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Original Research

Relationship Between Green Complexity and Carbon Dioxide Emissions: Evidence from Global Panel Data

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Abstract:

This study explores the nexus between the recently developed green complexity index, which shows the sophistication of countries to produce green products, and carbon gas emissions. We employ the Augmented Mean Group (AMG) and Mean Group (MG) estimators besides conventional techniques, considering cross-sectional dependency and parameter heterogeneity using a panel for 111 countries over the period 1999-2019. Our findings indicate the presence of an inverse relationship nexus between green complexity and carbon emissions in low and medium-low income countries. However, as income levels rise, this relationship disappears.

Keywords: Green Complexity; Carbon Emissions; Crosssectional dependency

JEL Codes: Q50, Q56, O50

Introduction

The latest developments in the world economy have led to a rise in the importance and awareness of the climate crisis. On the other hand, the upward movements in energy and commodity prices due to the pandemic in 2020 caused global inflation. Global inflation and geopolitical risks have triggered concerns about the supply of raw materials by increasing the pressure on the prices of agricultural, energy, and industrial products. In such a period, increasing energy demand and rising costs stimulate the usage of fossil fuels. Whereas growth in economic activity is expected to increase carbon emissions with a substantial adverse impact on the environment, it is still crucial for emerging markets to boost welfare. Developed economies have announced many measures to reduce carbon emissions, providing the transition to a green economy and fighting against the climate crisis. At the end of 2019, the European Commission introduced the European Green Deal and the European Union is targeted to become the first carbon-neutral continent in the world by 2050. China, responsible for approximately thirty percent of the world's greenhouse gas emissions, announced its goal of being carbon-neutral by 2060 in 2020. As per the report of the International Energy Agency (IEA), many countries presented their net zero

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emissions commitments under the Paris Agreement. As of 2021, the EU and 44 countries, which account for approximately seventy percent of carbon emissions, have pledged a zero-emission target [1].

Both developed and developing countries have wrestled with carbon emissions, loss of biodiversity, and air and water pollution by using many policies at the international level. However, more should be done to address these challenges. While the number of countries that pledge zero carbon emissions surges, demand for environmental goods such as wind turbines and solar energy materials expands [2]. International cooperation and the development of global environmental goods and services are necessary to transition to low-carbon economies. Besides, trade liberalization in environmental goods and services is essential to accelerate green growth and the development of green products. According to the OECD's definition,

"Green growth is accelarating economic growth and development while safeguarding the natural assets that continue to supply the resources and environmental services [3]."

Similarly, the United Nations Environment Program [4] defines a green economy as

"One that leads to improved human well-being and social equity while noticeably reducing environmental risks [4]."

As one can infer from the different definitions of international institutions, green growth aims to generate economic prosperity while reducing environmental risks and improving environmental quality.[1] In this context, studies in the related literature investigate the relationship between green growth and the environment. [5] investigates the role of green growth in reducing carbon emissions in the United States. In order to measure the environmental impacts of growth, they use pollution-adjusted GDP growth as a metric to assess green growth, which is different from conventional measures. They find that increasing green growth is an effective way to reduce carbon emissions, and using renewable energy and making institutional and organizational improvements are essential to achieving carbon neutrality. [6] investigates the relationship between green growth and carbon neutrality by considering factors such as environmental taxes, green energy, and ecological innovation. They find that, in the long run, green growth, environmental taxes, and renewable energy have a reducing effect on carbon emissions. On the other hand, green growth, ecological innovation, and renewable energy are negatively associated with CO2 emissions in the short run.

There are also regional or country group studies in the literature exploring the nexus between green growth and carbon emissions. For instance, [9] investigates the effect of green growth and environmental taxes on carbon emissions for G-7 countries. Their results demonstrate an inversion relationship between carbon emissions and all explanatory variables, including human capital, renewable energy consumption, and technological innovation, with the exception of GDP.

Some studies scrutinize the relationship between green growth and carbon emissions primarily for China, which causes about 30 percent of the world's greenhouse gas emissions. [10] investigates the relationship between green growth and carbon emissions by developing a green growth composite index as a proxy for green growth with the formation of three main sub-indices, such as economic growth, the welfare of the population, and the ecological environment. Although their findings suggest mixed results for different regions of China, it is emphasized that regional policies would be important in combating carbon emissions. Just as firms are the main producing units in a country, in the fight against carbon emissions, they play a key role in becoming carbon neutral, aiming to switch to greener production processes. In this context, there are also studies in the literature evaluating the relationship between firm-specific carbon emissions and green growth. [11] finds a negative relationship between green R&D and carbon emissions for Japan's manufacturing industry, where they define green R&D as the R&D activities of firms to increase productivity and reduce environmental pollution.

The link between green growth and pollution in the environment has attracted more attention recently. Besides, according to different institutions' definitions of green growth, developing green products and spreading green technologies are vital to ensuring green growth [12]. To achieve green growth and a green transition in economies, green products need to be increased, green production processes need to be supported, and green technologies need to be developed. In this instance, developing green product capabilities and ramping up green production sophistication are critical elements of green transition and green growth. In the meantime, in order to ensure a green economy and green growth, determining which products are environmentally friendly and which countries have the capacity to develop such products are essential questions. Accordingly, measuring the countries' green product sophistication and green product-related capabilities is of great importance. In their pioneering study, [12] provided a novel index to measure the sophistication of green products. Using the economic complexity index methodology of [13], their Green Complexity Index (GCI) ranks countries by the complexity of green products exported competitively. [12] suggests that countries with higher Global Competitiveness Index (GCI) scores tend to display reduced carbon emissions, enforce more stringent environmental regulations, and generate a greater number of environmental patents.

The aim of this study is to explore the impact of green complexity on carbon emissions by using the novel complexity index for 111 countries over the period 1999-2019. As [12] proposes, we explore the presence of a negative relationship between carbon emissions and green complexity at the country level. While there are

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[1] Carbon dioxide emissions is an important and reliable indicator of environmental quality or environmental degradation in the literature [7, 8].

only a few papers analyzing the nexus between green complexity and carbon emissions, we contribute to this limited literature by providing a detailed analysis at cross-country level. Methodologically, we consider cross-sectional dependency and perform six different estimation techniques that are conventional and newly developed. To our knowledge, this is the first study evaluating cross-sectional dependency while analyzing the relationship between the green complexity index and carbon dioxide emissions. We further expand our analysis by performing our estimations based on the income level of countries using the World Bank's income classification.

This paper is structured as follows: In the following section, we present a brief review of contemporary literature related to determinants of carbon emissions as well as the relationship between green complexity and carbon dioxide emissions. Section 3 introduces the data sources and methodology. In Section 4, the results of our empirical investigation are presented. Section 5 concludes.

Background Literature

Economic Complexity Index and Environmental Studies

Over the past decade, the concept of economic complexity with its applications to economic and export diversification have received considerable attention. Economic diversification is essential to ensure economic development, which mitigates the effect of external shocks, creates qualified employment, and increases high-technology investments. Related to this, export diversification is one of the most critical components of economic complexity. Complexity metrics are generally produced based on international bilateral trade data [13]. In the related literature, as a proxy for complexity, export diversification is commonly evaluated by some indices, such as Herfindahl-Hirschman and Theil, depending on the shares of products or commodities in total exports. On the other hand, many criticize these indexes for not measuring product capabilities across countries [14]. The Economic Complexity Index (ECI), which was first introduced by [13], aims to capture the sophistication of a country's exports, production capabilities, and knowledge embedded in production. ECI is computed using the country's diversification and product ubiquity.

