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RESEARCH ARTICLE

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Economic complexity and environmental degradation: Evidence from OECD countries

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Abstract

We augment the existing knowledge on the role of economic complexity in the environment and sustainable development debate by examining the effect of economic complexity on environmental degradation (measured by ecological footprint, CO_2 emissions, N_2O emissions and greenhouse gas emissions) contingent on income, using data from 35 OECD countries between 1998 and 2017. With the fixed effects model estimator, we find that income facilitates economic complexity to mitigate ecological footprint, CO_2 emissions, N_2O emissions and greenhouse gas emissions. Also, we fit a partial linear functional-coefficient model to find that income influences economic complexity to exert a nonlinear effect on ecological footprint, CO_2 emissions, N_2O emissions and greenhouse gas emissions. We find that economic complexity leads to an increase in ecological footprint, CO_2 emissions, N_2O emissions and greenhouse gas emissions at lower income levels but gradually dampens them as income rises. Finally, by applying the Method of Moments Quantile regression to control for distributional heterogeneity, we also find that the mitigating effect of economic complexity on ecological footprint, CO_2 emissions, N_2O emissions and greenhouse gas emissions is transmitted through income across quantiles. The policy implications are discussed.

KEYWORDS

economic complexity, environmental degradation, income, method of moments quantile regression, partially linear functional-coefficient model, sustainable development

1 | INTRODUCTION

The climate has experienced changes over the years due to human activities associated with farming, building, natural resources extraction, fossil fuel burning, solid waste generation and deforestation, and so forth. These activities are causing harm not only to human life but also lead to environmental degradation because they produce anthropogenic greenhouse gases. The issue of climate change is ubiquitous, and virtually, all countries are susceptible to its attendant impacts. In the light of this, there has been international pacts signed by countries to deal with climate change. These pacts include United Nations Framework Convention on Climate Change (UNFCCC), Kyoto Protocol, and the Paris Agreement, among others. The common goal of these pacts is to limit global greenhouse gases (GHG) emissions, particularly global carbon dioxide (CO_2) emissions, which largely drive climate change.

In recent years, economic complexity has become an important consideration in the ongoing climate change global discourse.

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Economic complexity refers to the structural changes existing in the production structure as it moves towards more technological- and knowledge-based production processes. There is a consensus among climate change experts that climate change is the consequence of environmental degradation. It is important to understand how environmental degradation is influenced by economic complexity in order to design effective climate change mitigation policies (Romero & Gramkow, 2021). It is present in existing literature that economic complexity and environmental degradation are interdependent of each other (see Abbasi et al., 2021; Balsalobre-Lorente et al., 2022; Caglar et al., 2022; Majeed et al., 2021; You et al., 2022; Zheng et al., 2021). In the theoretical context, the environment is believed to degrade when income or economic growth rises. Economic complexity explains and predicts cross-country variations in income as well as economic growth trajectories (Hidalgo, 2021; Hidalgo & Hausmann, 2009); thus, economic complexity may have significant implications for environmental degradation.

Economic complexity measures account for present and future international and regional differences in GHG emissions (Hidalgo, 2021), which are largely responsible for environmental degradation. Romero and Gramkow (2021) argue that economic complexity would reduce future emissions of greenhouse gases. However, more opportunities become available as economic complexity rises, and this makes the density of their product space larger that resultantly leads to environmental degradation (Swart & Brinkmann, 2020). Less than a decade ago, researchers began to query how economic complexity is associated with environmental degradation and this has sparked a debate. Some researchers argue that economic complexity can trigger environmental degradation (Abbasi et al., 2021; Boleti et al., 2021; Li et al., 2021), while others argue that economic complexity can be a mitigating tool for environmental degradation (Can & Gozgor, 2017; Doğan et al., 2021; He et al., 2021). As a result, policymakers have been thrown into a dilemma on whether or not to drive towards making economies more complex.

