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Research Article

A Comparative Analysis on Ecological Footprint of Consumption and Import in Premature Deindustrialized Countries[a]

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This study aims to analyze the factors influencing the ecological footprint of consumption and import as indicators of environmental degradation in premature deindustrialized countries. Using advanced Method of Moments Quantile Regression (MMQR) analysis, we examined a panel of 27 countries from 1991 to 2021. The main findings indicate that income, income inequality, and industrialization are positively correlated with the ecological footprint stemming from consumption, but an increase in the share of renewable energy consumption exhibits a mitigation effect. The ecological footprint stemming from imports, on the other hand, is exacerbated by income, industrialization, de facto trade globalization, and democracy, whereas it is negatively affected by the higher share of renewable energy consumption. Importantly, MMQR analysis reveals that the effect of each independent variable is non-linear, with the magnitude of coefficients varying across different quantiles of the ecological footprint of both consumption and import. From a policy standpoint, effective mitigation of different aspects of environmental degradation requires prioritization of income redistribution, the promotion of green industrialization, and the enhancement of renewable energy adoption, as well as careful management of trade globalization and democratic governance in premature deindustrialized countries.

JEL codes: O1, O14, Q01, Q56

Keywords: Premature deindustrialization, Structural transformation, Environmental degradation, Ecological footprint, MMQR

1 Introduction

Environmental challenges, along with their underlying causes and consequences, represent a major discussion area within the realm of economics literature. The history of the emphasis on the detrimental effects of environmental degradation on economic growth and the idea of considering pollution as a limiting factor for ensuring sustainable growth can be traced back to the publication of the Limits to Growth report by the Club of Rome in 1972 (Meadows et al., 2013). The primary message of the Limits to Growth report is

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how factors such as population growth, agricultural production, natural resource utilization, industrialization, and pollution collectively shape and ultimately constrain growth levels in the near future. Although the discussion about these factors remains relevant, it is now being approached from new perspectives and is attracting the attention of scholars from a range of disciplines in today's academic discourse. In recent years, as the ramifications of climate change become increasingly apparent, there has been a heightened focus on environmental degradation to ensure not only growth but also sustainable development, considering planetary boundaries. This has led to a significant body of both theoretical and empirical research, with the research agenda shifting its focus to understanding the determinants of environmental degradation to ensure mitigation and adaptation.

Understanding the multifaceted factors influencing environmental degradation is quite complex. Many studies focus on unraveling these factors, often employing macroeconomic variables such as income, industrialization, energy consumption, various dimensions of globalization, population growth, and urbanization. Among these factors, industrialization stands out as one of the most important contributors to environmental degradation. Historical trends, especially after the Great Acceleration, show that industrial production is often seen as the main cause of anthropogenic climate change. Although some of the empirical literature presents mixed findings, there is still a strong consensus on the negative effects of industrialization on environmental quality (Chaitanya, 2007; Moore, 2009; Szirmai, 2013; Steffen et al., 2011, 2015; Rekha & Babu, 2022; Rosa et al., 2015; Wadanambi et al., 2020).

If industrialization is historically the main cause of environmental degradation, how can we explain the higher levels of environmental degradation in prematurely deindustrialized countries? To address this question, it is first necessary to define the concept of deindustrialization. The term "deindustrialization" describes a process that occurs in advanced economies after a country has reached a mature level of industrial development. This process follows a U-shaped pattern of industrialization relative to the country's development level. To elucidate further, it can be defined as a decline in the proportion of employment in manufacturing relative to total employment or in manufacturing output relative to total output, accompanied by a transfer of resources from the manufacturing sector to the service sector. This is caused by a combination of internal factors, such as rising income, productivity differences, relative price changes or policy preferences, and external factors, including changes in the economic structure of the global economy (Rowthorn & Ramaswamy, 1999). In contrast, premature deindustrialization may occur at an earlier stage of development, as highlighted by Rodrik (2016). The phenomenon of premature deindustrialization, defined as a decline in industrial activity at a level of income per capita below that which would be expected based on international standards, has been observed in a range of countries, including those with middle and low-income levels (Tregenna, 2016). Essentially, the timing of this deindustrialization process differs from the typical pattern seen in advanced capitalist countries, making the others premature. In brief, the growth model in some developing countries relies on the service sector without having undergone a proper experience of industrialization.

As Rodrik (2016), by focusing on manufacturing output and employment trends, emphasized that deindustrialization also occurs in low- and middle-income countries, which have experienced a declining manufacturing share in employment and real value-added. This reflects the traditional measurement of deindustrialization (Aiginger & Rodrik, 2020; Dasgupta & Singh, 2006; Rodrik, 2016). Figure 1 shows the share of manufacturing value-added in GDP in prematurely deindustrialized countries based on the recent study by Rekha & Babu (2022), where the manufacturing value-added in GDP is quite low, with a few exceptions in the last 5 years.

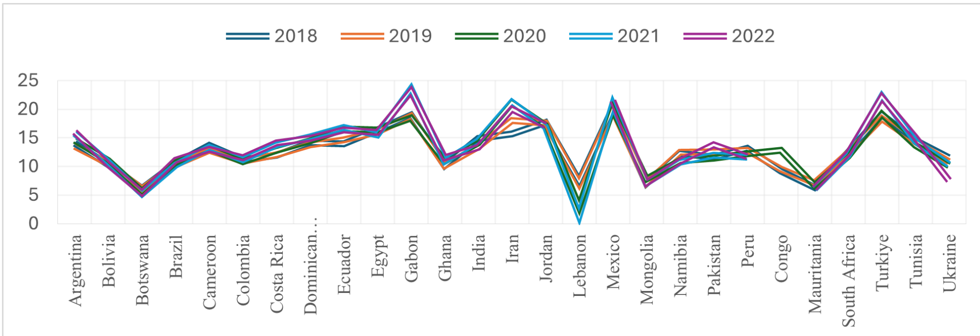

Figure 1: Manufacturing, value added (% of GDP)
Source: Worl Bank (2024)