ECI is a very popular indicator in research on global development, studies on innovation, and economic geography [15]. In the beginning, it was used to estimate GDP due to the high correlation between ECI and economic growth. Then, the economic complexity has been used in a much-extended research area, from predicting greenhouse emissions to explaining regional variations in income, GDP, and industrial policy analysis. In addition, its methodology led to new innovative tools such as green complexity.

Recently, the nexus between economic complexity and environmental issues has been drawing much more attention. An increasing number of papers have scrutinized the effect of economic complexity on carbon emissions [4, 16-18]. To this extent, it is essential to briefly present the literature on the determinants of carbon emissions—where they are fundamentally based on the theory of the Environmental Kuznets Curve (EKC). Among them, [19] suggests an inverse U-shaped relationship between economic growth and environmental pollution. According to them, up to a certain level of GDP, environmental quality is negatively affected, and after a certain threshold, it is positively affected by any increase in GDP. However, the presence and form of the Environmental Kuznets Curve (EKC) remain subjects of debate in the relevant literature [20].

A line of literature varies with different model specifications, explanatory variables, and shapes of EKC. In these studies, carbon emissions are widely used to measure environmental degradation. Within the related literature, the determinants of carbon emissions have been primarily investigated and attached to great importance, where the relationship between economic activity and carbon emissions is extensively studied conventionally. Accordingly, GDP is an essential variable in determining carbon emissions [21-24]. Variables such as trade openness, population, urbanization, energy consumption, and foreign direct investments are introduced to the models on the determinants of carbon dioxide emissions [25-29]. Recently, some studies have probed the impact of human capital on carbon emissions. Among them, [30] indicates that enhanced human capital mitigates carbon emissions. [31-34] conclude similar results and show that increased human capital leads to cleaner production processes. In contrast, [35] identifies an inverted U-shaped association nexus between human capital and carbon emissions.

Recently, there has been an interest in studying the association between economic complexity and carbon emissions, where economic complexity is used instead of growth to validate the EKC [36-38]. In some studies, bidirectional causality is found [16], where carbon emissions and economic complexity are ongoing processes that stimulate each other. Once analyzed by income levels, an increase in economic complexity in low and middle-income countries leads to a surge in carbon emissions. So, this requires a balanced and fine-tuned policy for environmental protection and economic development policies for low-income countries. On the other hand, as the income level increases, environmental awareness and investment in green areas increase, and thus economic complexity leads to cleaner production [18].

Green Complexity and Theoretical Background

Another line of the literature examines the economic complexity and environmental issues in terms of green competitiveness, where developing green technologies leads to producing more environmentally friendly products with fewer emissions. Accordingly, various measures have been used to assess the green production capabilities of countries. In this respect, the economic complexity methodology of [13] has inspired many studies. In their seminal paper, [39] tries to determine the green products with the highest growth potential, drawing on the product space and product proximity of the economic complexity methodology. [39] hypothesizes that green products having the highest growth potential are close to the products that a country produces with a high Relative Comparative Advantage (RCA). To test their hypothesis, they use Eurostat's (2009) green product classification, including 41 products for 141 countries over the period of 2005-2013. [39] finds evidence that the green products with the highest growth potential are closely linked to products with a high Relative Comparative Advantage.

In another pioneering study, [12] introduces the green complexity index (GCI), utilizing the economic complexity methodology. They identify and consolidate 293 HS6 products as green by considering different international institutions' green product lists, such as the WTO, APEC, and OECD. Secondly, drawing on the Economic Complexity Index methodology, they suggest GCI, which allows them to rank countries based on their green capabilities and make comparisons between countries. Third, by applying the relatedness criteria developed by [13] to their green product set, the Green Adjacent Possible (GAP) for countries is calculated, providing green export opportunities. Another measure, referred to as Green Complexity Potential (GCP), is also developed to calculate a comparable that combines the data within each country's GAP. Mealy and Teytelboym indicate the existence of a positive association between environmental patents, the environmental stringency index, and GCI. Besides, they find a negative relationship between GCI and carbon emissions per capita. The authors argue that these findings confirm the ability of GCI to approach issues regarding production and the environment.

The relationship between the novel GCI and carbon emissions is of great importance. Green growth necessitates the implementation of eco-friendly production methods and the development of ecologically sustainable products, namely those with green product capabilities, resulting in reduced carbon emissions. In their study, [12] asserts that countries exhibiting elevated Global Competitiveness Index (GCI) levels tend to exhibit correspondingly diminished levels of carbon emissions. [40] presents a significant theoretical perspective on the Economic Complexity Index. As a matter of fact, [40] points out the scale and substitution effects in his research studies. They also revealed that in order to achieve greater ECI levels, a major investment will be necessary in the existing industrial infrastructure to transform it, which would result in an increase in carbon emissions in the first place. It is expected that the scale impact will be less pronounced in nations that possess the essential production components and are more likely to adopt environmentally friendly generation technology. As a result of the proliferation of environmentally friendly items on the market and the subsequent reduction in the prices of these products, the replacement effect will prevail, and the substitution of green products will result in a reduction in carbon emissions. In light of the fact that GCI is technically composed of the application of the ECI technique to environmentally friendly products, the explanations that [40] provided can also be directly applied to GCI. Recently, [41] highlighted that the development of green capabilities may lead to a rise in carbon emissions due to the requirement of additional energy, investments, and sources of production for technological transformation, describing a theoretical relationship between Global Carbon Intensity (GCI) and carbon emissions.

Micro-based studies can also contribute to explaining the relationship between green product capabilities and carbon emissions. The Porter hypothesis, well known in the literature, posits a win-win situation between environmental regulations and firms' financial development. Strict environmental regulations are expected to increase the efficiency of firms [42, 43]. In this case, manufacturing industry companies that cause carbon emissions will increase their green capabilities, and carbon emissions will decrease. [44], in his recent study, theoretically examined the relationship between green product innovation and firm profitability by utilizing Instrumental Stakeholder Theory (IST) and Resource Dependence Theory (RDT) and revealed that green product innovation is an important tool in structuring and maintaining the relationship between stakeholders and firms and that green product innovation will reduce dependence on external financing. On a micro basis, it is assessed that firms' carbon emissions will be positively affected through the development and enhancement of green product capabilities, or, in other words, the green complexity index.

Empirically, although the relationship between GCI and carbon dioxide is remarkable, there exist very few studies on this subject in the literature. Among them, [41] scrutinizes the relationship between green complexity and carbon emissions, considering institutional quality. They explore a non-linear relationship between carbon dioxide emissions and GCI, taking institutional quality into account by performing a finite mixture model on a balanced panel including 78 countries over the period 1995-2014. Their results suggest that green product ability can lessen carbon emissions in countries with better institutional quality. For countries with lower institutional quality, an increase in green product sophistication leads to a surge in carbon emissions. In their research, [41] does not discuss cross-sectional dependency. However, common factors such as financial crises, international trade, and foreign direct investment flows, which affect all countries, might lead to such dependency.

