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KEYWORDS	ABSTRACT
Green innovation, energy transition, natural resource abundance, EKC and CS-ARDL.	The reckless extraction of natural resources is wrecking biodiversity, increasing earth temperature and posing environmental pressure to curtail sustainability. Therefore, developed and emerging economies are posing stress on green innovation, energy transition and accessible natural resources to acquire sustainable footprint. In this perspective, a panel dataset of Paris Club economies for green innovation, energy transition and natural resource abundance coupled with sustainable footprints are employed for the period 1990-2025 which is sourced from World development indicator (WDI) and global footprint network (GFN). For this objective Cross-sectionally augmented ARDL model (CS-ARDL) coupled with Dynamic Common Correlated Effects Mean Group (DCCEMG) is employed as a robustness. The findings revealed that green innovation, energy transition substantially alleviate pressure on sustainable footprint by 0.072%, and 0.104% respectively. In contrast, natural resource abundance increases the sustainability footprint (0.143), consistent with resource-curse mechanisms associated with intensive extraction and resource-dependent production. However, DCCEMG validates the findings of CS-ARDL that common shock and heterogeneous slopes are stable. The results suggest that the energy transition to renewables and the promotion of green innovation can help alleviate resource-related pressures, and that resource-rent management continues to play a key role for policy makers.
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Introduction

Human pressure on biosphere is still higher than its regenerative capacity. This is reflected in the ecological footprint, it is one of the most direct indicators of environmental pressures over time with respect to food, energy and land use. That pressure extends to advanced creditor economies. The Paris Club is an informal club of the major official creditor countries, some of the largest world economies are members of this club. So, the extent of their reaction to innovation, energy and resource endowments is significant beyond their national borders. An increasing number of studies wonder about the effect of renewable energy, innovation and environmental policy on footprints in advanced economies, such as Europe (Sohag et al., 2024), the United Kingdom (Wada, 2026) and broader collections of countries (Zhou et al., 2023).

There are three channels on which most of the focus is on. The first one is innovation in green technology. The two theories of induced innovation and ecological modernization predict that, with the new technology, the amount of environmental load will be reduced per unit of output. Recent studies investigate technological innovation and the ecological footprint in the E-7 economies (Dam et al., 2024); green innovation and material flows in the framework of environmental Kuznets curve (Pata & Karlilar, 2024); green innovation and energy use and carbon emissions (Kirat et al., 2024); and digital finance and footprint within the context of green-biased technological innovation (Feng et al., 2022). In addition, evidence of policy instruments related to green outcomes with innovation, such as clean taxes in OECD countries associated with green finance (T. Wang et al., 2023), and green bonds (Lee et al., 2023) have been found.

The second one is the energy transition. The obvious path to lessen the effects of production and consumption is a cleaner fuel mix, and there is a wealth of evidence. Panel studies include renewable resources and the transition to a green economy (B. Li et al., 2023); renewable energy and energy import dependency with cross-sectionally augmented estimators (Yadav & Mahalik, 2024); and joint movement of renewable energy, environmental taxes and the footprint in the United Kingdom (Zhou et al., 2023). Another layer, namely “environmental policy stringency”, is also introduced as it appears to be a moderating factor between the footprint and renewable energy and innovation (Sohag et al., 2024).

The third is the rich natural resources, which is the least settled channel. Although it can be argued that resource rents can be used to invest in cleaner capital, the extraction and energy intensive activity continues to be the bone as far as the resource curse argument is concerned. Some recent panel studies investigate mineral rents and the footprint (Kang et al., 2023), resource rents and green technological innovation and renewable energy (Ma et al., 2024), and government efficiency and green technology in resource management (E. Wang et al., 2024). The environmental Kuznets curve (R. Li et al., 2023) of the role of resource rents is also impacted by corruption governance. In the studies that focus on the G7 economies, fintech is added (Gu et al., 2023; Xia & Liu, 2024), and other studies involve human capital and globalization and technological moderation (Jahanger et al., 2022; Zhou et al., 2022). Carbon taxes have been analyzed along with the studies on resource

rents in BRICS countries (Meng & Li, 2023). All but one of these models features a role for economic growth, usually in the form of a scale effect control (Chen et al., 2023).

However, there are three gaps in this literature. Income levels, regional or trade and political bloc are the most common classifications of country in most studies. Although, as far as we can tell, no one has studied the Paris Club as a whole (because they are creditors), they provide a coherent test case for the three channels above because of their high income and advanced innovation systems. Second, many of the studies have considered one channel at a time. Green innovation, energy transition and resource dependence are intertwined and estimation in one model provides insights into which of them plays a role once the others are controlled for. Third, estimators based on the assumption of common slopes and independence of cross-sections can be used in the panel evidence of advanced countries. Energy and technology-trading countries should not neglect potential common shocks, like fuel price volatility, and policy changes elsewhere in the world that could impact the size and sign of the estimates.

This paper seeks to address these gaps by exploring how the sustainability footprint (SF) of Paris Club economies is affected by green innovation (GI), energy transition (ET) and natural resource abundance (NRA) between 1990 and 2025 and adding a control variable named economic growth (EG). SF is measured as the ecological footprint per person (in global hectares). Firstly, we test for serial correlation, slope heterogeneity, endogeneity and cross-sectional dependence and then test for the order of integration using CIPS, PSADF and PANIC tests. A Kim (2003) segmented cointegration test is used to study the relationship in the long-run, allowing for a possible permanent break in the equilibrium relationship. It estimates the impact of short run and long run using the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) model, and the dynamic common correlated effects mean group (DCCEMG) estimator is used for robustness check. The results show that there is a negative relationship between green innovation and energy transition and the footprint, while there is a positive relationship between the footprint and natural resource abundance and the results are robust to both estimators.

The study makes three contributions. As far as we are aware it is the first footprint analysis of the Paris Club as a set of advanced creditor economies. It combines green innovation, energy transition and resource abundance in one framework which is connected to four theories (ecological modernization, induced innovation, the resource curse and endogenous growth), allowing the relative strength of the theories to be compared. After diagnostics which indicate slope heterogeneity, endogeneity and common shocks, it employs an estimation strategy that is matched to the data: CS-ARDL as the benchmark and DCCEMG for robustness. The results serve as a piece of evidence for creditor country policy makers to consider when deciding on the significance of innovation support, the rate of the energy transition and resource rent management.

