capita GDP	Urbanization	Openness
Mean	1.95	2.83	18.02	7.358,94	79.32	23.02
Median	1.97	2.84	13.96	6.823,03	81.55	22.77
Maximum	2.73	3.07	34.35	9.366,74	87.55	38.82
Minimum	1.39	2.50	10.33	5.664,96	65.47	14.39
Standard deviation.	0.37	0.15	8.29	1.178,30	6.63	5.79

Source: Authors' own elaboration based on WDI (2025) and Global Footprint Network (2025).

The average per capita CO_2 emissions and ecological footprint in Brazil were 1.85 metric tons (t CO_2) and 2.83 global hectares (gha), respectively. The maximum CO_2 emissions reached 2.73 t in 2014, while the ecological footprint peaked at 3.07 gha in 2011. The minimum values for the two indicators – 1.39 t CO_2 and 2.50 gha – were recorded in 1984 and 2020, respectively. It is also worth noting that CO_2 emissions showed a stronger growth trend and greater volatility over the 1980-2023 period (standard deviation of 0.37 t) compared to the ecological footprint (standard deviation of 0.15 gha).

Figure 1 – Trends in per capita CO_2 emissions, per capita ecological footprint (EF), and manufacturing value added (VAmanuf) in Brazil, 1980-2023



Source: WDI (2025) and Global Footprint Network (2025)

On the other hand, the industrialization process – whose average share of GDP was 18.02% – peaked in Brazil between 1980 and 1990, reaching a maximum of 34.35% in 1981. From that point onward, there has been a clear downward trend in the manufacturing value added share in GDP, hitting a low of 10.33% in 2019. These dynamics provide a strong rationale for investigating whether Brazil's industrial activity has produced distinct short- and long-run effects, as well as potential asymmetries, on the country's environmental degradation indicators.

Table 3 – Unit Root tests

	ADF	PP	KPSS	Decision
CO2 emissions	-2.5856	-2.9520	0.9482*	I(1)
D_ CO2 emissions	-6.3484*	-6.3608	0.1156	I(0)
Ecological footpring	-2.1985	-2.4132	0.0728	I(1)
D_ Ecological footprint	-5.8243*	-5.8095*	0.0634	I(0)
VAmanuf	-1.5740	-2.1602	0.1635**	I(1)
D_VAmanuf	-5.1352*	-10.3461*	0.1151	I(0)
Per Capita GDP	-2.6021	-2.8595	0.1150	I(1)
D_Per Capita GDP	-5.1620*	-5.1559*	0.1004	I(0)
Urbanization	-2.2299	-2.6938	0.8046*	I(1)
D_Urbanization	-1.2554	-1.3731	0.1543**	I(0)
Trade openness	-2.6887	-2.7770	0.0831	I(1)
D_Trade openness	-6.0569*	-6.1621*	0.0887	I(0)

Source: Authors' own elaboration based on results from Eviews 14.
ADF and PP: H_0: Series has a unit root.
KPSS: H_0: Series does not have a unit root.
Critical values: ADF and PP: 1% (-4.1923) and 5% (-3.5208); KPSS: 1% (0.2160) and 5% (0.1460).
(*) and (**) indicate rejection of H_0 at the 1% and 5% significance levels, respectively.
D_ denotes variables in first differences.
Estimates include constant and trend.

Table 3 presents the results of the stationarity tests for the variables including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. Such tests are necessary to confirm that the variables have at most an order of integration equal to one. For each variable, at least one of the tests indicated the presence of a unit root in the level series. However, all variables became stationary after first differencing, confirming that they are integrated of order one, I(1), and supporting the use of ARDL and NARDL cointegration methods.