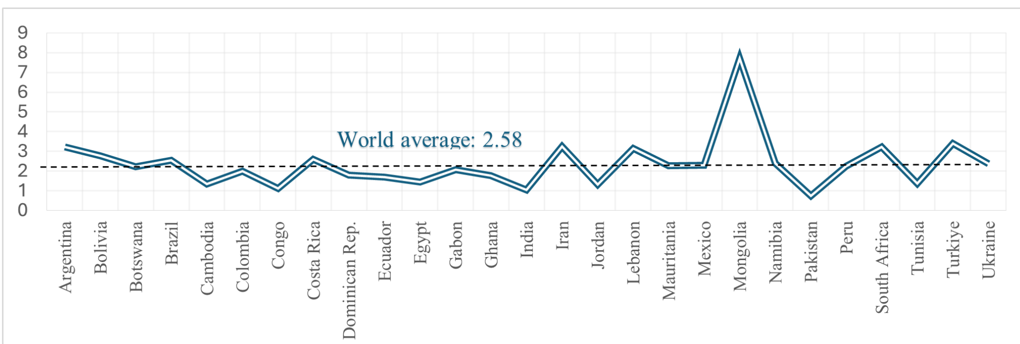

Figure 2: Ecological Footprint of Premature Deindustrialized Countries and World Average (2022, Gha per capita)
Source: Worl Bank (2024)

Despite the lower levels of industrialization, a higher ecological footprint can be seen in Figure 2; in 2022, most of these countries' ecological footprints are above the world average of 2.58 Global hectares (Gha) per capita. In this respect, turning back to the question is crucial: What are the determinants of environmental degradation in prematurely deindustrialized regions? Examining the growth characteristics of these countries, it becomes evident that they heavily rely on imports due to the early deindustrialization process, as illustrated in Figure 3. This dependence underscores a significant aspect of their economic structure and growth models.

The objective of this study is to examine the factors influencing environmental degradation in countries that have undergone premature deindustrialization between the years 1991 and 2021. To this end, the analysis is conducted from a macroeconomic perspective, with the environmental degradation indicator proxied by two metrics: the ecological footprint stemming from consumption (EF) and the ecological footprint stemming from imports (EFI). The research seeks to answer two important sub-questions: *1) Are there any differences or similarities in the factors affecting the ecological footprint of consumption and the*

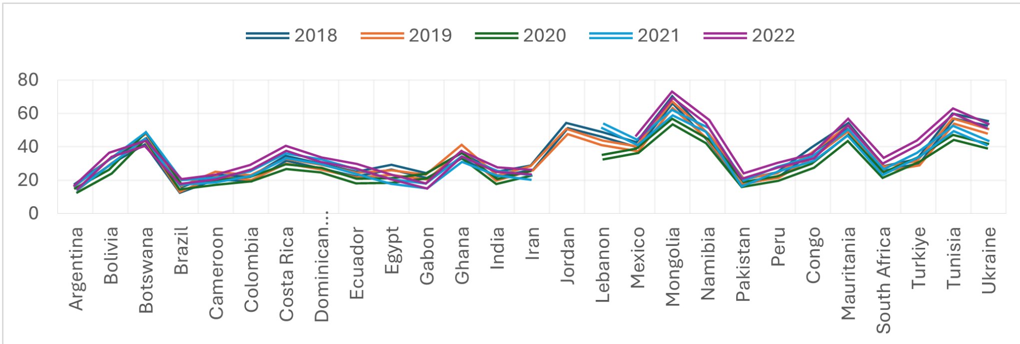

Figure 3: Imports of goods and services (% of GDP)
Source: Worl Bank (2024)

ecological footprint of imports in a setting of low industrialization and high import dependency? 2)What is the role of economic factors (overall economic activity, industrialization, renewable energy consumption, and trade globalization) and political factors (the rule of law) on environmental degradation, and are these effects homogeneous across distinct levels of ecological footprint? The implementation of the advanced Method of Moments Quantile Regression (MMQR) technique to elucidate the heterogeneous effects of economic activity, industrialization, *de facto* trade globalization, renewable energy consumption, and rule of law can markedly enhance the quality of policymaking in prematurely deindustrialized nations. This, in turn, can facilitate both industrial development and the mitigation of environmental degradation. It is crucial to address the existing gap in the literature regarding the factors affecting ecological footprint, with a specific focus on prematurely deindustrialized countries. This is due to two primary reasons: First, the countries in question lack a strong industrial structure, despite this being a significant contributor to environmental degradation. Second, given the distinctive economic structures of these countries, which are highly import-dependent, a comparative analysis of the ecological footprint resulting from consumption and import can serve as a valuable tool for understanding how to mitigate environmental degradation in prematurely deindustrialized countries effectively.

The rest of the paper is organized as follows. Section 2 presents a brief literature review on the dynamics of environmental degradation. Section 3 explains the data, followed by the methodology in Section 4. Section 5 presents the empirical findings, and Section 6 concludes the study.

2 Literature Review

A vast body of literature exists exploring the factors influencing environmental degradation. Thanks to the leading studies by Grossman & Krueger (1991, 1995), Shafik & Bandyopadhyay (1992), Arrow et al. (1995), and Selden & Song (1994), income has emerged as the most significant factor explaining differences in pollution levels among countries. Introducing the well-known Environmental Kuznets Curve (EKC) hypothesis helps us understand the relationship between income per capita and environmental degradation, which indicates a positive relationship between the two variables in the initial stages of development. However, after a certain point of income per capita, environmental degradation begins to decline.

Even though this non-linear relationship is confirmed by several studies so far (Anwar et al., 2023; Suki et al., 2020; Wang et al., 2024), there is also a vast amount of literature that indicates no evidence of the nonlinear relationship between income per capita and environmental degradation (Doğan et al., 2020; Murshed et al., 2022; Özokçu & Özdemir, 2017). Considering in a broader perspective, because income can be accepted as a proxy of the overall economic activity of a country, it remains widely acknowledged as a primary determinant of environmental degradation, regardless of whether the relationship conforms to nonlinear expectations. In addition to this, as income inequalities worldwide are deepening, there is growing attention on understanding whether income inequality impacts environmental degradation, using the GINI index as an explanatory variable. Even though there are studies indicating a direct positive correlation between environmental degradation and income inequality, such as Khan et al. (2022), on the contrary, there are also studies to highlight the nonlinear relationship nature of this relationship as indicated in Grunewald et al. (2017) and Chen et al. (2020) depending on the income level of the countries.