The remainder of the paper is laid out as follows. Literature is reviewed in Section 2, a description of the theoretical framework data and methods are described in Section 3, results and discussion are provided in Section 4, and policy implications and conclusions are provided in Section 5.

Review of literature

Green innovation and sustainability footprint

The induced innovation theory and ecological modernization theory predict that as environmental pressures increase, and/or policy, the environmental cost of dirty production increases, and firms increase research into cleaner production alternatives, the environmental load per unit of output decreases. This is reflected in the empirical record of advanced and large economies in general. Given that green technological innovation leads to reduction in the ecological footprints of the quantiles within the G-7 group (Javed et al., 2024), it is logical to believe that green energy innovation also would exert a similar impact on ecological footprints of the quantiles within the BRICST group. Furthermore, using the CS-ARDL and MMQR estimators, the footprints of technological innovation and renewable energy deployment are found to be reduced in ten developing economies (Shi & Smith, 2025). Some of the relevant research includes impact of technological innovation on ecological footprints in E-7 economies (Dam et al., 2024), Green innovation and material footprint under the environmental Kuznets curve (Pata & Karlilar, 2024) and green innovation, energy use and carbon emissions (Kirat et al., 2024).

That's not the case when institutions and policy are added. European Union countries are heterogeneous in terms of their innovation impacts on the energy system and national institutional and energy-system conditions underlie the innovation impact (Aydin et al., 2023). Similarly, enabling conditions research is pointing to the same direction. The footprint is connected to environmental policy stringency via renewable energy and innovation (Sohag et al., 2024), green bond policy has been explored for its impact on green innovation (Lee et al., 2023), and green finance and clean taxes have been investigated for their effect on carbon emissions in OECD countries (T. Wang et al., 2023). The footprint debate has also shifted the focus to the role of digital finance and technology innovation with green bias (Feng et al., 2022). The addition of measurement adds another challenge. The results can vary depending on the outcome measured and the type of innovation used as proxy, as revealed by a panel of OECD countries, research and development also contributes to carbon emissions but is positive and statistically significant on the ecological footprint (Akpanke et al., 2024).

Green Innovation decreases the footprint, this will vary according to the innovation measure, the environmental indicator and the institutional setting. There is little thought given to how this impact is compounded over the short versus long term, and most evidence cited is reporting an average impact. This is relevant for creditor economies with a high amount of patenting and for which diffusion can be time-consuming.

Energy Transition and sustainability footprint

The main channel for the impact of the energy transition on the footprint is through fuel mix and through efficiency. The results on renewables in the advanced economies are generally similar. From 1990 to 2020, renewable energy is associated with a negative ecological footprint and carbon

emissions while economic growth is associated with positive ecological footprint and carbon emissions in OECD countries (Akpanke et al., 2024). Renewable energy use reduces footprints at all quantiles in the G-7 (Javed et al., 2024) and renewable energy deployment reduces footprints in developing economies, too (Shi & Smith, 2025). This is supported by UK-based findings and other European and global studies, such as the co-movement between renewables, environmental taxes and footprint (Zhou et al., 2023); renewables and footprint in Europe in the context of governance and regulations (Wada, 2026); and more broadly, transitioning economies to a green economy (B. Li et al., 2023).

In this literature three qualifications are mentioned. The first is that efficiency cannot be confused with renewable supply. Although energy efficiency is important for the reduction of carbon emissions in the OECD, it does not have a significant effect on the ecological footprint (Akpanke et al., 2024) and thus an energy transition based on an efficiency measurement may fail to capture some of the impact on the ecological footprint. Secondly country level outcomes may vary. Renewable energy has some positive associations with environment in the European Union, but some negative associations with the footprint in the European Union (Aydin et al., 2023). Third, outcomes are influenced by policy design as the impact of the stringency of environmental policy on the footprint is dependent on renewable energy and innovation (Sohag et al., 2024). The importance of choice of estimator is also clear from methodological papers in the energy field. Yadav and Mahalik (2024) employ CS-ARDL and panel causality for analysing renewable energy development, which is appropriate for panels with common shocks among countries.

The literature thus offers a footprint reducing impact of renewable energy in technologically advanced economies, without it being clear how this impact changes from the short to the long run, and what happens to the impact if green innovation and the endowment of resources are included in the same equation.

Natural resource abundance and sustainability footprint

The literature on the resource curse indicates that the natural abundance of resources can negatively affect the environment because it can help to sustain use, as energy-intensive production can be pursued and less can be invested in modernization. This is consistent with evidence from resource dependent groups. BRICST economies have a higher ecological footprint because of exploitation of resources (Gu et al., 2024). Other recent studies include mineral rents and the footprint in countries with various energy production and consumption status (Kang et al., 2023), mineral rents and resource depletion in high-emitting countries (He et al., 2024), and the combined effect of resource rents and efficiency of natural resource management, government efficiency and green technology (E. Wang et al., 2024).

A few papers illustrate that the resource effect is not permanent but rather varies. In the environmental Kuznets curve setting, resource rents have an interaction with green technological innovation and renewable energy in 158 countries (Ma et al., 2024), and with corruption governance in 158 countries (R. Li et al., 2023). Natural resources are being studied in combination

with fintech (Xia & Liu, 2024) and with environmental regulation (Xia & Liu, 2024) and with green finance and green growth (Gu et al., 2023). In other panels, natural resources are combined with economic growth, human capital, urbanization and globalization (Jahanger et al., 2022; Zhou et al., 2022), and likewise the impact of the resource rents and carbon taxes in BRICS countries (Meng & Li, 2023).

Two limits of special interest exist. The first is the concept of measurement: rents, depletion and dependence can measure different phenomena and may not be concurrent or impact the footprint in the same manner. The second is composition. The members of the Paris Club span from economies that are rich in natural resources like Norway, Canada and Australia, to others that lack any natural resources, like Japan and Switzerland. In this group the average effect of resource richness on the footprint is an open empirical question and cannot be read off studies of resource dependent developing economies.