Data and Methodology

[12] proposes a green complexity index to measure the sophistication of green products built on the economic complexity methodology. They build their GCI on the Product Complexity Index (PCI) defined by [45].

$$GCI_c = \sum_m \rho^c_m \widetilde{PCI}_m \tag{1}$$

ρ^c_m takes the value of one if a country c has RCA>1 in green product m or else zero. $\widetilde{PCI}_m$ is standardized to get a value between zero and one. Similar to the economic complexity methodology, [12] standardizes the GCI values. However, they emphasize that green complexity differs from economic complexity concerning a few aspects. One of them is that economic complexity covers all the traded goods, but green complexity covers a subset of all traded goods that are environmental. Second, whereas economic complexity represents the average product complexity index for all traded goods that a country is competitive in, green complexity sums product complexity values for green traded goods that the country was revealed as having a comparative advantage. In this paper, to scrutinize the relationship between green complexity and carbon dioxide emissions, we employ a panel covering 111 countries over the period 1999-2019. Annual carbon emissions per capita for countries are obtained from Our World in Data. The Green Complexity Index is received from [12]. Definitions and sources of control variables, including primary energy use, trade openness, and gross domestic product per capita, are presented in Table 1.

Table 1. Description of Variables

Variable	Definition	Source
gci	Green Complexity Index	Mealy and Teytelboym (2022)
co2	The per capita CO_2 Emissions (t/co2)	OurWorldInData.org
pec	Primary Energy Usage	OurWorldInData.org
gdp	GDP Per Capita (Constant 2015 US$)	World Bank
trade	Trade (% of GDP)	World Bank

This study fundamentally depends on the widely known EKC model [46]. [46] states that until a specific threshold point, increases in GDP result in environmental degradation, whereas after that threshold, any increase in GDP leads to improvements in environmental quality. A plethora of research within the broader literature has investigated the determinants of carbon dioxide emissions by using the well-known EKC model [20, 22, 24, 38]. Notably, we modify the EKC model by adding a new variable, namely the green complexity index, to investigate the relationship. In addition, following the existing EKC literature, we employ some additional control variables, such as trade openness [47] and primary energy usage [48], to overcome the omitted variables bias.

We establish our model as the following:

$$\begin{gathered} CO_2 = f(gci, gdp, pec, trade) \\ CO_{2\,it} = a_i + \beta_{1i} gci_{it} + \beta_{2i} gdp_{it} + \end{gathered} \tag{2}$$

$$\beta_{3i} pec_{it} + \beta_{4i} trade_{it} + \varepsilon_{it} \tag{3}$$

$$\varepsilon_{it} = \delta_i g_t + \vartheta_{it} \tag{4}$$

where, $i = 1,2,\dots,N$, $t = 1,2,\dots,T$ and a_i denotes fixed individual effects, $CO_{2\,it}$ is country i's carbon emissions at time t, gci_{it} is the green complexity index of country i at time t, pec_{it} is primary energy usage for i's country at time t, $trade_{it}$ denotes trade openness as a share of total import and export of GDP, gdp_{it} stands for gross domestic product per person. The unobserved common factor is denoted by g_t which leads to cross-sectional dependency and coefficients of common factor to vary across countries. All variables are in logarithms except for gci.

Cross-Sectional Dependency

Cross-sectional dependency is one of the most critical econometric problems that may cause inefficient estimation results [49]. When the common shocks and unobserved factor in the error term affecting all cross-sections are not included in the model or, in the presence of the spatial dependence, there may be a cross-sectional dependency problem [49, 50]. Especially when cross-section units are countries, some linkages, such as international trade, bilateral investment, and some kind of financial relations, may lead to cross-sectional dependency. One cross-sectional dependency test (CD test) suggested by [50] has been employed intensively in the related literature. Pesaran's test yields robust results even if there is a structural break and non-normality of error terms. When the cross-sectional dimension (N) is greater than the time dimension (T), the CD test is more valid [50, 51]. Building upon these, before performing our estimations, we employ the CD test of [50, 51] to ascertain the presence of cross-sectional dependency in our panel dataset. Subsequently, the presence of unit root, cointegration, and estimation methods should be determined based on whether cross-sectional dependency exists in the panel.

Namely, the CD statistic developed by [50] is presented as follows:

$$\begin{gathered} CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\widehat{\rho_{ij}}\right) \\ CD \sim N(0,1) \end{gathered} \tag{5}$$

$i, j = 1,2,3,\dots N$ and $\hat{\rho}$ is the sample estimate of the pair-wise residuals correlation received by OLS estimations. Accordingly, the null hypothesis of no cross-sectional dependence is not accepted for all the variables employed (see Table A.1).

Homogeneity Tests, Unit Root and Cointegration

In the existence of cross-sectional dependency, second-generation panel unit root tests considering cross-sectional dependence and parameter heterogeneity should be used [52]. First-generation panel unit root tests, including [53-56], ignore the parameter heterogeneity, which is a critical weakness. Therefore, this study utilizes the second-generation unit root test suggested by [51]. Tables A.2. and A.3. presented in Appendix show the unit root test results. As per Pesaran's cross-sectionally augmented Dickey-Fuller (CADF) test results, the null hypothesis that "the cross-section has the unit *root*" is not rejected. Besides, cross-sectionally augmented IPS[2] (CIPS) test values of the first differences of variables are presented in Appendix (see Table A.2).

According to the test results, series are integrated in different orders. Thus, in order to test the cointegration relation, this study performs a panel cointegration test developed by [57]. The cointegration test in [57] has a few advantages. First, this methodology allows for investigating cointegration relations even if series are integrated at different orders. Moreover, it considers parameter heterogeneity and cross-sectional dependency. Another important diagnostic test is related to slope coefficient heterogeneity. To test slope coefficient homogeneity, we use the homogeneity test suggested by [58].

The cointegration relation between variables is tested using the Durbin-Hausman test developed by [57] (see Table A.3 in Appendix). The Durbin-Hausman test calculates two statistics: Durbin-Hausman group statistics and Durbin-Hausman panel statistics. According to the results of these two tests, the null hypothesis of "there is no cointegration" was rejected. According to [58], homogeneity test results and the null hypothesis of slope homogeneity was also rejected. Recently, panel estimation methods considering cross-sectional dependency and parameter heterogeneity have been developed in the literature. The Mean Group (MG) estimator developed by [59, 60] claims that in the presence of cointegrating relationships within each cross-section, the MG estimator allows for heterogeneous coefficients for each cross-sectional unit. On the other hand, the MG estimator does not consider the cross-sectional dependency. Subsequently, the Augmented Mean Group (AMG) estimation method was suggested by [61-63], which allows for both cross-sectional dependency and parameter heterogeneity.

Considering parameter heterogeneity and cross-sectional dependency, we employ AMG estimation in this study. Another important facet of this methodology is that it enables us to observe slope coefficients at each individual panel. Before performing the AMG and MG estimations, we prefer to proceed with conventional panel estimation methodologies such as pooled OLS, Fixed Effect, Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS) estimations in order to provide robust and comprehensive analysis. Dynamic ordinary least squares (DOLS), developed by Kao and Chiang (2001), is an expanded version of OLS with lags and leads of explanatory variables to control for endogeneity and serial correlation. Because of these advantages, the DOLS approach has been widely used in the related literature [64, 65]. The DOLS methodology further allows for estimating long-run coefficients to vary across countries to deal with parameter heterogeneity [66]. The other estimation technique, namely Fully Modified Ordinary Least Squares (FMOLS), is suggested by [67]. Extending the [68] approach, they suggested FMOLS. By drawing on the finite sample simulations, they showed that the performance of FMOLS is better than OLS, even in cases of regressor endogeneity and serial correlation. These methodologies are preferred in related literature. By employing different estimators, we aim to provide robust estimation results.