Industrialization has also long been recognized as a significant factor influencing environmental degradation, with studies offering diverse perspectives on the nature of this relationship. Although some research indicates that industrialization is an inevitable contributor to environmental degradation, other studies have demonstrated that the effects are heterogeneous and vary depending on several factors, including the stage of economic development of the countries in question and the structure of their manufacturing sectors. Anwar et al. (2020) for Belt and Road Initiative partner countries and Zafar et al. (2020) for Asian economies found a positive long-run relationship between industrialization and CO_2 emissions. Cherniwchan (2012), using a broader sample of 157 countries between 1970 and 2000, revealing a significant positive effect of industrialization on emissions per capita. One of the most recent studies of Destek et al. (2024) focused on the effects of premature deindustrialization on environmental quality and found that both in the developed and developing world and the countries at risk of premature deindustrialization, a shock in industrialization results in environmental degradation. Yet, Nasir et al. (2021) found no direct relationship between CO_2 emissions and industrialization in Australia. In the same vein, Opoku & Aluko (2021), using quantile regression models, observed a heterogeneous environmental impact of industrialization on CO_2 emissions for 37 African countries. Li et al. (2019) found an N-shaped relationship between industrialization and air pollution in China, indicating that while industrialization initially contributes to environmental degradation, it may mitigate it at further stages of development.

The energy structure of a country is also accepted as one of the important dynamics in environmental quality. Especially in the literature, there is a consensus about the mitigation effects of the increasing share of renewable energy use in environmental challenges, as stated in several studies. Al-Mulali et al. (2015) for 58 developed and developing countries; Alola et al. (2019) for BRICS, Dam et al. (2024) for E7 countries; Destek & Sinha (2020) for 24 OECD countries; Nathaniel & Khan (2020) for ASEAN countries found a positive correlation between increase in share of renewable energy consumption and environmental quality using different empirical strategies.

The other important factor is trade openness, which shapes environmental degradation. It can potentially impact environmental degradation through various channels with positive or negative effects depending on a nation's level of development and industrial structure. In most developed nations, trade openness can contribute to economic growth and development through technology transfer or the transfer of know-how (Destek & Sinha, 2020). However, for less developed or developing regions, the impact may differ. These countries might import dirtier industrial products for consumption or adopt polluted industrial techniques due to their cost-effectiveness. Furthermore, with the combined effects of trade globalization and foreign direct investment (FDI) flows, less developed and industrialized regions can become pollution havens (Gill et al., 2018), leading to deteriorating environmental quality. Although some recent studies have found a positive impact of trade openness/liberalization on environmental degradation, such as Abdullahi et al. (2024) for ECOWAS, Udeagha & Ngepah (2022) for South Africa in the long run, Wenlong et al. (2023) for a group of Asian countries, and Usman et al. (2023) for the G7 countries, there are no universal effects. The effects can depend on the development level and industrial structure of the countries (Covino & Boccia, 2014; Bekmez & Ozsoy, 2016). In the same vein, Aşıcı & Acar (2016) noted that trade openness had a negative impact on the per capita production footprint but a positive impact on the per capita import footprint for 116 countries. Aydın & Turan (2020) observed that trade openness reduced environmental pollution in China and India, but trade openness has a negative effect on pollution in South Africa.

Political institutions are complex, and it is hard to emphasize their universal effects on economics, with measurement methods varying widely. Therefore, researchers often use proxies, such as government/governance effectiveness, type of democracy (electoral or non-electoral), legal system efficiency and rule of law, freedom of speech and civil liberties, to gauge the impact of political institutions. The role of democracy and political institutions, broadly speaking, is important to understand environmental degradation because they all shape the environment that we live in. Despite clear theoretical expectations of a positive relationship and the capacity of political institutions, empirical research shows that the relationship between democracy and environmental degradation is mixed. For instance, Adams & Acheampong (2019); Buitenzorgy & Mol (2011); Farzin & Bond (2006), and Güngör et al. (2021) have found that strong democratic structures mitigate CO_2 emissions or the *EF*. However, findings from Wang et al. (2018) for G20 countries and Akalın & Erdoğan (2021) for OECD countries suggest an increase in environmental degradation with democracy or a nonlinear impact of democracy on environmental degradation. The extant literature on the relationship between economic activity, income inequality, industrialization, renewable energy use, trade globalization, and democracy remains inconclusive, particularly concerning country groups exhibiting diverse economic and political structures. In this regard, the potential for non-linearity in economic and political variables, particularly in countries undergoing premature industrialization in the 21st century, has been largely overlooked in the context of environmental degradation. This study aims to address this gap in the literature and provide a policy perspective.

3 Data

Deindustrialization is traditionally measured using two indicators: the share of manufacturing in GDP and the share of manufacturing employment in total employment; deindustrialization emerges where both indicators exhibit a diminishing trend after reaching a peak (Rodrik, 2016). According to Rodrik (2016), besides focusing solely on manufacturing value-added and employment, understanding the "premature" characteristics of deindustrialization, income level and status of the manufacturing sector should be considered together.

Building on these ideas, Rekha & Babu (2022), focusing on the premature version of deindustrialization, create five-dimensional selection criteria -GDP per capita (threshold income <= \$11,750), manufacturing value-added, employment in manufacturing, moving average of manufacturing value-added and employment- to categorize countries whether they are experiencing premature deindustrialization or not.[1] The countries undergoing premature deindustrialization were classified into three categories as follows. The initial category encompasses countries that satisfy all five criteria characteristics of premature deindustrialization. The second category comprises countries where the manufacturing employment share is considered, while the third category comprises countries where the manufacturing value-added share is considered separately. This study examines regions undergoing premature deindustrialization, as defined by Rekha & Babu (2022), by satisfying all the criteria and manufacturing value-added or manufacturing employment share criteria for premature deindustrialization between 1991 and 2021. The final dataset comprises 27 countries meeting all five criteria[2], but excludes countries with missing/limited data.[3] All variables, except *RULEOFLAW*, are presented in their natural logarithmic forms.

Table 1: Variables, Descriptions and Sources

Variable	Description	Source
Dependent Variables		
EF	Ecological footprint of consumption per person (Gha)	GFN (2024)
EFI	Ecological footprint of import per person (Gha)	GFN (2024)
Independent Variables		
INCOME	GDP per capita (constant 2015 US\$)	Worl Bank (2024)
MVA	Manufacturing, value added (% of GDP)	Worl Bank (2024)
GINI	Measure of inequality ranging 0 (perfect equality) to 100 (perfect inequality)	WID (2024)
TRADE_DF	De facto trade globalization index (ranging from 0-100)	KOF (2024)
RENEWABLE	Renewable energy consumption (% of total final energy consumption)	Worl Bank (2024)
RULEOFLAW	v2x_rule index, (ranging from 0-1, worst to good)	Coppedge et al. (2024)

Source: Compiled by the author.