Research gap

The review lists five gaps. First, evidence in relation to the G-7, E-7, BRICST, the European Union and developing country samples is presented. No footprint study was found that has the structure of the Paris Club (that is, a group of advanced creditor economies with good innovation systems and high incomes and very different resource endowments). Second, green innovation, energy transition and resource abundance are often studied one or two at a time. Lots of papers do not have all three attributes in a single model, which is required to compare the amount of explained variance each of the three attributes adds to the model, controlling the other two. Thirdly, there are no studies that automatically calculate carbon emissions or only one part of the footprint. For instance, while energy efficiency has an impact on emissions, it does not have an impact on the ecological footprint in OECD countries (Akpanke et al., 2024).

Fourth, there are still some opportunities for improvement in the estimation decisions. In recent OECD and developing country literature, the notions of cross-sectional dependence and slope heterogeneity are now recognized as central in this area, and the use of CS-ARDL and DCCEMG are employed. However, very few studies apply CS-ARDL as the benchmark model and DCCEMG as robustness check and the cointegration test allowing for temporary breaks is applied on the same panel. Fifth, most samples are only up to 2020. The time frame is 1990 to 2025, allowing the window to both exclude the impact of the Paris Agreement and the recent energy price shocks, and to capitalize on the impact of innovation and the energy transition. This study aims to fill this gap by estimating the effect of green innovation and energy transition, and the abundance of natural resources on the sustainability footprint of the Paris Club economies in the period 1990-2025 as a control of economic growth using CS-ARDL and DCCEMG estimators.

Theoretical framework, Data and Methodology

The findings in this study provide some empirical evidence that lends support to the environmental Kuznets curve (EKC) hypothesis for different types of environmental pressures and groups of

countries. Ecological and material footprints studies reveal that the coefficient of economic growth is positive, and the coefficient of the squared growth is negative so that the relationship between economic growth and environmental pressure is inverted U (Javed et al., 2024; Aneja et al., 2024; Shi & Smith, 2025). This nonlinear shape also appears in the resource-based EKC of G-20 economies, implying a possible deterioration of the environment with the passage of time and with the increase in the level of economic activity but a possible improvement beyond a threshold. Technological and energy-related factors are key contributors to environmental outcomes, in addition to economic growth. In the G-7 economies, the ecological footprint reduction is found to be positive for various quantiles of green technological innovation (Javed et al., 2024) and green energy innovation is also found to be reducing ecological footprint in the BRICST economies (Gu et al., 2024). Evidence from the EU, however, indicates that impacts on the environment due to technical change may vary across countries, meaning that the impacts of technical change on the environment may be country specific and dependent on national institutional, structural and energy-system features. (Aydin et al., 2023). Renewable energy usage also positively affects the environment and is found to lower footprint at all the quantiles of distribution in G-7 economies (Javed et al., 2024); on the other hand, some of the European Union member economies are found to have positive relationship whereas others are negative (Aydin et al., 2023). In line with this wider evidence, the deployment of renewable energy and technological innovation has been found to reduce ecological footprints in developing economies (Shi & Smith, 2025). However, in contrast, natural resource dependence is often related to greater environmental pressures, especially for BRICST economies where an increased ecological footprint is related to increased resource exploitation (Gu et al., 2024). The top ten resource abundant economies also display another pattern: resource rents exert a more negative impact on the environment, but green innovation can help with this negative trend. Likewise, the relationship between resource dependence and technological innovation seems to dampen the environmental impacts of resource exploitation, especially in more innovation-capable economies. They all together suggest that impacts of growth, resource dependence, renewable energy and technological innovation on the environment are not necessarily always and everywhere uniform or linear, but depend on income levels, income quantiles, institutional context and national innovation capacities.

Data

This paper analyzes the factors driving the sustainability footprint (SF) of the Paris Club economies in the period 1990-2025. The empirical analysis is based on four explanatory variables: green innovation (GI), energy transition (ET), natural resource abundance (NRA), and economic growth (EG). The ecological footprint per capita (in global hectares, gha) is used to measure the sustainability footprint. Green innovation is measured as environment-related patents and energy transition as the share of renewable energy in total energy consumption. Total natural-resource rents as a percentage of GDP are used as a measure of natural resource abundance, while GDP in current US dollars is used as a measure of economic growth. Data sources are mainly the Global Footprint Network (GFN) and the World Development Indicators (WDI). The variables are

naturally logged prior to estimation to reduce scale differences and ease the interpretation of elasticity, as reported Table 1.