The adopted model we utilize for the Augmented Mean Group (AMG) estimation method suggested by [63] and [61, 62] is presented below.

$$y_{it} = \beta_i' x_{it} + u_{it} \qquad u_{it} = a_i + \lambda_i' f_t + \varepsilon_{it} \quad (6)$$

$$x_{mit} = \pi_{mi} + \delta_{mi}' g_{mt} + \rho_{1mi} f_{1mt} + \cdots + \rho_{nmi} f_{nmt} + \upsilon_{mit} \quad (7)$$

Where, $m = 1, \dots k, i = 1, \dots N, t = 1, \dots T$ and x_{it} is observable control variables, a_i represents country-specific fixed effects, f_t the common factors affecting all cross-sections, and λ_i' represents cross-section factor loadings. In equation (7) an empirical representation of the k observable regressors are added, which are represented as linear functions of unobserved common and country-specific factor loadings. Augmented Mean Group estimation is conducted in a two-stage process. In the first stage, the first-differenced standard OLS model, as below, is estimated where the year dummies variables are expressed as $c_t = \mu_t$.

$$\Delta_{yit} = b'\Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + e_{it} \quad \text{Stage (I)} \quad (8)$$

$$y_{it} = a_i + b_i' x_{it} + c_i t + d_i \mu_t + u_{it} \quad \text{Stage (II)} \quad (9)$$

$$b_{AMG} = N^{-1} \sum_i b_i \quad (10)$$

In the second stage, estimated c_t coefficients are added to country or cross-section equations to capture omitted idiosyncratic processes. This study uses more than one-panel estimators to see the impact of green complexity on carbon dioxide emissions elaborately built upon different methodologies.

Results and Discussion

Panel estimations for the whole sample according to six different methodologies are performed to analyze the relationship between green complexity and carbon emissions. Results from both these and country-based estimations obtained from the Augmented Mean Group estimator (AMG) are exhibited in Table 2.

Table 2 illustrates the estimation findings for the whole panel, employing diverse estimation techniques.

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[2] [56] suggested IPS test.

Table 2. Estimation Results by Different Estimators

	POLS	FE	DOLS	FMOLS	MG	AMG
gci	-0.03** (0.01)	-0.04* (0.02)	-0.04** (0.05)	-0.08* (0.04)	-0.08* (0.04)	-0.09** (0.04)
lgdp	0.85*** (0.01)	0.66*** (0.14)	0.89*** (0.03)	0.92*** (0.04)	0.26** (0.10)	0.34*** (0.10)
ltrade	0.34*** (0.02)	-0.003 (0.01)	0.49*** (0.08)	0.62*** (0.10)	0.08*** (0.03)	0.08*** (0.03)
lpec	0.12*** (0.01)	0.29*** (0.02)	0.09*** (0.02)	0.10*** (0.02)	0.33*** (0.07)	0.32*** (0.07)
Const	-8.55***	-6.53***	-9.88***	-10,63***	-3.70***	-4.24***
R-square	0,81	0,44	0,82	0,22		
F Test	536.9***	421.4***				
Wald Test					61.9***	74.2***
N	2297	2297	2297	2297	2297	2297

* p<0.1; ** p<0.05; *** p<0.01, Standard errors in parentheses.

It is observed that economic activity is positively significant, while related literature asserts that an increase in economic activity is one of the main reasons for the increase in carbon emissions. Indeed, the increase in economic activity requires an increase in production inputs and energy use. Carbon emissions increase with the growing usage of non-renewable energy resources. According to all estimators, the relationship between primary energy use and carbon dioxide emissions is positive. The increase in carbon emissions as energy use increases is due to the use of fossil energy resources and non-renewable sources. Trade openness is also determined to have statistical significance and a positive relationship. As countries' trade openness increases, the level of carbon emissions increases. A recent study of [69] argues that trade openness has indirect effects on carbon emissions, namely scale effect, technical effect, and structure effect, which are all positively associated with carbon emissions. In a general sense, it is expected that as foreign trade increases, the production and use of non-renewable resources will increase, having a negative impact on the environment [70]. On the other hand, due to increased environmental measures in developed countries, dirty industries are shifting to developing countries. Therefore, it harms the environment through trade.

According to Table 2, for all the estimators performed, the coefficient of GCI is negatively significant where increases in the green complexity index reduce carbon dioxide emissions at panel level. Namely, the capability of a country to produce green products affects emissions negatively. Estimators considering heterogeneity and cross-sectional dependency robustly imply a negative relationship between green complexity and carbon emissions for our panel, which includes 111 countries. These findings are in parallel to the study of [12], where control variables such as trade openness and primary energy use were not incorporated and cross-sectional dependency was not investigated. Using recent data from 1999-2019, our study provides up-to-date contributions to the literature. While the ECI is calculated over all traded products, the GCI is calculated with the same methodology by considering the subset of green products among all traded products.

Due to this similarity between economic complexity and green complexity, it is reasonable to interpret our results in parallel with the literature exploring the nexus between economic complexity and carbon emissions. For instance, [18] argues that cleaner production processes are used as economic complexity increases and complex products have lower emission intensity. [40] finds that an increase in economic complexity increases energy efficiency. Thus, a decline in carbon emissions is led by increases in product complexity with the increase in technological development, which in turn improves energy efficiency. Within this context, it can be argued that increases in green product complexity support green technologies, and the widespread use of environmentally friendly products is expected to reduce carbon emissions. [40] and [41] mention scale and substitution effects while examining the impact of economic and green complexity on carbon emissions. Scale effect is defined as the increase in carbon emissions due to the use of production factors to produce goods needed in the evolution to a greener economy. The substitution effect, on the other hand, is the decrease in carbon emissions due to the increased use of more environmental products with the transformation to an environmentally friendly economy. Our estimations suggest that the substitution effect is more pronounced for our country panel, yet the results might vary for different countries or sub-country groups.

Further, the countries in our sample are divided into four groups according to the World Bank's classification as low-income, low-middle income, middle-high income, and high-income (see Appendix). We opt to use the Augmented Mean Group Estimator for estimating

Table 3. Augmented Mean Group Estimations by Income Groups

	Low Income	Low-Middle Income	Upper-Middle Income	Upper Income
gci	-0.35** (0.15)	-0.23** (0.09)	-0.03 (0.09)	0.02 (0.02)
lgdp	0.67 (0.33)	0.59*** (0.22)	0.46*** (0.1)	0.17* (0.09)
lpec	0.16* (0.17)	0.28** (0.14)	0.40*** (0.11)	0.21** (0.09)
ltrade	0.16 (0.11)	0.13** (0.05)	0.13** (0.06)	0.05 (0.03)
Constant	-7.77***	-6.67***	-6.56***	-1.89***
Wald Test	23.1***	51.6***	37.2***	123.38***

* p<0.1; ** p<0.05; *** p<0.01, Standard errors in parentheses

income levels within sub-country groups. This choice is driven by the presence of cross-sectional dependency and heterogeneity in our panel data. According to the model estimation using the Augmented Mean Group estimator (Table 3), there is a negative relationship between green complexity and carbon emissions in low and medium-low income countries. As income levels increase, this relationship disappears. The negative relationship between green complexity and carbon dioxide gas emissions in low-income countries is more pronounced than that in low-middle income countries. Whereas very few studies investigate the relationship between green complexity and carbon emissions, it is plausible to evaluate the relationship between green complexity and carbon emissions, considering the literature on carbon emissions and economic complexity. Results are controversial. [71] find a stronger relationship for the sub-panel of more complex countries within the EU, suggesting that the tendency towards fossil energy and dirty industries may increase as complexity increases. [36], on the other hand, found in their study of 55 countries that there is a positive relationship between economic complexity and carbon emissions for the low and middle-income groups and a negative relationship for the high-income country group. [18] argue that economic complexity favors more technological processes and leads to productivity gains with lower emissions.