Tables 4 and 5 summarize the results of the ARDL estimations (Models 1 and 2) and NARDL estimations (Models 3 and 4), respectively. Before presenting the main findings of interest, it is worth noting that the estimated models were found to be appropriate according to the diagnostic tests performed. For each model, a maximum of three lags was used, with the significant lag structures for each variable being (1,0,2,2,2) in Model 1, (3,3,1,0,3) in Model 2, (1,2,2,2,3) in Model 3, and (3,1,1,3,1) in Model 4. The LM autocorrelation tests indicated no evidence of autocorrelation in any of the models (rejecting the null hypothesis of autocorrelation). In addition, the bounds tests produced F-statistics greater than the critical values at the 1% significance level, confirming the existence of cointegration relationships among the variables analyzed.

Table 4 – Results of ARDL Models Estimates

	Model 1 – Dependent variable: CO_2 emissions		Model 2 – Dependent variable: ecological footprint	
Long run	Coefficient	P-value	Coefficient	P-value
VAmanuf	-0.1964*	0.0012	-0.1125***	0.0635
GDPpercapita	1.5668*	0.0000	0.7788**	0.0234
URB	2.7957*	0.0049	-0.7949	0.1474
OPEN	0.2114**	0.0411	-0.6956*	0.0046
Short run	Coefficient	P-value	Coefficient	P-value
ΔVAmanuf			-0.0075	0.8423
ΔVAmanuf $_{t-1}$			-0.0901**	0.0213
ΔVAmanuf $_{t-2}$			0.0793*	0.0165
ΔVAmanuf $_{t-3}$				
ΔGDPpercapita	1.2352*	0.0000	1.0733*	0.0000
ΔGDPpercapita $_{t-1}$	-0.5135	0.0003		
ΔGDPpercapita $_{t-2}$				
ΔGDPpercapita $_{t-3}$				
ΔURB	8.1234	0.1454		
ΔURB $_{t-1}$	9.2884	0.1216		
ΔURB $_{t-2}$				
ΔURB $_{t-3}$				
ΔOPEN	0.0984*	0.0026	-0.0423	0.1711
ΔOPEN $_{t-1}$	-0.0782**	0.0151	0.0786**	0.0438
ΔOPEN $_{t-2}$			0.0997*	0.0067
ΔOPEN $_{t-3}$				
Diagnostic tests	Coefficient	P-value	Coefficient	P-value
Bounds Tests (F-Wald)	9.6095*		7.2039*	
ECM $_{t-1}$	-0.5695*	0.0000	-0.2799*	0.0000
Autocorrelation LM	2.2606	0.1061	0.5906	0.6274
Lags	(1, 0, 2, 2, 2)		(3, 3, 1, 0, 3)	
Dummies	Subprime		-	

Source: Authors' own elaboration based on results from Eviews 14.

(*) (**) (***) indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5 – Results of NARDL Models Estimates

	Model 3 – Dependent variable: CO_2 emissions		Model 4 – Dependent variable: ecological footprint	
Long run	Coefficient	P-value	Coefficient	P-value
VAmanuf $^{+}$	-0.6825*	0.0018	-0.7292*	0.0074
VAmanuf $^{-}$	-0.2984*	0.0006	-0.1851**	0.0137
GDPpercapita	1.6504*	0.0000	0.,8282*	0.0049
URB	1.5149	0.2458	-1.0776**	0.0264
OPEN	0.1542	0.2543	-0.3921**	0.0461
Short run	Coefficient	P-value	Coefficient	P-value
ΔVAmanuf $^{+}$	0.0554	0.5739	-0.0075	0.8423
ΔVAmanuf $^{+}_{t-1}$	0.3481**	0.0101		
ΔVAmanuf $^{+}_{t-2}$				
ΔVAmanuf $^{+}_{t-3}$				
ΔVAmanuf $^{-}$	-0.1259*	0.0096	-0.0901**	0.0213
ΔVAmanuf $^{-}_{t-1}$	0.0196	0.6428		
ΔVAmanuf $^{-}_{t-2}$	0.3821*	0.0088		
ΔVAmanuf $^{-}_{t-3}$				
ΔGDPpercapita	1.3803*	0.0000	1.1505*	0.0000
ΔGDPpercapita $_{t-1}$	-0.5249*	0.0004		
ΔGDPpercapita $_{t-2}$				
ΔGDPpercapita $_{t-3}$				
ΔURB	2.8978	0.6234	-6.1050*	0.0000
ΔURB $_{t-1}$	10.1721***	0.0952		
ΔURB $_{t-2}$				
ΔURB $_{t-3}$				
ΔOPEN	0.0838**	0.0231	-0.0318	0.3017
ΔOPEN $_{t-1}$	-0.0986*	0.0048	0.0232	0.4874
ΔOPEN $_{t-2}$	-0.0333	0.4391	0.0564***	0.0821
ΔOPEN $_{t-3}$				
Diagnostic tests	Coefficient	P-value	Coefficient	P-value
Bounds Tests (F-Wald)	5.7694**		6.9375*	
ECM $_{t-1}$	-0.7670*	0.0000	-0.3895*	0.0000
Autocorrelation LM	1.1759	0.3482	0.0808	0.9697
Teste Simetria (χ^2)	3.2055***	0.0734	4.4966**	0.0340
Lags	(1, 2, 2, 2, 3)		(3, 1, 1, 3, 1)	
Dummies	-		-	