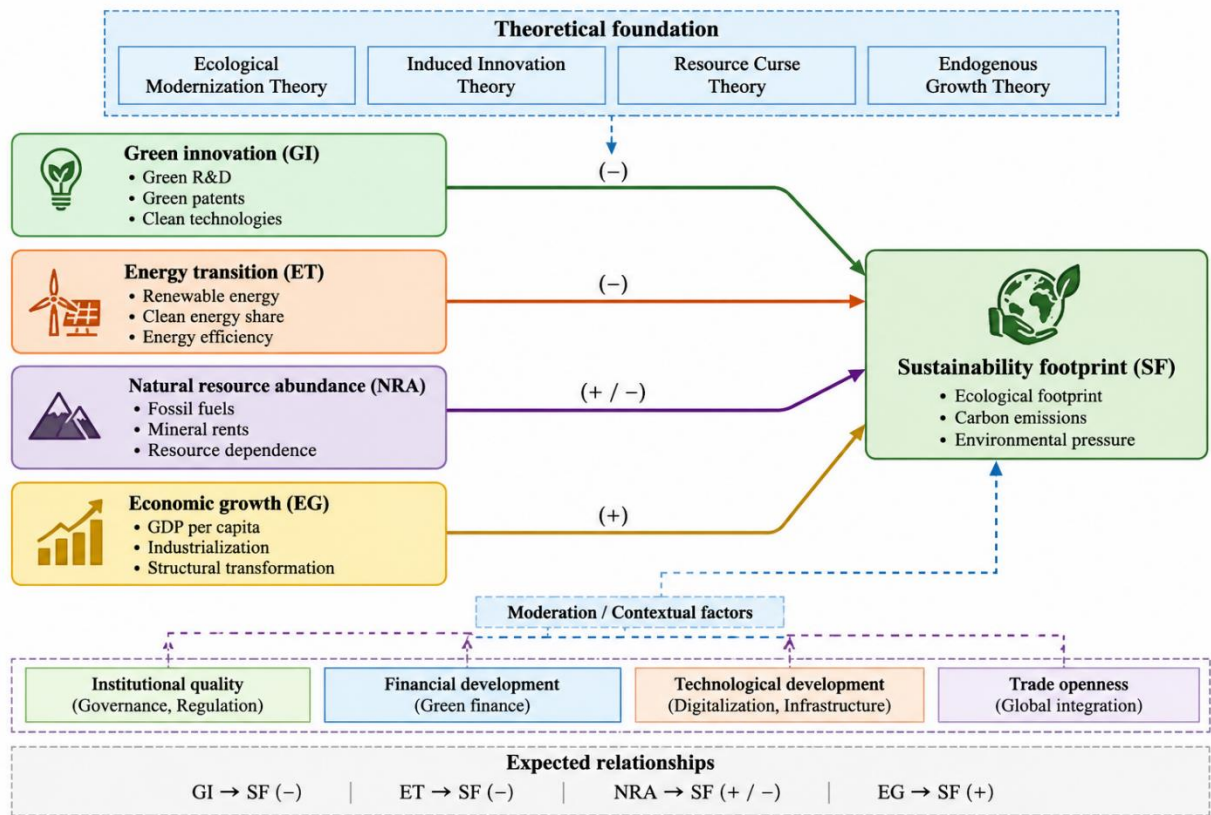


Figure 1: Theoretical framework

Table 1: Variables description

Symbol	Pictogram	Measurement Unit	Source
SF	Sustainability Footprint	Ecological Footprint (gha per person)	GFN
GI	Green Innovation	Environment-related patents	WDI
ET	Energy Transition	(% of total energy consumption)	WDI
NRA	Natural Resource Abundance	Total natural resources (%GDP)	WDI
EG	Economic Growth	GDP (current US\$)	WDI

Model specification

The baseline relationship is defined as:

$$SF_{it} = f(GI_{it}, ET_{it}, NRA_{it}, EG_{it})$$

where country is indicated by i and year by t . The empirical model is log-linear and is:

$$\ln SF_{it} = \alpha_i + \beta_1 \ln GI_{it} + \beta_2 \ln ET_{it} + \beta_3 \ln NRA_{it} + \beta_4 \ln EG_{it} + \varepsilon_{it}$$

Econometric methodology

The empirical approach is based on the diagnostic features of the Paris Club panel. The preliminary tests show that the data are cross-sectionally dependent, have significant slope heterogeneity, may be endogenous, are serially dependent, and have mixed orders of integration. The Cross-Sectionally Augmented ARDL (CS-ARDL) is a method that combines the ARDL and the cross-sectional approach. The CS-ARDL estimator is chosen as the main estimator since it allows for heterogeneous dynamic relationships and includes cross-sectional averages to control unobserved common factors and cross-sectional dependence. It is especially suitable for the current context as the variables are a combination of $I(0)$ and $I(1)$ processes and the diagnostic tests do not support slope homogeneity. A general CS-ARDL specification is:

$$\Delta \ln SF_{it} = \phi_i [\ln SF_{i,t-1} - \theta_{1i} \ln GI_{it} - \theta_{2i} \ln ET_{it} - \theta_{3i} \ln NRA_{it} - \theta_{4i} \ln EG_{it}]$$

$$+ \sum_{p=1}^{P-1} \lambda_{ip} \Delta \ln SF_{i,t-p} + \sum_{j=1}^4 \sum_{q=0}^{Q-1} \delta_{ijq} \Delta X_{j,i,t-q} + \sum_{m=0}^M \psi_{im} \bar{Z}_{t-m} + \varepsilon_{it}$$

The inclusion of cross-sectional averages enables the model to capture unobserved common factors, international spillovers, synchronized policy changes, and common macroeconomic shocks. The short-run coefficients describe immediate adjustments, whereas the long-run coefficients measure the equilibrium relationship between the explanatory variables and SF. The error-correction coefficient is expected to be negative and statistically significant, indicating convergence toward the long-run equilibrium following a temporary deviation.

The Dynamic Common Correlated Effects Mean Group (DCCCEMG) model is a dynamic version of the Mean Group (MG) model. The DCCCEMG estimator is used as the main robustness procedure. This is because it is driven by the high evidence of cross-sectional dependence and slope heterogeneity. DCCCEMG permits the coefficients to vary by country and includes cross-sectional averages to capture unobserved common factors.

The country-specific dynamic specification is conceptually:

$$\Delta \ln SF_{it} = \alpha_i + \rho_i \ln SF_{i,t-1} + \sum_{j=1}^4 \beta_{ij} X_{jit} + \sum_{m=0}^M \gamma_{im} \bar{Z}_{t-m} + \varepsilon_{it}$$

where β_{ij} are country-specific slope coefficients and Z_t are the cross-sectional averages of the variables in question. The mean-group estimates are computed as an average of the country-specific coefficients:

$$\hat{\beta}_{MG} = \frac{1}{N} \sum_{i=1}^N \hat{\beta}_i$$

This is beneficial as it does not impose the same impact of green innovation, energy transition, natural-resource abundance or economic growth on Paris Club economies.

Results and Discussion

Descriptive characteristics of the variables that entered empirical analysis are shown in Table 2. These results reveal substantial differences between the samples, particularly with the ET, SF and NRA, suggesting cross-sample and cross-temporal heterogeneity. The mean value of SF is 6.014, ranging from 1.877 to 10.343 and standard deviation equal to 1.518. The overall shape of the distribution is symmetric, with a slight right tail (as indicated by the positive, but low, skewness value) and the distribution is very peaked (as indicated by the high, but not so high as to be extreme, kurtosis value). The mean for GI is 2.173, and it ranges from -0.041 to 3.252 with a relatively low standard deviation of 0.424. The negative skewness value (-1.274) indicates that the distribution has a skewness to the right and the higher kurtosis (7.430) suggests that the distribution has heavier tails and possible extreme values. ET records a mean of 1.639, ranging from -1.836 to 2.485, with a standard deviation of 0.691. Highly leptokurtic (kurtosis of 8.275) and negative skewness (-2.181) indicates some deviation from normality with more observations at the higher end of the range and a few extreme observations.

NRA has the lowest mean value of -1.268, the widest range (from -7.031 to 3.091) and the highest standard deviation of 2.071 among all variables. It is a flat distribution (kurtosis 2.299) with a skewness close to 0 (0.046). EG has the highest mean value (27.352) with a relatively small range (24.621-30.780) with a standard deviation of 1.215. The positive skewness value of 0.419 is a slight right skewness and the kurtosis value is 2.737 which is near to the normal value of three.