According to [41], carbon emissions may inevitably worsen with the increase in production factors due to the transformation in the production process in the early stages of green transformation. This situation can be defined as the scale effect. On the other hand, a negative relationship between green complexity and carbon emissions is also possible through the substitution effect. In this framework, countries with a high green product production capacity can supply green products at lower prices, and carbon emissions may decrease with the increase of green products on the market. In addition, carbon emissions can also be reduced through the development and dissemination of green technologies. As green technology becomes more widespread, the weight of environmentally friendly products on the market will gradually increase, and carbon emissions will be reduced, which is the substitution effect.[3] From this point of view, our results confirm that the substitution effect of green complexity is high in low and low-middle income countries. In other words, carbon emissions can be reduced by increasing the ability to produce green products in low and low-middle income countries via the substitution effect of green complexity. In low-income countries, green transformation can be realized faster due to their already weak industrial capacity. In particular, it may be difficult for dirty industries operating in developed and high-income developing countries to transition to a green economy suddenly. Our findings support the view that in developing countries, prioritizing investments in green products to reduce carbon emissions, providing the necessary investment funds and advantageous loans, and facilitating international investments in these areas are vital.

For 24 out of 111 countries, we find a negative relationship between the green complexity index and carbon emissions, suggesting increases in green complexity trigger decreases in carbon emissions. Table 4. shows the division of countries according to the Augmented Mean Group estimation. According to the estimations for individual units for better elaboration, we detect a negative affiliation between green complexity and carbon emissions for 24 out of the 111 countries included. When these countries are examined according to their income and development levels, we observe a heterogeneous structure. Among these countries, there are relatively low-income countries such as Burkina Faso, Madagascar, Mali, and Rwanda, as well as some developed and high-income countries

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[3] [40] made a similar definition. [40] investigated the effect of economic complexity on renewable energy and, ultimately, carbon emissions. With increasing economic complexity, the scale effect will emerge due to additional investments and increased production for technological transformation, which will negatively affect carbon emissions. Nevertheless, carbon emissions will decrease with the technological and lower emission production processes activated by the substitution effect.

Table 4. Augmented Mean Group Estimations by Country

Country	Coef.	Country	Coef.	Country	Coef.	Country	Coef.
Burkina F.	-0.23**	Angola	-1.24	Egypt	0.08	Armenia	0.37**
Botswana	-0.64*	Benin	-0.26	Gabon	0.47	Bahrain	1.24**
Cameroon	-0.76**	Algeria	-0.16	Ghana	0.62	Malaysia	0.57***
Ethiopia	-1.28*	Kenya	-0.18	Mauritania	0.42	Philippines	0.47**
Madagascar	-1.38**	Lesotho	-1.46	Mauritius	0.02	Singapore	1.01**
Mali	-0.8***	Morocco	-0.06	Tunisia	0.008	Austria	0.29***
Niger	-1.32***	Iraq	-0.71	South A.	0.09	Switzerland	0.14***
Rwanda	-0.13**	Israel	-0.4	UAE	0.04	Czechia	0.18**
Senegal	-0.52***	Jordan	-0.04	Bangladesh	0.01	Germany	0.26**
Nicaragua	-0.27**	Japan	-0.01	Mexico	0.1	France	0.21*
India	-0.1**	Cambodia	-0.4	Panama	0.12	Belgium	0.28**
Kazakhstan	-0.29**	Nepal	-0.62	Iran	0.02	Canada	0.16***
South K.	-0.07***	Pakistan	-0.22	Kyrgyzstan	0.03	Guatemala	1.43**
Kuwait	-1.11**	Qatar	-0.34	Sri Lanka	0.09	Jamaica	0.83***
Spain	-0.61***	Thailand	-0.1	Saudi A.	0.25	El Salvador	0.26**
UK	-0.1***	Albania	-0.04	Turkey	0.14	Chile	1.02***
Croatia	-0.12**	Finland	-0.2	Vietnam	0.17	Italy	0.1*
Norway	-0.12*	Moldova	-0.11	Yemen	0.02	Greece	0.45*
Portugal	-0.3***	Poland	-0.06	Bulgaria	0.05		
Sweden	-0.22**	Romania	-0.08	Denmark	0.15		
Honduras	-0.83**	Russia	-0.004	Estonia	0.03		
Bolivia	-0.31**	Slovakia	-0.008	Hungary	0.14		
Colombia	-0.7***	Slovenia	-0.03	Ireland	0.008		
Peru	-1.75**	Namibia	-0.15	Lithuania	0.03		
		S.Leone	-0.27	Latvia	0.05		
		China M. Land	-0.008	Netherlnds	0.02		
		Hong K. China	-0.03	Ukraine	0.01		
		Indonesia	-0.18	Costa Rica	0.13		
		Brazil	-0.13	USA	0.04		
		Australia	-0.05	Argentina	0.1		
		N. Zealand	-0.18	Ecuador	0.12		
		Togo	-0.58	Paraguay	0.06		
		Tanzania	-0.17	Uruguay	0.02		
		Uganda	-0.21				
		Zimbabwe	-0.83				
		Dominicn R.	-0.17				

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

such as the UK, Norway, Sweden, and Spain. In this respect, the substitution effect, which is defined as the decrease in carbon emissions, due to the increased use of more environmental products with the transition to a green economy, between green complexity and carbon emissions might be at work in both high and low-income countries. However, the negative relationship between carbon emissions and green product capabilities in developed countries needs to be further researched. When the economic structure of each country is considered, another important concept, referred to as green complexity potential by [12], becomes important. According to Mealy and Teytelboym's green complexity potential index, Spain is ranked among the top countries with the highest potential in the world. Similarly, the UK, Sweden, and Portugal have high green complexity potential, respectively. On the other hand, the production and export structures of such countries might also trigger the substitution effect. For example, South Korea is at the forefront of green product exports globally, and the substitution effect might reduce carbon emissions with the domestic diffusion of exported products.

When we consider the countries for whom a positively significant relationship between green complexity and carbon emissions is found, it is observed that almost all of them are developed and high-income countries. An increase in green complexity increases carbon emissions in these countries. This finding particularly suggests the adaptation of established factories, production facilities, machinery, and production tracks towards green transformation. As stated by [41], increasing green product sophistication can be expected to increase carbon emissions in the first stage through the scale effect, as it will cause radical changes in the production structure. That is, while a total transformation is trying to be achieved, carbon emissions can be expected to increase with the scale effect, which is defined as the fact that an increase in carbon emissions due to the use of production factors to produce goods needed in the transition to a green economy. In parallel with the literature on the nexus of economic complexity and environmental pollution, it is observed that the scale effect of green complexity is higher in developed countries.[4]

Conclusion

This paper investigates the effect of green complexity on carbon emissions using [12], a novel green complexity index. Based on different estimators for our cross-country panel and by considering cross-sectional dependence, the findings suggest a negative relationship between green complexity and carbon emissions. Differentiating between sub-country groups by their income, a negative relationship is found between the green complexity index and carbon emissions, particularly in low and low-middle income countries. Supporting the point of view that reveals scale and substitution effects on carbon emissions, our findings show that the substitution effect is more pronounced in low and low-middle income countries. Indeed, once it is assumed that low- and low-middle-income countries still need solid industrial structures, achieving transformation towards a green economy can be relatively easy. With the funds and supports provided due to shallow commodity markets, the substitution effect of green products through imports will be enormous in such countries. On the other hand, we cannot find a significant relationship between green complexity and carbon emissions in the high-income countries group at the mean. Yet our individual country-level estimates provide further insights for these countries.