In this study, we consider two dependent variables to measure environmental degradation: the Ecological Footprint of Consumption (*EF*) and the Ecological Footprint of Import (*EFI*), both measured in per capita Gha. *EF* is a comprehensive environmental degradation indicator that quantifies the land required to sustain the consumption habits of a specific population. This includes the land needed for producing consumed materials as well as absorbing carbon dioxide emissions, covering consumption, production, export, and import footprints. *EFI* represents the ecological footprint embodied in domestically consumed products imported from other countries, which is crucial to monitor for countries with high levels of import dependency, as in our case.

[1] Please see Rekha & Babu (2022) for detailed explanation of the country categorization.

[2] These are Argentina, Bolivia, Botswana, Brazil, Cameroon, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, Gabon, Ghana, Lebanon, Mexico, Mongolia, Namibia, Pakistan, Peru, Ukraine, and South Africa, while Congo, India, Iran, Jordan, Mauritania, Tunisia, and Turkey are the countries that experience premature deindustrialization phases according to the manufacturing value-added or manufacturing employment share criteria in our sample.

[3] The excluded countries are Algeria, Armenia, Azerbaijan, Belize, Guyana, Jamaica, Kazakhstan, Kenya, Kyrgyzstan, Morocco, and Nigeria.

Six variables are used as independent variables, of which definitions and data sources are given in Table 1. *INCOME* is chosen as the proxy of overall economic activity, measured by real GDP per capita, expecting a positive impact on *EF* and *EFI*. Manufacturing value-added is identified as one of the core determinants of *EF* in the empirical literature. To control for the role of industrialization in premature deindustrialized countries on *EF*, the share of manufacturing value-added in GDP (*MVA*) is added to the model, for which there is a consensus regarding its positive relationship between *EF*. The Gini coefficient, which ranges from 0 to 100 and is frequently employed to address imbalances in redistributive policies within a society, is also considered. It is reasonable to posit that increasing *GINI* results in higher *EF* and *EFI* results.

The KOF globalization index serves as a general measurement of globalization encompassing various economic, social, and political dimensions. Specifically, in terms of economic dimensions, trade globalization, measured by the *de facto* and *de jure* indices by KOF, holds significant importance in understanding a country's incorporation into the world economy. The *de facto* globalization refers to actual international exchanges and activities, while the *de jure* globalization pertains to the policies and circumstances designed to support, facilitate, and encourage these exchanges and activities in principle. In this context, the *de facto* trade globalization index (*TRADE_DF*) is utilized since it is a more comprehensive indicator of trade openness. It is anticipated that higher levels of trade globalization will correspond to increased environmental degradation.

To comprehend the role of environmentally friendly energy systems in premature deindustrialized regions on *EF*, we incorporate renewable energy consumption as a percentage of total final energy consumption (*RENEWABLE*). The literature indicates a strong negative effect of renewable energy usage capacity and *EF*. Finally, the relationship between institutional structure and environmental degradation is examined using the rule of law (*RULEOFLAW*) data from the Varieties of Democracy (V-Dem) project, which presents a novel approach to defining and assessing democracy. It provides a comprehensive and detailed dataset designed to capture the multifaceted nature of democracy, viewing it as a phenomenon that encompasses more than the sole existence of elections. The V-Dem project identifies and assesses five key principles of democracy: electoral, liberal, participatory, deliberative, and egalitarian. To this end, the project gathers data to evaluate these dimensions. Furthermore, the data set provides all 500 V-Dem indicators and 245 indices, in addition to 57 other indicators from other data sources. The rule of law index, which is used in this analysis, is reflected in the following question: "To what extent are laws transparently, independently, predictably, impartially, and equally enforced, and to what extent do the actions of government officials comply with the law?" These reflect the broader proxy for institutional capacity (Coppedge et al., 2024). Expecting a mitigation effect of the higher institutional capacity makes sense, but the heterogeneity of the economic and political structures in the sample may result in mixed findings. The rule of law index ranges from 0 to 1, with a higher value indicating a stronger commitment to the rule of law. This index measures the extent to which laws are transparent, predictable, and uniformly enforced and whether government officials adhere to the law.

The descriptive statistics in Table 2 display significant deviations from normality, as indicated by the skewness and kurtosis probability values. The probability values of Jarque-Bera tests also provide further evidence of non-normality, rejecting the null hypothesis of a normal distribution.

Table 2: Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.	Pr(Skewness)	Pr(Kurtosis)	Pr(Jarqua-Bera)
EF	837	0.772	0.469	-0.386	2.050	0.000	0.299	0.000
EFI	837	-0.687	0.808	-3.912	0.892	0.000	0.012	0.000
INCOME	837	8.206	0.722	6.271	9.561	0.000	0.000	0.000
MVA	837	2.558	0.413	0.356	3.798	0.000	0.000	0.000
GINI	837	4.136	0.123	3.654	4.359	0.000	0.000	0.000
TRADE_DF	837	3.748	0.418	2.101	4.501	0.000	0.000	0.000
RENEWABLE	837	2.878	1.165	-0.821	4.505	0.000	0.162	0.000
RULEOFLAW	837	0.485	0.250	0.035	0.955	0.115	0.000	0.000

Source: Author's calculations.

The heterogeneity in the sample could potentially bias parameter estimates, particularly in estimation methodologies relying on the least squares approach and when dealing with non-normal data. Table 3 represents the pairwise correlations of independent variables. All the correlations between variables can be accepted at a reasonable level.

Table 3: Pairwise correlations

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) *INCOME*	1.000					
(2) *MVA*	0.130	1.000				
(3) *GINI*	0.426	-0.084	1.000			
(4) *TRADE_DF*	-0.118	-0.398	-0.214	1.000		
(5) *RENEWABLE*	-0.216	-0.250	0.295	-0.114	1.000	
(6) *RULEOFLAW*	0.321	0.049	0.433	-0.134	0.012	1.000

Source: Author's calculations.

4 Methodology

To ensure clarity in the methodology section, we will provide a step-by-step explanation of the panel data methodology employed. In our panel, N is the number of cross-sections (27), and T is the number of periods (31). Therefore, all tests and empirical strategies are selected based on the appropriateness of the condition where N is less than T.