Source: Authors' own elaboration based on results from Eviews 14.
(*) (**) (***) indicates statistical significance at the 1%, 5%, and 10% levels, respectively.

The validity of the short-run coefficients is also confirmed (ECM_{t-1} with p-values below 1%), with the models related to CO_2 emissions showing short-run adjustment speeds of less than two years (ECM_{t-1} = 57% in Model 1 and ECM $_{t-1}$ = 77% in Model 3). By contrast, the models for the ecological footprint exhibit slower adjustment toward long-run equilibrium (ECM $_{t-1}$ = 28% in Model 2 and ECM $_{t-1}$ = 39% in Model 4). Finally, the CUSUM and CUSUMSQ stability tests (Brown et al., 1975) indicated no evidence of parameter instability in the models, with the sole exception of Model 1, which required stabilization through the inclusion of a Subprime dummy (equal to 1 for the period 2007–2009).[1]

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[1] See Figure 1 in Appendix A.

Having addressed these preliminary points, we now turn to the ARDL results (Table 4). The findings indicate that, over the long run, a 1% increase in the manufacturing value added share in GDP (VAmanuf) is associated with reductions of 0.19% in CO_2 emissions and 0.11% in the ecological footprint. This suggests that a higher industrialization degree is linked to improvements in environmental quality over time. In the short run, however, shocks to VAmanuf show little relevance in explaining changes in environmental indicators: the variable has no discernible effect on CO_2 emissions (Model 1), and its net short-run effect on the ecological footprint (considering lags 0 to 2) is negligible (around −0.01%). These results align with the Environmental Kuznets Curve, supporting the view that expanding the industrial share on GPD contributes to reducing environmental degradation in the long run – assuming that industrial growth reflects a shift toward more technologically sophisticated and resource-efficient activities.

The NARDL results (Table 5) point to clear nonlinear dynamics between the manufacturing value added share (VAmanuf) and environmental degradation indicators. This is evidenced by the rejection of the null hypothesis of coefficient symmetry at the 10% significance level. The findings highlight the importance of distinguishing how positive shocks ($VAmanuf^+$) and negative shocks ($VAmanuf^-$) in manufacturing activity affect CO_2 emissions and the ecological footprint.

The results show that positive shocks from industrialization ($VAmanuf^+$) and negative shocks from deindustrialization ($VAmanuf^-$) in Brazil have different magnitudes of impact on the long-run indicators of environmental degradation. While the coefficients are negative in both cases, the industrialization elasticities are larger (−0.68% for CO_2 emissions and −0.73% for the ecological footprint) compared to those linked to deindustrialization (−0.30% and −0.18%, respectively). These findings suggest that expanding industrial activity – especially in technologically more advanced sectors – is more effective at reducing environmental degradation than deindustrialization. This is because deindustrialization in the Brazilian context tends to be associated with the growth of resource-based sectors or a shift toward mass-consumption service activities, both of which are traditionally more polluting.