On the back of the aforementioned discussions, we are motivated to join the economic complexity-environmental degradation nexus debate in an attempt to broaden the existing knowledge in empirical literature. To do this, we examine the effect of economic complexity on environmental degradation contingent on the income effect. By extension, we determine how economic complexity nonlinearly and heterogeneously affects environmental degradation taking the moderating role of income into consideration. This is the novelty the paper adds to literature. Our quest to determine the moderating role of income is mainly due to the fact that the income factor is considered important in both environmental degradation and economic complexity discourses. For example, following the Environmental Kuznets Curve (EKC) hypothesis and the pollution haven hypothesis (PHH), income is considered the most important element separating environmentally unclean countries from clean ones (Balsalobre-Lorente et al., 2022; Chu, 2021; Grossman & Krueger, 1991). The EKC postulates that as an economy starts to grow (as income increases), environmental degradation also increases; however, at higher levels of income environmental quality starts to set in. The PHH also argues that developing countries are susceptible to increasing environmental degradation due to their low levels of income resulting in non-stringent environmental regulations. The lax environmental regulations in developing countries is considered a bait for polluting firms in high income countries with strict environmental regulations to relocate to developing countries. Income is also considered an important factor explaining economic complexity. Economic complexity is considered a structural transformation process where an economy's productive system transforms from a simple technology production to a more complex one. This transformation influences economic growth, hence income levels. The income level of an economy also influences its economic complexity, due to its impact on the choice of goods to be produced, and the technology to be employed (Hidalgo, 2021; Hidalgo & Hausmann, 2009; Swart & Brinkmann, 2020). These expositions bring to light the role of income in the economic complexity-environment nexus.

We conduct this research in the context of the Organisation for Economic Co-operation and Development (OECD) region. This region is of interest to us because of its peculiarities with respect to economic complexity and environmental degradation. First, most of the countries in this region have high levels of economic complexity due to their high productive capabilities and competitive industrial structures, which facilitate their ability to produce goods and export them competitively. In the latest ranking by the Observatory of Economic Complexity in 2019, 31 out of the 38 OECD countries fall in the top 50 category. Second, OECD countries are likely to experience higher levels of environmental degradation due to their greater capacity to expand their industrial structures.

We set the rest of this paper as follows. Sections 2 and 3 provide the literature review and methodology, respectively. Section 4 discusses the empirical results. This paper concludes in Section 5.

2 | LITERATURE REVIEW

Economic complexity was conceptualized by Hidalgo and Hausmann (2009) as the diversity of the existing productive capabilities in a country and their interactions. It is a reflection of the diversity and ubiquity of a country's output for export trade. Diversity is the number of goods a country can produce and export competitively, while ubiquity is the number of countries that have the capability to export products competitively (Hidalgo & Hausmann, 2009). The complexity of an economy arises from the various productive structures that give rise to the knowledge shared among people for the production of goods and services. Thus, it is considered as the amount of productive knowledge accumulated and disseminated in an economy with respect to economic activities—an indicator of relative knowledge intensity of an economy. Economic complexity is crucial in understanding dynamics in economic development (Simoes & Hidalgo, 2011). Economic development is associated with economic complexity because it requires the accumulation and utilization of knowledge. Knowledge is one of the basic ingredients to produce goods (Chu & Hoang, 2020). Hidalgo and Hausmann (2009) argue that

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the criticality of economic complexity for economic development arises from the income convergence, which countries tend to experience due to the complexity of their productive structures. In recent studies, there is evidence to argue that a more complex economy is more likely to be better developed (see, for instance, Chávez et al., 2017; Doğan et al., 2020; Koch, 2021; Lee & Lee, 2020; Zhu & Li, 2017).

Understanding how economic complexity affects the environment has become popular in empirical research over the past few years. The seminal paper by Can and Gozgor (2017) brought this research discourse into limelight. Can and Gozgor (2017) examine the role of economic complexity in environmental degradation (measured by CO_2 emissions) in France. The authors find that economic complexity limits environmental degradation. Following Can and Gozgor (2017), the effect of economic complexity on environmental degradation has received further scrutiny in a myriad of empirical studies. The extant arguments in these empirical studies suggest that this effect remains a debatable issue, which has been mainly driven by variations in study area/sample, model specification, environmental degradation measurement and econometric procedure. Swart and Brinkmann (2020), for instance, show that the environmental effect of economic complexity depends on how the environment is assessed. The authors, using a panel dataset from Brazil, illustrate that economic complexity reduces waste generation but propels forest fires, whereas it does not contribute to deforestation and air pollution. Likewise, Boleti et al. (2021) utilize several measures of the environment. Using an index of environmental performance, they find that economic complexity boosts environmental performance; however, they also find that carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) emissions and exposure to particulate matter 2.5 ($PM_{2.5}$) rise with increasing economic complexity.