Step 1. Breusch-Pagan LM cross-sectional Dependency and Slope Heterogeneity Test

The first step is to check the cross-sectional dependency and heterogeneity of variables. For this aim, to assess cross-sectional dependence, Breusch & Pagan's (1980) LM test, eq. (1), providing consistent results if $N < T$, is used.

$$CD_{LM} = N \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{1}$$

where ρ_{ij} is the sample correlation of residuals between cross-sectional units i and j:

After checking the cross-sectional dependency of variables, Pesaran & Yamagata (2008) method based on Swamy (1970) approach is used to control the homogeneity of slope coefficients. Based on the null hypothesis with $(N, T) \to \infty$, error terms are normally distributed, and the statistic for the $\tilde{\Delta}$ test, eq. (2), and the adjusted $\tilde{\Delta}$ test for the small sample, eq. (3), are utilized.

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{2}$$

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{Z}_{iT})}{\sqrt{var(\tilde{Z}_{iT})}}\right) \tag{3}$$

with

$$\tilde{S} = \sum_{i=1}^{N}\left(\hat{\beta}_i - \hat{\beta}_{WFE}\right)' \frac{X_i' M_t X_i}{\tilde{\sigma}_i^2}\left(\hat{\beta}_i - \hat{\beta}_{WFE}\right) \tag{4}$$

where $E(\tilde{Z}_{iT})$ is the expected value of the statistic under the null hypothesis, and $var(\tilde{Z}_{iT})$ is its variance, $\tilde{S}$ is the Swamy's statistics is based on comparing each unit-specific coefficient ($\hat{\beta}_i$) to a pooled (or weighted fixed-effects) coefficient ($\hat{\beta}_{WFE}$) estimated under the assumption of homogeneity, X_i is the matrix of independent variables for unit i, M_t is the transformation matrix, and, finally, $\tilde{\sigma}_i^2$ is the variance of the residuals of each unit i.

Step 2. Testing unit root with Cross-Sectional Augmented Dickey-Fuller (CADF)

If there is a cross-sectionally dependent panel dataset, it is appropriate to use the second generation unit root test to check the stationary of each variable (Barbieri, 2009). In this study, Cross-Sectional Augmented Dickey-Fuller (CADF) is used, which is calculated by following Pesaran (2007):

$$\Delta Y_{it} = \alpha_i + \rho_i Y_{i,t-1} + \beta_i \overline{Y}_{t-1} + \sum_{j=0}^{k} \gamma_{ij} \Delta \overline{Y}_{i,t-1} + \sum_{j=0}^{k} \delta_{ij} \Delta Y_{i,t-1} + \epsilon_{it} \tag{5}$$

where α_i is the deterministic term, Y_{t-1} is the lagged dependent variable and $\overline{Y}_{t-1} = (1/N)\sum_{i=1}^{N} Y_{i,t-1}$ is its cross-sectional average, γ_{ij} and δ_{ij} are coefficients of the lagged changes and levels of $\overline{Y}$.

Equation (6) provides the CIPS statistics based on the average of individual CADF:

$$CIPSstatistic = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T) \tag{6}$$

where $t_i(N,T)$ are the individual ADF t-statistics for each unit i based on the sample size N and time T. The null hypothesis of the test is the variables within a panel data are not stationary, and the alternative hypothesis is that at least one individual is stationary.

Step 3. Preliminary Linear Regression Analysis: Feasible Generalized Least Square (FGLS)

The consistency and robustness of analysis in OLS-type regressions rely on strict requirements, such as no autocorrelation, normality, and no cross-sectional dependency. On the other hand, FGLS can be used in the presence of serial and cross-sectional correlations as well as in the heteroskedasticity problem (Bai et al., 2021). This approach provides more efficient and robust parameter estimates, making it suitable for panel data analysis where the number of periods exceeds the number of cross sections ($N < T$). As a result, GLS estimation is preferred over Fixed Effect and Random Effect OLS regression for the analysis.

Adopting a simple FGLS into our model can be written as:

$$EF_{it} = \alpha_i^{EF} + X_{it}'\beta^{EF} + \epsilon_{it}^{EF} \tag{7}$$

$$EFI_{it} = \alpha_i^{EFI} + X_{it}'\beta^{EF} + \epsilon_{it}^{EFI} \tag{8}$$

where EF_{it} and EFI_{it} are the natural logarithm of EF and EFI in the individual country i at time t, α_i is the unobserved individual-specific random effect, X_{it}' covers the matrix of all the explanatory variables given in Table 1, and β stands for the vector of coefficients.

Step 4. MMQR estimation

Due to the failure to meet the prerequisites of OLS-type linear regression, this study employs an advanced MMQR analysis. This method offers robust estimations concerning the factors influencing environmental degradation in prematurely deindustrialized nations. In addition to its technical benefits and superiority over linear OLS regressions, MMQR permits the examination of how each independent variable changes across different quantiles of the dependent variable. Firstly, the equations are expressed in the panel fixed effect form, equations (9) and (10), and then their transformed version into MMRQ specifications by following Machado & Silva (2019, p. 148) are given in equations (11) and (12).

$$EF_{it} = X_{it}'\beta^{EF} + \epsilon_{it}^{EF} \tag{9}$$

$$EFI_{it} = X_{it}'\beta^{EFI} + \epsilon_{it}^{EFI} \tag{10}$$

$$EF_{it} = \alpha_i^{EF} + X_{it}'\beta^{EF} + (\delta_i^{EF} + Z_{it}'\gamma^{EF}) + U_{it}^{EF} \tag{11}$$

$$EFI_{it} = \alpha_i^{EFI} + X_{it}'\beta^{EFI} + (\delta_i^{EFI} + Z_{it}'\gamma^{EFI}) + U_{it}^{EFI} \tag{12}$$

where α_i and δ_i are the individual and quantile-specific fixed effects for country i, respectively, Z_{it} is a vector of the known differentiable transformations of the explanatory variables satisfying the probability $p\{\delta_i + Z_{it}'\gamma > 0\} = 1$, and, finally, U_{it} is an unobserved random variable independent of X_{it}, normalized to satisfy the following moment conditions: $E(U_{it}) = 0,\ E(|U_{it}|) = 1$. Using this information and the exogeneity of the explanatory variables, the parameters $\alpha_i,\ \beta',\ \delta_i,\ \gamma'$ and $q(\tau)'$ were estimated based on the first moment conditions. In this framework, the conditional quantile representation of the model can be presented as follows.

$$Q_Y(\tau|X_{it}) = (\alpha_i + \delta_i q(\tau)) + X_{it}'\beta + Z_{it}'\gamma q(\tau) \tag{13}$$

where the term $(\alpha_i + \delta_i q(\tau))$ represents the quantile-τ fixed effect for i.