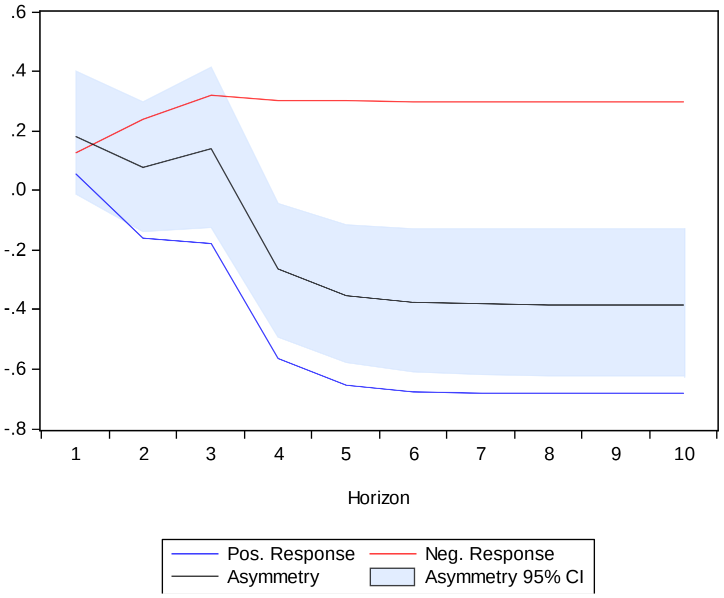
In the short run, CO_2 emissions respond positively (0.35%) to industrialization shocks ($VAmanuf^+$), although the corresponding coefficient in the ecological footprint (EF) model is not statistically significant. On the other hand, the cumulative effects of lagged deindustrialization shocks ($VAmanuf^-$) are not robust: they are positive for CO_2 emissions (0.25%) but negative for the ecological footprint (−0.09%).

Beyond the main explanatory variable (VAmanuf), it is worth highlighting that per capita GDP showed positive and consistent effects in both the ARDL and NARDL models. This suggests that economic growth tends to drive up CO_2 emissions and the ecological footprint over the long run and in its net short-run effects. In contrast, the long-run coefficient for urbanization was positive and significant in Model 1 (CO_2 emissions), but negative and significant in Model 4 (ecological footprint). A similar pattern emerged for trade openness.

The contrasting long-run coefficients for urbanization and trade openness, particularly the negative signs observed in the ecological footprint models, warrant further reflection. One possible explanation is that, over time, greater urbanization may be associated with gains in efficiency – such as better infrastructure, more compact city layouts, and a shift away from resource-intensive subsistence activities – that help reduce per capita ecological pressures. Similarly, trade openness may contribute to lower ecological footprints by facilitating access to cleaner technologies, altering the production mix toward less resource-intensive sectors, or enabling the import of goods with lower environmental costs relative to domestic production. Nonetheless, these results should be interpreted with caution, as they may also reflect complex interactions between structural change, global trade dynamics, and domestic environmental policies.