Individual estimation results show that countries have a heterogeneous outlook in terms of their income and development levels. This heterogeneity yields different results for developed and developing countries. The negative relationship between green complexity and carbon emissions in developed countries such as the UK, Spain, Sweden, Portugal, and South Korea suggests that the substitution effect is stronger than the scale effect in these countries. It can be inferred that despite these countries having advanced industrial structures, their high capacity for green product manufacturing may lead to substitution effects rising more rapidly than income effects. Interestingly, [12] claim countries such as Spain, Portugal, England, and Sweden are among the top 20 countries in terms of their green complexity potential. These countries are also at the forefront in terms of exporting green products. For example, while South Korea realizes approximately 4 percent of global green product exports, this rate has doubled in the last 20 years. Moreover, South Korea accounts for 6 percent of global exports in renewable energy products, 6 percent in air pollution control products, and 12 percent in waste management recycling products. Thus, due to its green product capability in exports, South Korea is to be able to reduce carbon emissions through the substitution effect channel from the increase in green complexity. On the other hand, almost all the countries where a positive relationship is found between green complexity and carbon emissions are in the middle-high and high-income groups. This might be due to the fact that increasing green product sophistication can be expected to increase carbon emissions in the first stage through the scale effect, as it will cause radical changes in the production structure.

In order to increase green sophistication, it is essential to increase the use of environmentally compatible technologies and environmentally friendly products. Due to the limitation of economic resources, both country and country-group-based policy implications play a vital role during the shift to a green economy. While our findings imply that increases in the green complexity level of low- and middle-low income countries reduce carbon emissions through the substitution effect, from a policy point of view, it is crucial to support investments that will provide green technology transfer in these countries. In other words, reducing bureaucracy and allocating resources to ensure the effective use of funds in these countries is of great importance. Additionally, necessary steps should also be taken to mitigate the scale effect on carbon emissions due to additional investments in developed countries. Increasing the green production capabilities of developed countries is also important to ensure green transformation and make existing capacity more environmentally friendly. Under these circumstances, it is possible to suggest that the adverse influence of the scale effect on carbon emissions can be limited by the importation of green products. In addition, tariffs and non-tariff barriers might be removed in the international trade of green products, and steps should be taken to facilitate trade for green products.

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[4] The results obtained for the entire panel may contradict individual results. Yet, as explained in the Data and Methodology section, the AMG method first conducts individual estimations for each cross-section and then takes their averages to arrive at the overall panel result. [61, 62] demonstrate, performing Monte Carlo simulations, that the results are both effective and consistent. Recently, [72] used the AMG estimator to test the presence of the Kuznets Curve for US states and found that while it holds true for the US as a whole, some states showed opposite results.

In conclusion, although empirical findings imply that there is an alteration between greener production and carbon emissions, even in countries with high green product capabilities, carbon emissions might be expected to increase with additional investments in green technologies. As [73] highlights, even though there are robust theoretical underpinnings, there remains a disconnect between the theoretical concepts and the tangible implementation of green growth policies. In this context, detailed studies to be conducted on a sectoral basis and at firm level might reveal further insights and policy implications about the efficient utilization of resources towards greener economies.

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Conflict of Interest

The authors do not have relevant financial or non-financial interests to declare.

References

1. IEA Net Zero by 2050. International Energy Agency, **2021**.
2. ANDRES P., MEALY P. Navigating the green transition: insights for the G7. London: Grantham Research Institute on Climate Change and the Environment and Centre for Climate Change Economics and Policy, London School of Economics and Political Science, **2021**.
3. OECD Green Growth Indicators 2014, **2014**.
4. UNEP Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication - A Synthesis for Policy Makers, **2011**.
5. YANG H., SHAHZADI I., HUSSAIN M. USA carbon neutrality target: Evaluating the role of environmentally adjusted multifactor productivity growth in limiting carbon emissions. Journal of Environmental Management, **298**, 113385, **2021**.
6. CHIEN F., ANANZEH M., MIRZA F., BAKAR A., VU H.M., NGO T.Q. The effects of green growth, environmental-related tax, and eco-innovation towards carbon neutrality target in the US economy. Journal of environmental management, **299**, 113633, **2021**.
7. AMIN A., AMEER W., YOUSAF H., AKBAR M. Financial Development, Institutional Quality, and the Influence of Various Environmental Factors on Carbon Dioxide Emissions: Exploring the Nexus in China. Frontiers in Environmental Science, **9**, **2022**.
8. ALI H.S., ZEQIRAJ V., LIN W.L., LAW S.H., YUSOP Z., BARE U.A.A., CHIN L. Does quality institutions promote environmental quality? Environmental Science and Pollution Research, **26** (11), 10446, **2019**.
9. HAO L.-N., UMAR M., KHAN Z., ALI W. Green growth and low carbon emission in G7 countries: how critical the network of environmental taxes, renewable energy and human capital is? Science of the Total Environment, **752**, 141853, **2021**.
10. ZHAO J., SHAHBAZ M., DONG K. How does energy poverty eradication promote green growth in China? The role of technological innovation. Technological Forecasting and Social Change, **175**, 121384, **2022**.
11. LEE K.-H., MIN B. Green R&D for eco-innovation and its impact on carbon emissions and firm performance. Journal of Cleaner Production, **108**, 534, **2015**.
12. MEALY P., TEYTELBOYM A. Economic complexity and the green economy. Research Policy, **51** (8), 103948, **2022**.
13. HIDALGO C.A., HAUSMANN R. The building blocks of economic complexity. Proceedings of the national academy of sciences, **106** (26), 10570, **2009**.
14. YALTA A.Y., YALTA T. Determinants of Economic Complexity in MENA Countries. JOEEP: Journal of Emerging Economies and Policy, **6** (1), 5, **2021**.
15. HIDALGO C.A. Economic complexity theory and applications. Nature Reviews Physics, **3** (2), 92, **2021**.
16. YOU W., ZHANG Y., LEE C.-C. The dynamic impact of economic growth and economic complexity on CO2 emissions: An advanced panel data estimation. Economic Analysis and Policy, **73**, 112, **2022**.
17. LAPATINAS A., GARAS A., BOLETI E., KYRIAKOU A. Economic complexity and environmental performance: Evidence from a world sample. Environmental Modeling and Assessment, **26**, 251, **2019**.
18. ROMERO J.P., GRAMKOW C. Economic complexity and greenhouse gas emissions. World Development, **139**, 105317, **2021**.
19. GROSSMAN G.M., KRUEGER A.B. Environmental impacts of a North American free trade agreement. National Bureau of economic research: Cambridge, Mass., USA, 3914, **1991**.
20. SHAHBAZ M., SINHA A. Environmental Kuznets curve for CO2 emissions: a literature survey. Journal of Economic Studies, **46** (1), 106, **2019**.
21. ANG J.B. CO2 emissions, energy consumption, and output in France. Energy Policy, **35** (10), 4772, **2007**.
22. APERGIS N., OZTURK I. Testing Environmental Kuznets Curve hypothesis in Asian countries. Ecological Indicators, **52**, 16, **2015**.
23. SOYTAS U., SARI R., EWING B.T. Energy consumption, income, and carbon emissions in the United States. Ecological Economics, **62** (3), 482, **2007**.
24. KASMAN A., DUMAN Y.S. CO2 emissions, economic growth, energy consumption, trade and urbanization in new EU member and candidate countries: A panel data analysis. Economic Modelling, **44**, 97, **2015**.
25. SHARMA S.S. Determinants of carbon dioxide emissions: Empirical evidence from 69 countries. Applied Energy, **88** (1), 376, **2011**.
26. SHAHBAZ M., NASREEN S., ABBAS F., ANIS O. Does foreign direct investment impede environmental quality in high-, middle-, and low-income countries? Energy Economics, **51**, 275, **2015**.
27. DOGAN E., OZTURK I. The influence of renewable and non-renewable energy consumption and real income on CO 2 emissions in the USA: evidence from structural break tests. Environmental Science and Pollution Research, **24**, 10846, **2017**.