5 Empirical Results

The Breusch-Pagan LM cross-sectional dependency test results in Table 4 strongly reject the null hypothesis of no cross-sectional dependence. Furthermore, we examine the bias-adjusted LM test of error cross-section independence, as proposed by Pesaran et al. (2008). This test also corroborates the presence of cross-sectional dependence.[4]

[4] The results of these tests are presented in the Appendix.

Table 4: Breusch-Pagan LM Cross-Sectional Dependency Test

Variable	Test statistics	Probability
EF	$\chi^2(351) = 2{,}410.479$	0.000
EFI	$\chi^2(351) = 1{,}431.257$	0.000

Source: Author's calculations.

Given the evidence of a strong cross-sectional dependence, it is necessary to consider both second-generation unit root tests and estimation techniques to account for cross-sectional dependence. As examining slope homogeneity is crucial for choosing the right econometric techniques (Bersvendsen & Ditzen, 2021), we employed the slope homogeneity test developed by Pesaran & Yamagata (2008). The findings indicate clear evidence of heterogeneity among the countries included in our estimation sample as displayed in Table 5.

Table 5: Testing for Slope Homogeneity

		Delta	p-value
EF	$\tilde{\Delta}$	15.377	0.000
	$\tilde{\Delta}_{adj}$	17.852	0.000
EFI	$\tilde{\Delta}$	17.332	0.000
	$\tilde{\Delta}_{adj}$	20.122	0.000

Source: Author's calculations.

The findings presented in Table 6 display the outcomes of the second-generation unit root test developed by Pesaran (2007). These results indicate that certain series are non-stationary at levels but became stationarity at first differences, signifying they are integrated of first order, denoted as I(1). Conversely, some series are already stationary at their levels. Consequently, both I(0) and I(1) versions of integrations exist among the variables, making it challenging to ascertain a uniform level of integration.

Table 6: Pesaran (2007) CIPS panel unit root test results

	Level (with intercept)	Level (intercept and trend)	First difference (with intercept)	First difference (with intercept and trend)
EF	-2.435***	-3.003***	-	-
EFI	-2.834***	-3.277***	-	-
INCOME	-1.782	-2.182	-4.213***	-4.232***
MVA	-1.388	-1.743	-4.579***	-4.792***
GINI	-1.269	-2.269	-3.469***	-3.556***
TRADE_DF	-2.305*	-2.883***	-	-
RENEWABLE	-1.996	-2.274**	-5.229***	-5.312***
RULEOFLAW	-1.451	-2.019	-4.407***	-4.638***

Note: *** denotes significance at 1% level. Critical values are 2.58, -2.65 and -2.78 for 10%, 5% and 1% significance level, respectively. No intercept nor trend estimation critical values are -2.08, -2.16 and -2.3 for 10%, 5% and 1% significance level, respectively.
Source: Author's calculations.

Table 7 illustrates the results of the preliminary analysis conducted using FGLS regression. It's recognized that due to cross-sectional dependency and non-normality of variables, OLS-type regression analysis may not be suitable. However, given the sample characteristics where $T > N$ and the need to account for heterogeneity, FGLS is considered a benchmark method despite its potential biases.

Table 7: Preliminary Analysis based on a Linear Regression: FGLS

	EF	EFI
INCOME	0.324***	0.321***
	(0.055)	(0.115)
MVA	0.007	0.040
	(0.019)	(0.036)
GINI	0.014	0.068
	(0.102)	(0.226)
TRADE_DF	-0.017	0.256***
	(0.020)	(0.044)
RENEWABLE	-0.202***	-0.235***
	(0.015)	(0.029)
RULEOFLAW	0.131***	0.206**
	(0.048)	(0.094)
constant	1.364***	-1.011***
	(0.097)	(0.207)
Observations	837	837

Note: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1
Source: Author's calculations.

Based on FGLS regression results, income and good governance seem to have a positive, whereas an increase in renewable energy consumption in total energy consumption resulted in a negative effect on *EF* and *EFI*. The statistically insignificant results observed for the other variables (*MVA*, *GINI*, *TRADE_DF*) may be attributed to the lack of normality in the variables, potentially leading to nonlinear relationships between the dependent variables and their determinants. In this framework, as mentioned earlier in the methodology section, MMQR enables the estimation of parameters that may vary across quantiles of the dependent variable, offering several advantages. This approach allows for a nuanced analysis of independent variables across different quantiles, leading to more meaningful insights and policy recommendations. Additionally, MMQR provides technical benefits, such as flexibility in modeling complex relationships and robustness to outliers. Unlike OLS regression, MMQR does not assume normality in residuals, making it effective for handling skewed data distributions. This method obtains robust outcomes even in the presence of non-linearity and non-normality issues (Awad, 2022; Jahanger et al., 2023).

Table 8 presents the results of the MMQR analysis using the ecological footprint of consumption as the dependent variable, and Figure 4 illustrates the coefficients' trends and confidence intervals. Firstly, income demonstrates a consistent positive association with *EF* across all quantiles. However, this positive association diminishes at higher levels of *EF*, suggesting a signal of rising awareness of environmental issues and the implementation of environmentally friendly economic programs at more advanced stages of economic development. However, it is worth noting that there is no direct mitigation effect observed here; rather, only a slowing of the trend of environmental degradation is mentioned. The positive effect of income on *EF* also signifies the limitations of the growth model pursued in prematurely deindustrialized nations. The characteristics of the growth path can create a structural change burden in those countries, implying that an increasing share of services leads to a productivity slowdown (Baumol's law, Baumol (1967, 1986)) in the early stages of development, as stated in Szirmai (2012, 2013). Secondly, *MVA*, utilized as a proxy for industrialization, also positively correlates with *EF*. Interestingly, this positive impact becomes statistically insignificant for the highest quantile of *EF* (0.9). This finding