Table 2: Features of variables

Factors	Mean	Min	Max	SD	Skewness	Kurtosis
SF	6.014	1.877	10.343	1.518	.305	3.404
GI	2.173	-.041	3.252	.424	-1.274	7.43
ET	1.639	-1.836	2.485	.691	-2.181	8.275
NRA	-1.268	-7.031	3.091	2.071	.046	2.299
EG	27.352	24.621	30.780	1.215	.419	2.737

The correlation matrix and multicollinearity diagnostics of the variables of the study is presented in Figure 2. Generally, pairwise correlation is weak with the highest absolute correlation of -0.409 between LET and LEG, and LGI and LNRA (0.327) indicating that there is not too much linear dependence between the explanatory variables. The VIFs range from 1.201 to 1.310 while the mean value of the VIFs is 1.260 which is significantly less than the value of 5 . Also, the values of $1/VIF$ are between 0.763 and 0.832 , which is well above the critical value of 0.20 . The results offer solid evidence that there is no severe multicollinearity in the empirical specification. The explanatory variables, therefore, have enough variation to be able to estimate coefficients reliably.

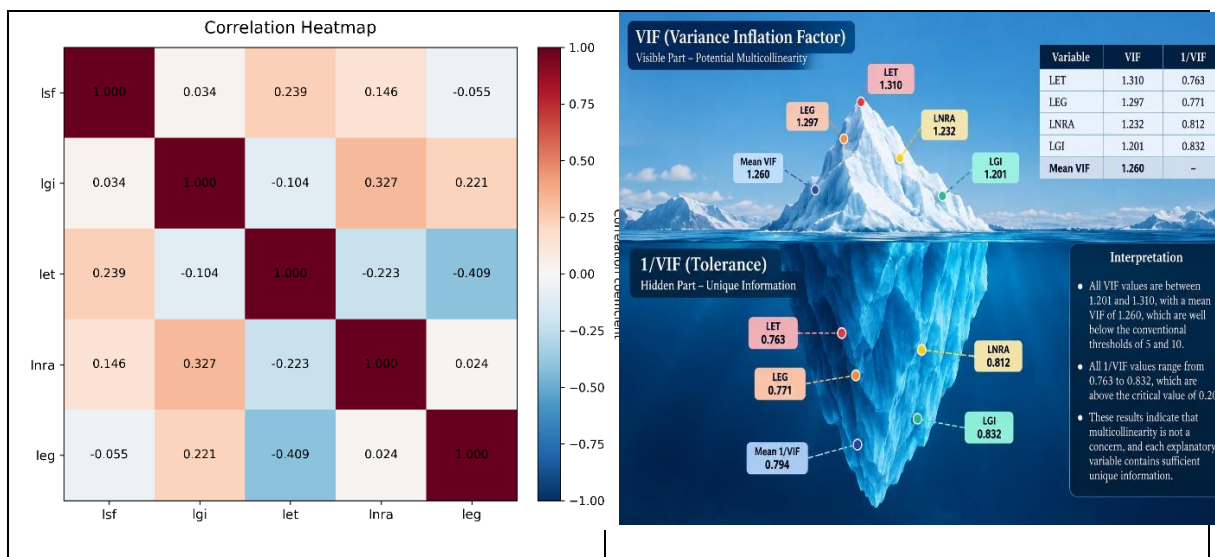


Figure 2: Correlation and Multicollinearity test

Diagnostic tests for serial correlation, slope heterogeneity and endogeneity are reported in Table 3. The Wooldridge test suggests that there is some evidence of first order autocorrelation at 10% but not at the typical 5% level, with an F-statistic of 4.026 and a p-value of 0.0632. This indicates that serial dependence cannot be completely disregarded when specifying the dynamic panel model. What is more important is that the null hypothesis of homogeneous slopes is strongly rejected in the Pesaran-Yamagata slope heterogeneity tests ($\Delta = 14.861$, $p < 0.001$; $\Delta = 16.505$, $p < 0.001$).

The Blomquist-Westerlund HAC adjusted statistics show even more; Delta = 24.731 ($p < 0.001$) and adjusted Delta = 27.468 ($p < 0.001$). These results show that the effects of the different explanatory variables have systematically varied from country-to-country, pointing towards non-homogeneous slope estimators.

The results of the endogeneity diagnostics also indicate that endogeneity is an important econometric issue. Both the Durbin score test [$\chi^2(1) = 25.538, p < 0.001$] and the Wu-Hausman test [$F(1,503) = 26.680, p < 0.001$] strongly reject the null hypothesis of exogeneity. Thus, standard pooled estimators, which assume that the regressors are strictly exogenous, may result in inconsistent estimates. All these three aspects, along with the already mentioned cross-sectional dependence, indicate the need for an estimator that can account for general country shocks and heterogeneous country responses in a dynamic context, namely serial dependence.

According to these diagnostics, Cross-Sectionally Augmented Autoregressive Distributed Lag (CS-ARDL) is the most suitable baseline estimator to detect short and long run integration relationships. CS-ARDL is thus preferred as it combines both the ARDL methodology of disaggregating the short-run dynamics and long-run equilibrium effects and the cross-sectional augmentation to account for unobserved common factors and cross-country spillovers. It is particularly appropriate when some of the variables are stationary of order $I(0)$ and some are stationary of order $I(1)$, but not $I(2)$ as indicated by the previous stationarity tests.

The Dynamic Common Correlated Effects Mean Group (DCCEMG) estimator is a highly stable estimator and can be used as a very good complement to use as a long run estimator. The main advantage of it is that it lets these country-specific coefficients be heterogeneous (allow them to vary across countries), while also holding the common factors down by taking their average across the cross section. This is in direct line with the high heterogeneity of the slopes and the cross-section dependence found on the diagnostic tests. Thus, DCCEMG is a good test to examine the stability of the estimated long-run relationship when the dynamic assumption of CS-ARDL is relaxed.