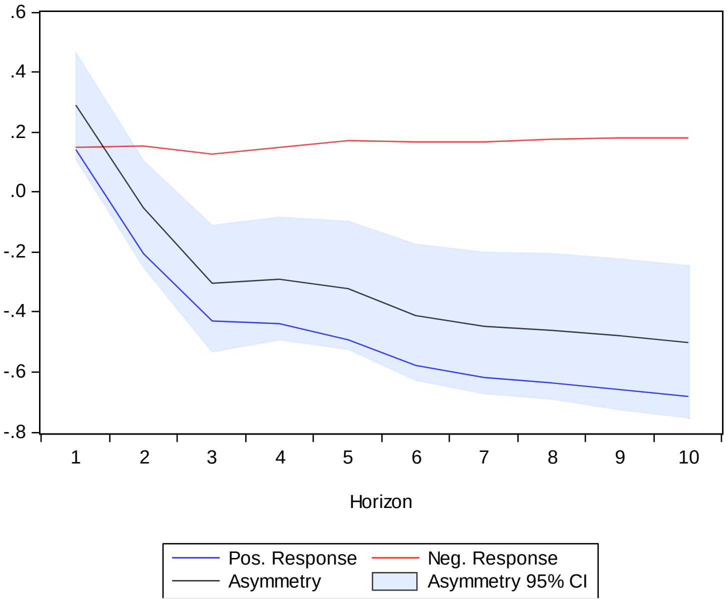
Additionally, Figures 2 and 3 illustrate the predicted marginal contribution of positive and negative shocks in the manufacturing value added share to CO_2 emissions and the ecological footprint, respectively. These graphs represent the cumulative sum of dynamic multipliers (CDM) at each point in time, starting from an initial point and spanning the length of the horizon. The horizon was set 10 years ahead.

Figure 2 – Cumulative Dynamic Multipliers: Response of CO_2 emissions to nonlinear shocks in manufacturing value added as a share of GDP



Source: Estimates from Eviews 14.

Figure 3 – Cumulative Dynamic Multipliers: Response of the ecological footprint to nonlinear shocks in manufacturing value added as a share of GDP



Source: Estimates from Eviews 14.

The CDM graphs for shock evolution show the response to a one-unit positive change in the cumulative positive asymmetric differences, and the response to a one-unit negative change in the cumulative differences for the negative asymmetric case. Over time, the graphs converge toward the theoretical long-run values of the cumulative dynamic multiplier.

The results show that environmental degradation indicators respond negatively to positive shocks in the share of manufacturing value added in GDP ($VAmanuf^{+}$). This suggests that over a 10-year horizon, green reindustrialization tends to reduce CO_2 emissions and the ecological footprint, moving toward the long-run equilibrium level. By contrast, deindustrialization ($VAmanuf^{-}$) tends to increase CO_2 emissions during the first three years following the shock, before converging toward the long-run trajectory. In the case of the ecological footprint, convergence to a higher long-run level of environmental degradation occurs soon after the shock.

The ARDL results reinforce the importance of considering the role of productive structure in the debate on environmental degradation. The manufacturing value added share was found to be associated with reductions in CO_2 emissions and the ecological footprint over the long run, although the effect on the ecological footprint was only marginally significant. This finding aligns with recent literature pointing to the potential environmental benefits of more complex and diversified productive structures (Neagu, 2019; Lapatinas et al., 2019; Romero and Gramkow, 2021). The impact of urbanization on emissions highlights the relevance of the arguments made by Cantero-Galiano et al. (2025) on the importance of urban and institutional policies in moderating the environmental impacts of economic transformation.

The NARDL models allowed for a deeper examination of the asymmetries in the impacts of structural change, producing results that closely align with studies such as Destek (2021), Destek et al. (2024) and Guarini and Oreiro (2023). The finding that the expansion of manufacturing is linked to a greater reduction in CO_2 emissions and the ecological footprint compared to its contraction reinforces the case for green reindustrialization as a central strategy for environmental mitigation, as advocated by new-developmentalist and structuralist approaches. The evidence of environmentally inefficient sectoral shifts during deindustrialization echoes the warnings of Oreiro and Guarini (2025) about the risks of reprimarization and the emphasis by Isabella et al. (2024) on the need for integrated policies that combine structural change, ecological transition, and social inclusion. The asymmetries identified suggests that the direction of structural change – not just its intensity – is crucial in shaping environmental outcomes. Furthermore, the results highlight that trade openness and urbanization contribute to sustainability only when accompanied by deliberate public policies that enhance potential gains and prevent regressive trajectories.