Table 8: Dependent variable: Ecological Footprint of Consumption

	Location	Scale	Quantiles				
			0.1	0.25	0.5	0.75	0.9
INCOME	0.236***	-0.021*	0.268***	0.253***	0.235***	0.217***	0.203***
	(0.019)	(0.011)	(0.026)	(0.021)	(0.019)	(0.021)	(0.025)
MVA	0.105***	-0.048***	0.181***	0.145***	0.104***	0.063***	0.030
	(0.020)	(0.012)	(0.029)	(0.023)	(0.021)	(0.023)	(0.028)
GINI	0.169**	0.112***	-0.009	0.074	0.172**	0.269***	0.347***
	(0.068)	(0.040)	(0.096)	(0.078)	(0.068)	(0.076)	(0.091)
TRADE_DF	-0.007	-0.007	0.005	-0.001	-0.007	-0.014	-0.019
	(0.018)	(0.011)	(0.025)	(0.021)	(0.018)	(0.020)	(0.024)
RENEWABLE	-0.177***	0.015*	-0.202***	-0.190***	-0.177***	-0.163***	-0.153***
	(0.015)	(0.009)	(0.020)	(0.017)	(0.015)	(0.016)	(0.019)
RULEOFLAW	0.029	-0.016	0.053	0.042	0.028	0.014	0.004
	(0.037)	(0.022)	(0.052)	(0.042)	(0.037)	(0.041)	(0.049)
constant	-1.607***	-0.111	-1.431***	-1.514***	-1.610***	-1.706***	-1.783***
	(0.303)	(0.179)	(0.426)	(0.346)	(0.303)	(0.336)	(0.405)

Note: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1
Source: Author's calculations.

suggests that even in countries experiencing premature deindustrialization, efforts toward industrialization may have a detrimental effect on *EF*. This underscores the importance of transforming the manufacturing industry toward greener practices, particularly in countries where the share of manufacturing value-added in GDP is relatively low. Such a shift could mitigate the adverse environmental impacts associated with industrialization while promoting sustainable economic development. Income inequality contributes to *EF*, but this effect emerges only in and above the 0.5 quantiles in line with the findings of Grunewald et al. (2017), which indirectly highlights the importance of redistributive policies in premature deindustrialized nations to mitigate environmental degradation.

Surprisingly, *de facto* trade globalization shows no significant effect on *EF*. In line with expectations, renewable energy consumption has a negative impact on *EF*, indicating that as renewable energy use increases, there is potential for greater mitigation of environmental challenges. This negative impact remains consistent across all quantiles, although the mitigation effect of renewable energy diminishes at higher levels of *EF*. *RULEOFLAW* is statistically insignificant across all quantiles.

Table 9 outlines the findings from the MMQR analysis, with the ecological footprint stemming from imports serving as the dependent variable. Furthermore, Figure 5 depicts the trends of the coefficients via an MMQR plot. As expected, the effects of independent variables on *EF* and *EFI* show some similarities but also important variations. Income has a positive effect on *EFI*, as evidenced by a statistically significant coefficients across all quantiles. However, the strength of this relationship appears to diminish at higher quantiles. Unlike the results of estimation with *EF*, *MVA* effect *EFI* positively but only in the quantiles of 0.5, 0.75, and 0.9. In countries with a high ecological footprint from import, industrialization results in more environmental degradation. Income inequality is statistically insignificant at all quantiles. This can be explained by all the countries being highly import-dependent, with income inequality having no meaningful effect on *EFI*. However, in terms of consumption, we found a positive effect of income inequality on *EF*. *TRADE_DF*, as a proxy of trade openness, in line with expectations, has a positive impact on *EFI* in all quantiles except the 0.9 quantile. In countries with a higher level of ecological footprint

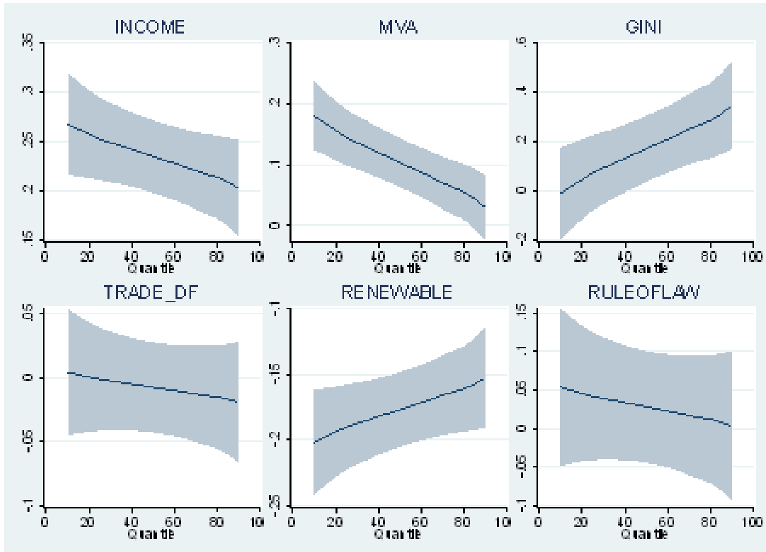

Figure 4: Estimation parameters from MMQR Regression (Dependent Variable: EF)
Source: Authors calculation

stemming from import, the positive impact of trade globalization shows a diminishing trend. The relationship between *de facto* trade globalization and both *EF* and *EFI* is in line with the findings of Aşıcı & Acar's (2016). Similar to the results with *EF*, renewable energy consumption negatively affected *EFI* in line with the previous studies (e.g., Dam et al., 2024; Alola et al., 2019).

Table 9: Dependent variable: Ecological Footprint of Import

	Location	Scale	Quantiles				
			0.1	**0.25**	**0.5**	**0.75**	**0.9**
INCOME	0.608***	-0.054**	0.653***	0.653***	0.605***	0.559***	0.524***
	(0.040)	(0.024)	(0.046)	(0.046)	(0.040)	(0.043)	(0.051)
MVA	0.059**	0.014	0.047	0.047	0.060**	0.071**	0.080**
	(0.027)	(0.016)	(0.031)	(0.031)	(0.027)	(0.029)	(0.035)
GINI	-0.193	0.190*	-0.353*	-0.353*	-0.183	-0.025	0.099
	(0.170)	(0.101)	(0.198)	(0.198)	(0.169)	(0.183)	(0.218)
TRADE_DF	0.214***	-0.075***	0.277***	0.277***	0.210***	0.1480***	0.099
	(0.047)	(0.028)	(0.055)	(0.055)	(0.047)	(0.051)	(0.061)
RENEWABLE	-0.303***	0.002	-0.305***	-0.305***	-0.303***	-0.301***	-0.299***
	(0.033)	(0.020)	(0.039)	(0.039)	(0.033)	(0.036)	(0.043)
RULEOFLAW	0.377***	0.007	0.372***	0.372***	0.378***	0.384***	0.388***
	(0.070)	(0.042)	(0.082)	(0.082)	(0.070)	(0.076)	(0.090)
constant	-5.137***	0.047	-5.177***	-5.177***	-5.135***	-5.096***	-5.065***
	(0.837)	(0.498)	(0.976)	(0.976)	(0.835)	(0.904)	(1.075)

Note: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1
Source: Author's calculations.