Table 3: Pre-diagnostic tests

Test / Diagnostic	Null hypothesis (H_0)	Statistic	p-value
Wooldridge test for serial correlation	No first-order autocorrelation	$F(1,15) = 4.026$	0.0632
Pesaran-Yamagata Δ test	Homogeneous coefficients	slope $\Delta = 14.861$	0.0000
Pesaran-Yamagata adjusted Δ test	Homogeneous coefficients	slope $\Delta_{adj} = 16.505$	0.0000
Blomquist-Westerlund HAC Δ test	Homogeneous coefficients	slope $\Delta = 24.731$	0.0000
Blomquist-Westerlund adjusted HAC Δ	Homogeneous	slope $\Delta_{adj} = 27.468$	0.0000

Test / Diagnostic	Null hypothesis (H_0)	Statistic	p-value
test	coefficients		
Durbin score test	LET is exogenous	$\chi^2(1) = 25.538$	0.0000
Wu-Hausman test	LET is exogenous	$F(1, 503) = 26.680$	0.0000

The results of the CIPS, PSADF and PANIC panel unit-root tests, which collectively are very strong in telling stationarity properties of the variables, are reported in Table 4. Results from the CIPS and PSADF suggest that SF, GI, ET and EG are non-stationary in levels but stationary in first differences, which means that these variables are integrated of order one (I(1)). In contrast, NRA is stationary at level, meaning that it follows an I(0) process since both CIPS and PSADF reject the unit-root null in levels. The results overall support the non-stationarity of the IDC, LGI, ET and EG while NRA is stationary, despite the explicit consideration of the unobserved common factors and the idiosyncratic components in the PANIC framework. Combined the evidence shows that the integration is mixed, I(0) and I(1), and there is no evidence of being integrated beyond the first order. The combination of stationarity properties provides some economic foundation for the use of econometric methods that can accommodate the mixed integration order as well as cross sectional dependence and heterogeneous dynamics.

Table 4: Stationery tests

	CIPS				PSADF			
Series	@ Level		@ diff		@ Level		@ diff	
SF	-1.861		-5.301***		-1.400		-3.774***	
GI	-1.792		-3.893***		-1.415		-3.123***	
ET	-0.986		-3.671***		-1.112		-2.547***	
NRA	-2.490**		-5.460***		-1.863		-4.662***	
EG	-1.396		-4.406***		-1.768		-3.322***	
PANIC panel stationarity test								
Variables	P (Fisher χ^2)	p-value	Pm	p-value	Z	p-value	W (Hadri LM)	p-value
IDC	106.794	0.000***	7.070	0.000***	-4.645	0.000***	7.445	0.000***
LGI	86.178	0.000***	6.327	0.000***	-3.766	0.000***	7.070	0.000***
ET	108.969	0.000***	7.307	0.000***	-4.494	0.000***	2.678	0.004***
NRA	42.461	0.451	0.050	0.480	-0.517	0.302	0.579	0.281
EG	148.686	0.000***	11.640	0.000***	-6.535	0.000***	10.997	0.000***

The findings of cross-sectional dependence diagnostics are highly against the hypothesis of cross-sectional independence as reported in Table 5. All variables are statistically significant according to Pesaran's CD and CD_w+ statistics with CD* being significant in the case of LET, LNRA and LEG. While CD_w and/or CD* are not significant for all variables, evidence overall suggests that there is significant cross-country dependence due to common shocks and unobserved factors. The size of the CD_w+ statistics for LSF, LGI, LET, LNRA and LEG are particularly large, further confirming the strong interconnectedness across the sample. As a result, the conventional first-generation estimators of panels may produce errors due to bias or inefficiency, and this may be overcome by using second generation panel estimators which are robust against cross sectional dependence and slope heterogeneity.

Table 5: cross-sectional dependence (CSD)

Factors	CD	CD _w	CD _w +	CD*
lsf	27.300 (0.000)	2.520 (0.012)	502.690 (0.000)	-0.730 (0.463)
lgi	27.730 (0.000)	1.750 (0.080)	431.950 (0.000)	-1.860 (0.063)
let	6.320 (0.000)	-0.660 (0.512)	342.440 (0.000)	-3.770 (0.000)
lnra	22.520 (0.000)	1.030 (0.304)	461.170 (0.000)	3.170 (0.002)
leg	74.530 (0.000)	6.140 (0.000)	1086.240 (0.000)	2.860 (0.004)

CD: Pesaran (2015, 2021); CD_w: Juodis, Reese (2021); CD*: Pesaran, Xie (2021) with 4 PC(s)

H₀: weak cross-section dependence; H₁: strong cross-section dependence

The Kim (2003) segmented cointegration results, reported in Table 6, suggest that there is a long-run equilibrium relationship between LSF, LGI, LET, LNRA and LEG even if there is some temporary structural instability. Rejecting the null hypothesis of no cointegration, the statistics of Z_p^* and Z_t^* are -189.789 and -11.460 respectively, which are significant at 1 per cent level. Similarly, the statistics $ADF_p^* = -140.281$ and $ADF_t^* = -10.693$ reject the null at 1% and 5%, respectively. It is found that throughout most of the sample the variables are cointegrated and not constantly "out of equilibrium. Notably, the estimated non-cointegration interval is in the range (0.130, 0.250) of the sample, and the Lambda-max procedure identifies the nearby interval (0.189, 0.254) of the sample, suggesting a transitory non-cointegration. The overall evidence indicates that the data is cointegrated in the stable long run equilibrium with a finite break, implying that the estimators robust to heterogeneous dynamics and possible structural changes are appropriate.

Table 6: Segmented cointegration

Test statistic	Statistic	1% CV	2.5% CV	5% CV	10% CV	Decision
$Z\rho^*$	-189.789	-130.860	-106.230	-87.070	-69.280	Reject H_0^{***}
Zt^*	-11.460	-11.330	-10.030	-8.700	-7.210	Reject H_0^{***}
$ADF\rho^*$	-140.281	-130.860	-106.230	-87.070	-69.280	Reject H_0^{***}
$ADFt^*$	-10.693	-11.330	-10.030	-8.700	-7.210	Reject H_0^{**}

***, ** denote significance at the 1% and 5% levels, respectively.

According to estimates from CS-ARDL as reported in Table 7, the LSF determinants have an impact on the economy not only in the short run but also in the long run through their relationship. LGI has a negative and significant impact in the short run (-0.072 , $p < 0.05$) while in the long run, it has a higher negative influence (-0.118 , $p < 0.01$), reflecting that the environmental impact of green innovation is more significant over time as cleaner technologies diffuse and are accepted as replacement for the resource intensive production processes. Also, the impact of LET on LSF is negative for both horizons ($p < 0.05$ for short run and $p < 0.01$ for long run), indicating that the benefits of clean energy systems are more pronounced as the economic transition towards cleaner energy systems delves deeper. Contrary to this, LNRA is positively associated with LSF (SR: 0.087 , LR: 0.143 , $p < 0.10$ and $p < 0.01$, respectively), which can intensify the environmental pressure when the economy is dependent on natural-resource extraction. Both periods show a negative relationship between LEG and LSF, although the coefficient of the long term is higher ($p < 0.05$) than the coefficient of the short term ($p < 0.10$), which means that the promotion of economic growth oriented towards the environment can gradually help reduce the footprint. Finally, the negative and highly significant ECT (-1) coefficient (-0.602 , $p < 0.01$) supports the convergence towards the long-run equilibrium. Overall, the illustrative pattern indicates that green innovation and energy transition and green economic growth lead to greater environmental benefits over time while natural-resource dependence has a constant negative effect on environmental sustainability.