28. ACHEAMPONG A.O. Economic growth, CO2 emissions and energy consumption: What causes what and where? Energy Economics, **74**, 677, **2018**.
29. YOU W., LV Z. Spillover effects of economic globalization on CO2 emissions: A spatial panel approach. Energy Economics, **73**, 248, **2018**.
30. MAHMOOD N., WANG Z., HASSAN S.T. Renewable energy, economic growth, human capital, and CO2 emission: an empirical analysis. Environmental Science and Pollution Research, **26** (20), 20619, **2019**.
31. KHAN M. CO2 emissions and sustainable economic development: New evidence on the role of human capital. Sustainable Development, **28** (5), 1279, **2020**.
32. YAO Y., IVANOVSKI K., INEKWE J., SMYTH R. Human capital and CO2 emissions in the long run. Energy Economics, **91**, 104907, **2020**.
33. ÇAKAR N.D., GEDIKLI A., ERDOĞAN S., YıLDıRıM D. Ç. Exploring the nexus between human capital and environmental degradation: The case of EU countries. Journal of Environmental Management, **295**, 113057, **2021**.
34. YAMEOGO C.E.W., COMPAORE E., YAMEOGO K.W.O. Assessing the nexus between energy consumption, urbanization, and carbon dioxide emissions: does human capital matter? Environmental Science and Pollution Research, **29** (57), 86840, **2022**.
35. GNANGOIN T.Y., KASSI D.F., EDJOUKOU A.J.-R., KONGRONG O., YUQING D. Renewable energy, non-renewable energy, economic growth and CO2 emissions in the newly emerging market economies: The moderating role of human capital. Frontiers in Environmental Science, **10**, 1017721, **2022**.
36. DOĞAN B., SABOORI B., CAN M. Does economic complexity matter for environmental degradation? An empirical analysis for different stages of development. Environmental Science and Pollution Research, **26** 31900, **2019**.
37. CAN M., GOZGOR G. The impact of economic complexity on carbon emissions: evidence from France. Environmental Science and Pollution Research, **24**, 16364, **2017**.
38. PATA U.K. Renewable and non-renewable energy consumption, economic complexity, CO2 emissions, and ecological footprint in the USA: testing the EKC hypothesis with a structural break. Environmental Science and Pollution Research, **28** (1), 846, **2021**.
39. FRACCASCIA L., GIANNOCCARO I., ALBINO V. Green product development: What does the country product space imply? Journal of cleaner production, **170**, 1076, **2018**.
40. KHEZRI M., HESHMATI A., KHODAEI M. Environmental implications of economic complexity and its role in determining how renewable energies affect CO2 emissions. Applied Energy, **306**, 117948, **2022**.
41. WANG E.-Z., YANG M. Green complexity and CO2 emission: Does institutional quality matter? Energy Economics, **110**, 106022, **2022**.
42. PORTER M.E., VAN DER LINDE C. Toward a New Conception of the Environment-Competitiveness Relationship. Journal of Economic Perspectives, **9** (4), 97, **1995**.
43. PORTER M.E. Towards a dynamic theory of strategy. Strategic Management Journal, **12** (S2), 95, **1991**.
44. RAHMAN M. The virtuous circle between green product innovation and performance: The role of financial constraint and corporate brand. Journal of Business Research, **154**, 113296, **2023**.
45. HAUSMANN R., HIDALGO C. A., BUSTOS S., COSCIA M., SIMOES A. The atlas of economic complexity: Mapping paths to prosperity, 2nd ed. MIT Press: Cambridge, **2014**.
46. GROSSMAN G.M., KRUEGER A.B. Economic Growth and the Environment*. The Quarterly Journal of Economics, **110** (2), 353, **1995**.
47. ZHANG S., LIU X., BAE J. Does trade openness affect CO2 emissions: evidence from ten newly industrialized countries? Environmental Science and Pollution Research, **24** (21), 17616, **2017**.
48. AL-MULALI U., WENG-WAI C., SHEAU-TING L., MOHAMMED A.H. Investigating the environmental Kuznets curve (EKC) hypothesis by utilizing the ecological footprint as an indicator of environmental degradation. Ecological Indicators, **48**, 315, **2015**.
49. DE HOYOS R.E., SARAFIDIS V. Testing for cross-sectional dependence in panel-data models. The stata journal, **6** (4), 482, **2006**.
50. PESARAN M.H. General diagnostic tests for cross section dependence in panels. Empirical Economics, **60**, 13 **2021.**
51. PESARAN M.H. A simple panel unit root test in the presence of cross-section dependence. Journal of applied econometrics, **22** (2), 265, **2007**.
52. HURLIN C., MIGNON V. Second generation panel unit root tests. Working papers, **2007**.
53. MADDALA G.S., WU S.A comparative study of unit root tests with panel data and a new simple test. Oxford Bulletin of Economics and statistics, **61** (S1), 631, **1999**.
54. HADRI K. Testing for stationarity in heterogeneous panel data. The Econometrics Journal, **3** (2), 148, **2000**.
55. LEVIN A., LIN C.-F., CHU C.-S.J. Unit root tests in panel data: asymptotic and finite-sample properties. Journal of econometrics, **108** (1), 1, **2002**.
56. IM K.S., PESARAN M.H., SHIN Y. Testing for unit roots in heterogeneous panels. Journal of econometrics, **115** (1), 53, **2003**.
57. WESTERLUND J. Panel cointegration tests of the Fisher effect. Journal of applied econometrics, **23** (2), 193, **2008**.
58. BLOMQUIST J., WESTERLUND J. Testing slope homogeneity in large panels with serial correlation. Economics Letters, **121** (3), 374, **2013**.
59. PESARAN M.H., SMITH R. Estimating long-run relationships from dynamic heterogeneous panels. Journal of Econometrics, **68** (1), 79, **1995**.
60. PESARAN M.H., SHIN Y., SMITH R.P. Pooled Mean Group Estimation of Dynamic Heterogeneous Panels. Journal of the American Statistical Association, **94** (446), 621, **1999**.
61. EBERHARDT M., TEAL F. Econometrics for grumblers: a new look at the literature on cross-country growth empirics. Journal of economic Surveys, **25** (1), 109, **2011**.
62. TEAL F., EBERHARDT M. Productivity analysis in global manufacturing production. Discussion Paper Series. Department of Economics (University of Oxford), **2010**.
63. EBERHARDT M., BOND S. Cross-section dependence in nonstationary panel models: a novel estimator. Economics, **2009**.
64. NGUYEN D.K., HUYNH T.L.D., NASIR M.A. Carbon emissions determinants and forecasting: Evidence from G6 countries. Journal of Environmental Management, **285**, 111988, **2021**.
65. NASIR M.A., DUC HUYNH T.L., XUAN TRAM H.T. Role of financial development, economic growth & foreign direct investment in driving climate change: A case of emerging ASEAN. Journal of Environmental Management, **242**, 131, **2019**.
66. PEDRONI P. Fully modified OLS for heterogeneous cointegrated panels. Emerald Group Publishing Limited, Volume **15**, **2001**.
67. HONG S.H., WAGNER M. Cointegrating polynomial regressions: fully modified ols estimation and inference. Econometric Theory, **32** (5), 1289, **2016**.