Taken together, the findings suggest that industrial, trade, and urban policies should be designed as part of a broader project of productive transformation, rooted in clean technologies and guided by the principles of a just transition. Promoting green reindustrialization, aligning trade openness with environmentally efficient value chains, and strengthening sustainable urban policies emerge as key elements for reconciling economic growth, structural change, and the mitigation of environmental degradation – consistent with the directions highlighted in recent literature. Moreover, the identification of asymmetries in the impacts of structural transformations points to the need for active policies that are sensitive to the direction of structural change, combining tools to strengthen sustainable sectors with mechanisms for productive reconversion in declining industries.

5. Concluding remarks

This study explored how structural change, economic growth, and environmental degradation interact in the Brazilian context, with particular attention to the impacts of industrialization and deindustrialization on CO_2 emissions and the ecological footprint, across both short- and long-run horizons. The ARDL and NARDL estimations showed that a higher manufacturing value added share is linked to reductions in environmental degradation indicators over the long run. These results lend support to the idea that a more complex and technologically advanced productive structure can help drive gains in material and energy efficiency. In contrast, economic growth – as captured by per capita GDP – was positively associated with environmental degradation, echoing critiques from ecological economics that growth alone does not guarantee improvements in environmental quality.

This study makes a novel contribution by advancing the understanding of the adverse environmental effects of Brazil's premature deindustrialization – an often overlooked dimension in the literature, which tends to focus more on the economic and social impacts of this process. The NARDL models revealed that industrial expansion has a stronger effect in mitigating environmental degradation than industrial decline, reinforcing the centrality of reindustrialization guided by ecological principles. The findings suggest that effective public policies must integrate industrial, trade, and urban strategies within a coherent project of sustainable productive transformation – one that is attentive to the direction and environmental quality of structural change and guided by the principles of a just transition. The articulation of green reindustrialization, strategically oriented trade openness, and sustainable urban planning emerges as a necessary path for aligning economic development with environmental preservation.

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Appendix A: Figure 1 –CUSUM and CUSUMSQ tests

Figure 1(a) – Model 1 (CO$_2$ emissions)

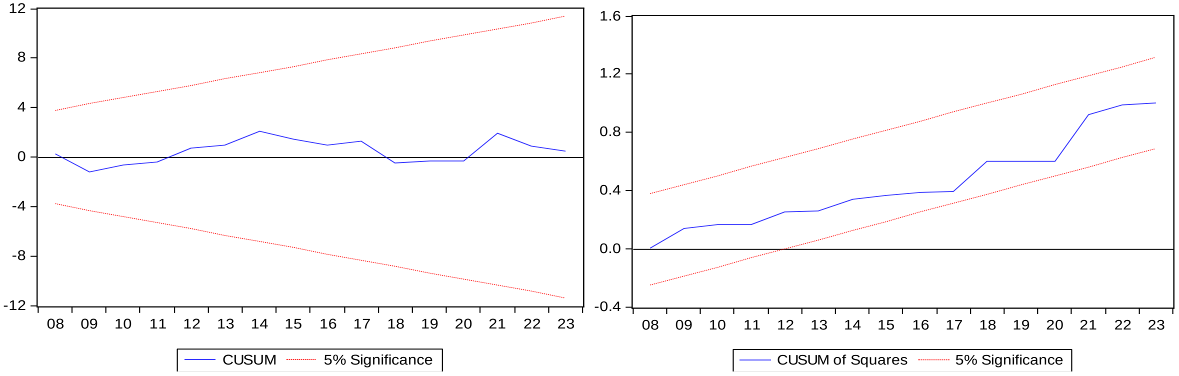


Figure 1(b) – Model 2 (ecological footprint)