Table 7: CS-ARDL

Variable	Short-run Coef.	p-value	Long-run Coef.	p-value
LGI	-0.072^{**}	0.031	-0.118^{***}	0.004
LET	-0.104^{**}	0.047	-0.176^{***}	0.001
LNRA	0.087^*	0.082	0.143^{***}	0.006
LEG	-0.061^*	0.094	-0.092^{**}	0.028

Variable	Short-run Coef.	p-value	Long-run Coef.	p-value
ECT(-1)	-0.602***	0.000	—	—

The Dynamic Common Correlated Effects Mean Group (DCCEMG) estimator is employed as a robustness specification to check the sensitivity of results in Table 8 to the choice of estimator. This kind of estimator is particularly relevant in the presence of cross-sectional dependence and slope heterogeneity, as it provides country-specific coefficients, but also common, unobservable factors via the cross-sectional averages. The DCCEMG estimates in Table 8 are reasonably corroborating the signs and statistical significance of the baseline CS-ARDL long-run relationships. Specifically, LGI has a negative and statistically significant coefficient of -0.125 with a p value of 0.001 in comparison with -0.118 ($p = 0.004$) in the CS-ARDL estimates, which confirms that green innovation consistently has a negative impact on LSF. Similarly, LET is very negative and statistically significant (-0.184; $p < 0.001$), close to the baseline coefficient (-0.176; $p = 0.001$), which supports the idea of an environmental effect of energy transition. In contrast, the estimate of LNRA is still positive (0.151, $p = 0.001$) and is like that of the CS-ARDL (0.143, $p = 0.006$), indicating that an increase in dependence on NRAs continues to exert environmental pressure. Lastly, LEG continues to have a negative and significant relationship with LSF at -0.097 ($p = 0.021$) as opposed to -0.092 ($p = 0.028$) under CS-ARDL. Of key interest is that all the coefficients retain their sign and that the sizes of the coefficients are very similar between the two estimators. Thus, the DCCEMG results provide significant robustness for the baseline CS-ARDL results and indicate that the results are not simply a consequence of the dynamic specification of the CS-ARDL estimator but may be more likely to be robust when cross sectional dependence and heterogeneous slopes and common stocks are considered.

Table 8: DCCEMG

Variables	DCCEMG Coef.	Std. Err.	p-value
LGI	-0.125***	0.038	0.001
LET	-0.184***	0.052	0.000
LNRA	0.151***	0.045	0.001
LEG	-0.097**	0.042	0.021
Constant	2.184***	0.391	0.000

Discussion

The estimates all convey the same message. As a result, the impacts of green innovation and energy transition are negative on the sustainability footprint of the Paris Club economies, natural resource abundance also impacts negatively on the sustainability footprint, while the growth control also impacts negatively both in CS-ARDL baseline and DCCEMG check. Signs and significance do not differ between the two estimators, and, in all cases, the long-term coefficients are not more than 0.01

point different (e.g., -0.118 versus -0.125 for green innovation). This stability is relevant since the diagnostics revealed high slope heterogeneity, high endogeneity and high cross-sectional dependence. The error correction term is -0.602 , which means that the footprint gets back to its long-run path fast, around 60% of a deviation is corrected in one period. Each of the results below is compared to the literature presented in the previous sections.

Short-run and long-run coefficients of green innovation are negative, and the long-run coefficient (-0.118) is more negative in absolute value than the short-run one (-0.072). In line with induced innovation and ecological modernization theory, the results suggest that the diffusion of cleaner technologies occurs over time and that the need for cleaner technologies takes time to replace resource-intensive processes. The finding is consistent with evidence that green technological innovation contributes to a reduction in the footprint across quantiles in the G-7 (Javed et al., 2024), green energy innovation does so in BRICST economies (Gu et al., 2024), and innovation does so in developing economies (Shi & Smith, 2025). It also resonates with the wider body of research on technological and green innovation, footprints and emissions (e.g. Dam et al., 2024; Kirat et al., 2024; Pata & Karlilar, 2024; Feng et al., 2022).

Two changes with respect to prior work should be noted. Aydin et al. (2023) note that the innovation effect is different for various European Union member countries and Akpanke et al. (2024) find that research and development contributes to increasing emissions in the OECD and has an insignificant effect on the footprint. DCCMG allows coefficient for each country, but our estimate is a group average. The innovation indicator can contribute to the solution, too. That general research spending is not necessarily directed towards cleaner technologies, but environment-related patents are, which is perhaps why a specific green measure is taken to receive a clearer signal. This might be attributed to the fact that policy support is included in the mechanism: green bonds and green finance with clean taxes were found to have a positive effect on innovation, or to reduce the environmental pressure (Lee et al., 2023; Sohag et al., 2024; T. Wang et al., 2023).

The energy transition is the parameter with the highest impact with a short run value of -0.104 and long run value of -0.176 . The pattern holds that the benefits will compound as the energy system develops, rather than come all at once. It corroborates the following evidence: Evidence from OECD countries revealed that renewable energy aids in reducing the ecological footprint (Akpanke et al., 2024); Evidence across quantiles from G-7 countries indicated that renewable energy helps reduce the ecological footprint (Javed et al., 2024); Evidence from developing economies found that renewable energy helps reduce ecological footprint (Shi & Smith, 2025). The relationship has also been explored in the context of the United Kingdom and Europe and beyond (B. Li et al., 2023; Wada, 2026; Zhou et al., 2023).