Finally, the rule of law exacerbates *EFI* in all quantiles, contrary to expectations but in line with the previous literature (e.g., Wang et al., 2018; Akalın & Erdoğan, 2021). This might stem from the good governance of premature deindustrialized countries, which are also classified as developing countries, showing great heterogeneity related to the rule of law and, more broadly, institutional capacity. As these countries are less industrialized and more import-dependent, good governance does not necessarily mitigate environmental challenges; on the contrary, it may lead to greater incorporation into the world economy economically.

In premature deindustrialized countries, democracy doesn't appear to significantly drive environmental sustainability; rather, it contributes to environmental degradation. This perspective aligns with the findings of Wang et al. (2018), which highlight the heterogeneous effects of democracy on environmental degradation. Notably, democracy seems to exacerbate environmental issues in higher-emission countries, as also suggested by Heilbroner (1974). You et al. (2015) further conclude that while democracy correlates positively with emissions in low-emission contexts, it shows a negative association in high-emission countries, contrary to the studies of Wang et al. (2018) and Heilbroner (1974). In line with our findings, Akalın & Erdoğan (2021) and Acheampong et al. (2022) also find an exacerbating effect of democracy in OECD and Sub-Saharan Africa, respectively. These insights collectively underscore the challenges of democratic governance in effectively addressing environmental concerns, particularly in regions undergoing premature deindustrialization. Results show that there are common points to mitigate environmental degradation, such as increasing renewable energy consumption and designing green industrial transformation in premature deindustrialized nations, but also differences such as designing trade policies to decrease the ecological footprint stemming from imports.

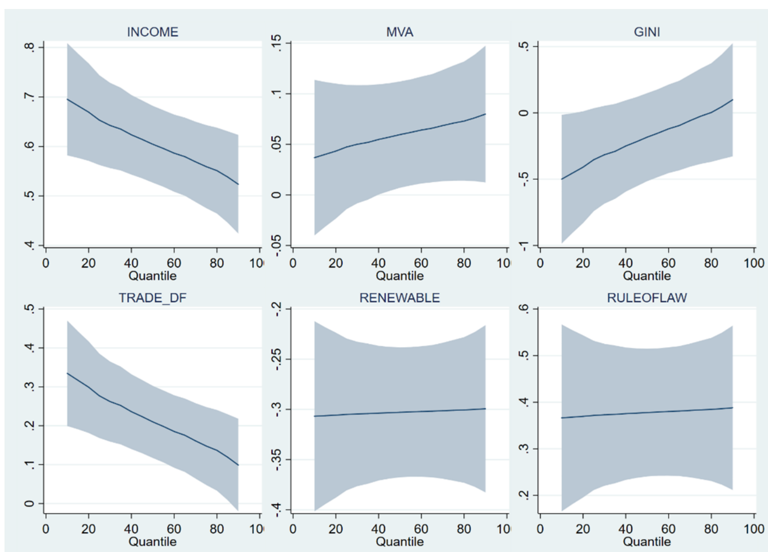

Figure 5: Estimation parameters from MMQR Regression (Dependent Variable: EFI)
Source: Authors calculation

6 Conclusion

This study aims to investigate the factors influencing environmental degradation, as measured by the ecological footprint of consumption and import, across 27 countries experiencing premature deindustrialization for 1991-2021 period. Utilizing advanced MMQR techniques, we found that income, industrialization, and income inequality exacerbates ecological footprint of consumption, while renewable energy consumption has a strong mitigation effect on it. However, these effects are non-linear, with magnitudes and significance varying across different quantiles of the ecological footprint. Examining the factors affecting the ecological footprint of import reveals both similarities and differences compared to the determinants of the ecological footprint of consumption. Income, industrialization, trade globalization, and democracy exacerbate the ecological footprint of import. Conversely, renewable energy consumption acts as a mitigating factor on the ecological footprint of import as well.

Considering the main economic characteristics and developmental stage of premature deindustrialized countries, a nuanced approach to mitigating various forms of ecological footprint is essential. These nations, while experiencing premature deindustrialization, still hold potential for increasing manufacturing value-added. However, our findings suggest that as manufacturing value-added increases and industrialization progresses, environmental degradation follows. This suggests that as economies industrialize, there is a notable increase in emissions, underscoring the environmental consequences of industrial growth. From a policy perspective, investments in green industrial initiatives are imperative, especially in countries witnessing premature deindustrialization.

Given the adverse effects of income, income inequality, and industrialization on ecological footprint, there's a critical need to reconsider growth models and implement redistributive policies in these countries. Our results indicate that achieving environmental sustainability entails addressing not only production aspects but also distributional concerns. Furthermore, reevaluating trade openness, which exacerbates environmental degradation, as our findings suggest, is crucial, particularly for countries heavily reliant on imports.

In light of these considerations, adopting green industrial strategies that emphasize import substitution could offer a viable solution for these countries in the 21st century. This approach aims to increase the share of manufacturing value-added while simultaneously controlling ecological footprint. By integrating policies that promote sustainable production, equitable distribution, and prudent trade practices, premature deindustrialized countries can chart a path toward environmental sustainability and economic resilience.

While this study contributes significant insights, it is not without limitations. One notable limitation is its focus solely on countries experiencing premature deindustrialization for a specific period. To provide a more comprehensive understanding and facilitate comparisons, future research could incorporate industrialized regions and extend the analysis over a longer time frame. Furthermore, instead of solely considering manufacturing value-added, future studies could delve into the structural composition of industries within these countries. This would provide a more nuanced understanding of industrial dynamics and their implications for environmental degradation. Additionally, the study could benefit from examining the effects of different governance quality indicators on environmental degradation. By incorporating a broader range of governance measures, such as transparency, accountability, and regulatory effectiveness, a more comprehensive analysis of the factors influencing ecological footprint could be achieved.

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Appendix : Bias-adjusted LM test of error cross-section independence

Panel A: Dependent Variable is EFI		
Test	Statistic	p-value
LM	470.900	0.000
LM adj*	7.120	0.000
LM CD*	3.934	0.000
Panel B: Dependent Variable is EFI		
LM	463.700	0.000
LM adj*	6.429	0.000
LM CD*	4.649	0.000

* two-sided test

Source: Author's calculations.