68. PHILLIPS P.C.B., HANSEN B.E. Statistical Inference in Instrumental Variables Regression with I(1) Processes. The Review of Economic Studies, **57** (1), 99, **1990**.
69. DOU Y., ZHAO J., MALIK M.N., DONG K. Assessing the impact of trade openness on CO2 emissions: evidence from China-Japan-ROK FTA countries. Journal of environmental management, **296**, 113241, **2021**.
70. LAVERDE-ROJAS H., GUEVARA-FLETCHER D.A., CAMACHO-MURILLO A. Economic growth, economic complexity, and carbon dioxide emissions: The case of Colombia. Heliyon, **7** (6), **2021**.
71. NEAGU O., TEODORU M.C. The Relationship between Economic Complexity, Energy Consumption Structure and Greenhouse Gas Emission: Heterogeneous Panel Evidence from the EU Countries. Sustainability, **11** (2), 497, **2019**.
72. SENCER ATASOY B. Testing the environmental Kuznets curve hypothesis across the U.S.: Evidence from panel mean group estimators. Renewable and Sustainable Energy Reviews, **77**, 731, **2017**.
73. RODRIK D. Green industrial policy. Oxford Review of Economic Policy, **30** (3), 469, **2015**.

APPENDIX

A.1 Cross-sectional Dependency Results

Variables	test-stat	p-value
lco2	20.51	0.00***
gci	2.09	0.00**
lgdp	239.28	0.00***
ltrade	63.46	0.00***
lpec	105.55	0.00***

Notes: Under the null hypothesis of cross-section independence CD ~ N(0,1) p<0.1;**p<0.05;***p<0.01.

A.2 Unit Root Test Statistics (CADF Test Pesaran, 2007)

	Level		First Difference	
	Constant	Constant+Trend	Constant	Constant+Trend
	t-stat	t-stat	t-stat	t-stat
lco2	-2.23	-2.62	-4.35***	-4.38**
gci	-1.93	-2.31	-4.01**	-4.20**
lgdp	-1.87	-1.91	-3.05**	-3.62*
ltrade	-1.61	-2.41	-3.79**	-3.97*
lpec	-2.41	-2.51	-4.31**	-4.34**

*p<0.1;**p<0.05;***p<0.01, for critical values, received from Pesaran (2007) Table 1.c and Table 1.b H0: bi=0 (has unit root)

A.3 Parameter Homogeneity, and Cointegration

	test-stat	p-value
D_p	2.13	0.000***
D_g	6.50	0.000***
Δ	38.78	0.000***
Δ_{adj}	46.03	0.000***

*, ** and *** demonstrate the significance level respectively, at the 10%, 5% and 1%.
Dg and Dp: Durbin-Hausmann group and panel tests, suggested by Westerlund (2008)
Δ and Δadj slope homogeneity tests (Blomquist and Westerlund (2013).

A.4 Country Groups by Income Level

Low	***Low-Middle***	***Middle-High***	***High***
Burkina Faso	Angola	Botswana	UAE
Ethiopia	Benin	Gabon	Bahrain
Madagascar	Cameroon	Mauritius	Panama
Mali	Algeria	Namibia	Hong Kong, China
Niger	Egypt	South Africa	Israel
Rwanda	Ghana	Armenia	Japan
Sierra Leone	Kenya	China Mainland	South Korea
Togo	Lesotho	Mexico	Kuwait
Uganda	Morocco	Iraq	Qatar
Yemen	Mauritania	Jordan	Saudi Arabia
	Senegal	Kazakhstan	Singapore
	Tunisia	Malaysia	Austria
	Tanzania	Thailand	Belgium
	Zimbabwe	Turkey	Switzerland
	Bangladesh	Albania	Czech
	Nicaragua	Bulgaria	Germany
	Indonesia	Moldova	Denmark
	India	Russia	Spain
	Iran	Ukraine	Estonia
	Kyrgyzstan	Costa Rica	Finland
	Cambodia	Dom. Republic	France
	Sri Lanka	Guatemala	United Kingdom
	Nepal	Jamaica	Greece
	Pakistan	Argentina	Croatia
	Philippines	Brazil	Hungary
	Vietnam	Colombia	Ireland
	Honduras	Ecuador	Italy
	El Salvadr	Peru	Lithuania
	Bolivia	Paraguay	Latvia
			Netherlands
			Norway
			Poland
			Portugal
			Romania
			Slovakia
			Slovenia
			Sweden
			Canada
			United States
			Australia
			New Zealand
			Chile
			Uruguay

Source: World Bank

A.5 Estimations by Developed and Developing Countries

	Developing	Developed
gci	-0.14** (0.07)	0.02 (0.02)
lgdp	0.36*** (0.12)	0.48*** (0.07)
lpec	0.29*** (0.09)	0.30*** (0.08)
ltrade	0.16*** (0.04)	0.08 (0.03)
Constant	-5.23***	-4.91***
Wald Test	49.38***	-15.65***

***According to the panel group estimates based on the developed/developing country classification made by UNCTAD, there is an inverse and significant relationship between green complexity index and carbon emissions in developing countries, while there is no significant nexus between green complexity and carbon emissions in developed countries. Similar to the panel analyses by income level, when green technology and green industry are supported, green products are expected to be offered to the market at more competitive prices, and carbon emissions are expected to decrease with the increase in green products offered in the market.*

A.6 Variance Inflation Factor

Variables	VIF	1/VIF
lgdp	4.99	0.20
gci	2.16	0.46
lpec	1.59	0.62
ltrade	1.55	0.64

** Since all VIF values are below 10, it is understood that there is no multicollinearity problem.*

A.7 Summary Statistics

	Mean	Std. Dev	Min	Max
gci	0.35	1.25	-0.88	5.07
lgdp	8.71	1.44	5.54	11.39
lco2	0.88	1.5	-3.13	4.20
ltrade	4.29	0.51	2.90	6.09
lpec	5.18	1.99	0.52	10.58

A.8 Correlation Matrix

	lco2	gci	lgdp	ltrade	lpec
lco2	1				
gci	0.47	1			
lgdp	0.88	0.57	1		
ltrade	0.33	0.07	0.29	1	
lpec	0.39	0.12	0.29	-0.09	1