Again, there are differences as the positive association between renewable energy and environmental pressure found by Aydin et al. (2023) for some European members is not apparent in the group average. Furthermore, our indicator is not energy efficiency as the impact of energy efficiency on the OECD footprint is very limited as demonstrated by Akpanke et al., (2024). More

than just efficiency improvements, it appears that a change in fuel mix has had a greater effect on the footprint. The Durbin and Wu-Hausman tests reject exogeneity and the coefficient of this variable is considered as a strong long-run relationship.

The only channel that has an impact on the footprint is the natural resource abundance, and the impact is stronger in the long run (0.143, significant at 1 percent), compared to the short run (0.087, significant at 10 percent). Weaker short run results showed that resource extraction and resource linked production slowly impact the footprint. This is consistent with the resource curse hypothesis and the fact that resource exploitation had been linked to greater footprint in BRICST economies (Gu et al., 2024). It uses the same logic to a cluster of advanced creditor economies, where the mineral-rent and resource-depletion aspects we have explored (He et al., 2024; Kang et al., 2023) have not been investigated.

The size of the coefficient is smaller than the combined offsetting effect of green innovation and the energy transition (-0.118 and -0.176), which hints at a policy opening. Previous studies reveal that the resource effect relies on green technology and renewable energy (Ma et al., 2024), government efficiency (E. Wang et al., 2024), and corruption governance (R. Li et al., 2023). These interactions were not tested but were a result of the reading of the pattern. The other caution that needs to be exercised in viewing the average is that there are some members of the group who are rich with resources and some who are poor with resources.

The economic growth in horizons are negative (-0.061 and -0.092) although the latter is only significant at 10 percent. This is unlike the footprint in Figure 1, which is expected to grow as well as the OECD evidence that growth expands the footprint (Akpanke et al., 2024). This might be interpreted as the extent that growth is accompanied by a structural change to services and a structural change to cleaner technologies, dominating the scale effect of growth, which leads to the downward portion of the environmental Kuznets curve. Since growth is both a control and a measure of GDP in current US dollars, the coefficient cannot be interpreted as proof of the fact that growth is good for the environment. Past research on growth and footprints in developing Asia also highlights that the relationship depends on the financing and characteristics of growth (Chen et al., 2023).

Conclusion and Policy Implication

This study analyzed the impact of green innovation, energy transition and natural resource abundance on the sustainability footprint of Paris Club economies over the period 1990-2025, with a control of economic growth. The diagnostic analysis showed the presence of cross-sectional dependence, significant slope heterogeneity, potential endogeneity, and mixed orders of integration. The Kim (2003) segmented cointegration test also showed that there was a stable long-run relationship with a temporary break in cointegration. These features led to the choice of CS-ARDL as the baseline estimator and DCCEMG as a robustness estimator to account for common shocks, heterogeneous country responses, and dynamic short- and long-run adjustments.

The results show that green innovation has a negative impact on the sustainability footprint, and that this impact is greater in the long run than in the short run. This strengthening effect is in line with the progressive diffusion and adoption of cleaner technologies. The energy transition has the largest footprint with a reduction in the short run and in the long run, highlighting the importance of shifting to cleaner energy. Natural resource abundance, on the other hand, has a positive impact on the sustainability footprint, which goes up in the short run to in the long run. This is common to production and extraction processes that put continuous pressure on the environment. The relationship between the footprint and economic growth is negative, but with a relatively small and less significant impact. This does not imply that economic growth is environmentally good, but it may be the impact of the structural transformation, technological upgrading and cleaner production in the sample.

The direction and statistical significance of all the principal relationships remain unchanged in the robustness analysis with DCCEMG, while the long-run coefficients are within 0.01 of the corresponding CS-ARDL estimates. This consistency gives more confidence that the primary results are not a consequence of the dynamic structure of the baseline estimator. Furthermore, the error-correction coefficient is -0.602 , which suggests a relatively quick adjustment towards the long-run equilibrium, as about 60.2% of the short-run disequilibrium is corrected within each period.

There are three policy implications of these findings. First, green innovation support should be sustained for sufficiently long time periods. The long-term effect is more significant, suggesting that the environmental effects of innovation can be cumulative, as cleaner technologies spread in production systems. Policy support should thus not only be restricted to the short-term patent creation, but also to commercialization, technology uptake, research collaboration and deployment. Second, the energy transition is the biggest footprint reducing channel in the model. Policies that promote the greater penetration of renewable and other low-carbon energy sources, enhance clean-energy infrastructure, and reduce reliance on carbon-intensive energy can therefore play a central role in reducing environmental pressure. Importantly, the larger long-run coefficient indicates that long-term energy-system transformation could offer more environmental benefits than short-term changes alone.

Third, there must be good institutional and fiscal management of natural resource rents. Resource abundance is positively correlated with sustainability footprint, and resource revenues should be channeled to clean infrastructure, technological upgrading, energy diversification and environmental protection. Carbon-pricing instruments and reinvestment of resource revenues into clean capital could provide complementary instruments to reduce environmental pressures related to resource extraction. The evidence on carbon pricing and resource rents in BRICS economies also provides a solid basis for considering the potential for policy combinations in other resource-rich economies.

There are some limitations that need to be considered. First, green innovation is measured as the number of patents related to the environment, but this does not necessarily reflect the quality of the patents, the commercialization of the technology or the actual diffusion of the technology. Future

research could differentiate between green patent quality, technological adoption and realized environmental performance. Second, economic growth is calculated in current U.S. dollars, which can include price and exchange-rate changes and real economic growth. Real and per-capita measures of economic growth should thus be considered in future studies. Third, the econometric framework allows for the possibility of endogeneity, but the energy-transition variable is not instrumented with an exogenous variable. Future studies might use instrumental-variable approaches or other identification designs to enhance causal interpretation. Lastly, the Paris Club is made up of very different institutional, technological and resource-based economies. The reported coefficients are thus average relationships that could mask significant cross-country variation.

Future studies may employ quantile-based estimation, time series-based analysis coupled with moderation of green innovation, natural resources and institutional quality. These extensions would help to determine the institutional and structural conditions in which green innovation and energy transition have the greatest impact on sustainability footprints. Overall, the evidence suggests that technological innovation and energy-system transformation, and effective management of resource rents, play a key role in alleviating ecological pressure in Paris Club economies.

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