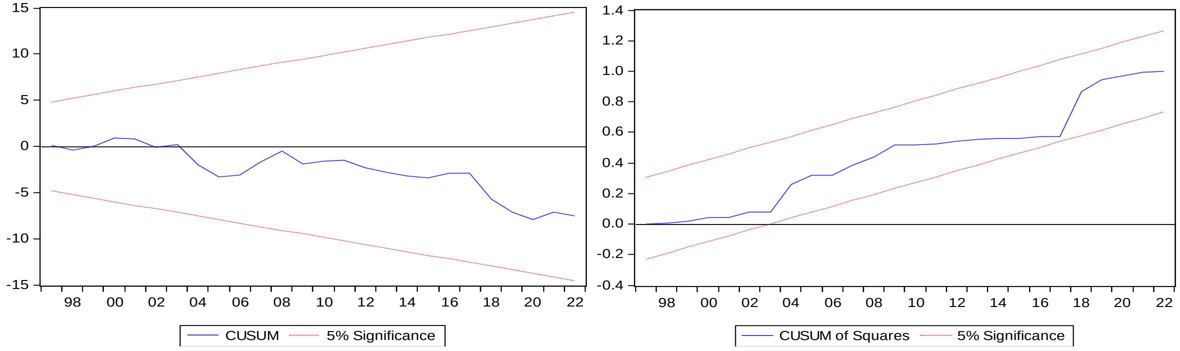


Figure 1(c) – Model 3 (CO$_2$ emissions)

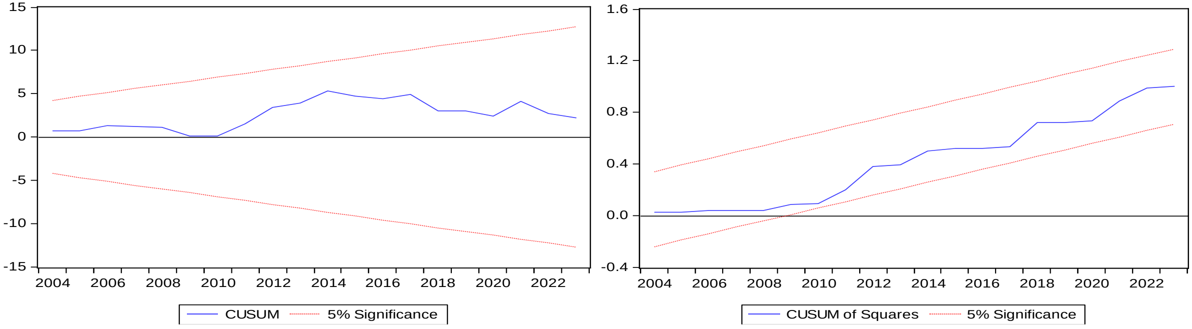
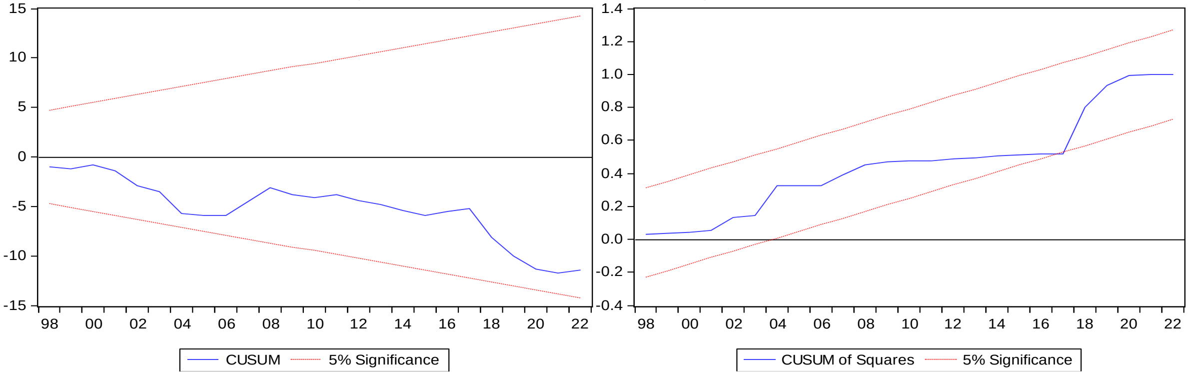


Figure 1(d) – Model 4 (ecological footprint)



Source: Estimates from Eviews 14.