Abbasi et al. (2021) demonstrate that economic complexity increases CO_2 emissions in the short- and long-run in a panel of 18 leading economic complexity countries for the period 1990–2019, based on the cross-sectional Autoregressive Distributed Lag (CS-ARDL) model. Li et al.'s (2021) study on top 15 exporting countries shares some similarities with Abbasi et al. (2021) in terms of estimation method, sample period and findings. On the contrary, He et al. (2021) use the CS-ARDL model to illustrate that economic complexity reduces short- and long-run CO_2 emissions in 10 top energy transition countries over the 1990–2018 period. In addition, the authors show that globalization magnifies the alleviating effect of economic complexity on short- and long-run CO_2 emissions. Based on an air pollution-based index of environmental degradation (constructed from greenhouse gas emissions, CO_2 emissions, N_2O emissions, CH_4 emissions and exposure to $PM_{2.5}$), Bashir et al. (2022) also use the CS-ARDL to establish that economic complexity slows down the degradation of the environment in the short- and long-run in 15 regional comprehensive economic partnership countries from 1990 to 2019. While it can be argued from the aforementioned studies that economic complexity has similar effect on the environment in the short and long run, the Yilanci and Pata (2020) observe otherwise. Using the Fourier bootstrap ARDL model and data on China for the period 1965–2016, they report that economic complexity expands the consumption of ecological footprint in the short-run but, in the long-run, this consumption reduces with rising economic complexity.

Doğan et al. (2021), with the aid of the augmented mean group (AMG), fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS) estimators, show that economic complexity reduces CO_2 emissions in a sample of 28 OECD countries from 1990 to 2014. The authors further show that more use of renewable energy facilitates economic complexity to have greater reduction effect on CO_2 emissions. Utilizing similar battery of estimators, Zheng et al. (2021) confirm Doğan et al. (2021) finding of the mitigating role of economic complexity in CO_2 emissions for 16 leading exporting countries over the period 1990–2019. Caglar et al. (2022), employing the continuously updated fully modified (CUP-FM) and continuously updated bias corrected (CUP-BC) estimators, also provide evidence consistent with the earlier findings by Doğan et al. (2021) and Zheng et al. (2021). The authors reveal that economic complexity lowers CO_2 emissions in BRICS countries over the 1990–2018 period. Ahmed et al. (2021) also apply the CUP-FM and CUP-BC estimators to demonstrate that increased economic complexity is associated with reduction in ecological footprint in G7 countries between 1985 and 2017. However, relying on the FMOLS and DOLS estimators and a sample of 48 countries for the 1995–2014 period, Neagu (2020) concludes that ecological footprint becomes higher as economies become more complex. This is supported by Rafique et al. (2021), which relied on the FMOLS, DOLS and system generalized method of moments (GMM) estimators and a panel of the top 10 most complex economies for the 1980–2017 period. Neagu and Teodoru (2019), with the FMOLS and DOLS estimators, earlier show that higher economic complexity causes more greenhouse gas emissions in 25 European Union countries between 1995 and 2016.

Some studies have addressed the heterogeneous effects of economic complexity on the environment by taking cognizance of the conditional distributions (quantiles) of the environmental degradation measure. Using data for OECD countries between 1971 and 2018, Majeed et al. (2021) employ the fixed effects quantile regression estimation to observe an increasing effect of economic complexity is evident in all CO_2 emissions quantiles except in the 90th and 95th quantiles where this effect is not noticeable. Interestingly, the authors find that this increasing effect reduces as the CO_2 emissions quantiles increase. Leitão et al. (2021) use the method of moments quantile regression (QR) estimator to show that economic complexity dampens CO_2 emissions in all quantiles, for BRICS countries over the 1990–2015 period. Later, in a closely related study, Sun et al. (2022) also use the method of moments QR estimator and a panel of BRICS countries from 1990 to 2015. Contrary to Leitão et al. (2021), Sun et al. (2022) show that economic complexity reduces CO_2 emissions in only higher quantiles (50th to 90th). Employing a battery of panel QR estimators, Alvarado et al. (2021) focusing on 17 Latin American countries from 1980 to 2016 find that economic complexity enhances ecological footprint in most quantiles. Kazemzadeh et al. (2021) estimate a panel quantile regression model to show how economic complexity affects ecological footprint in 25 countries for the period 1970–2016.

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They discover that economic complexity increases ecological footprint at lower quantiles but, at higher quantiles, economic complexity lessens ecological footprint. Ikram et al. (2021) use the quantile ARDL model to establish that Japan's economic complexity heightened its ecological footprint between 1965 and 2017 in all quantiles except the last quantile where it had no significant effect.

The EKC hypothesis has been tested in the context of economic complexity. The pioneering EKC hypothesis argues that, at early (lower) stages of economic development, a rise in income damages the environment but this damaging role switches to a favourable one at later (higher) stages of economic development (Grossman & Krueger, 1991). Similar phenomenon has been validated in literature with respect to economic complexity. Chu (2021) considers a sample of 118 countries for the period 2002–2014. The system GMM estimation shows that economic complexity contributes to CO_2 emissions at lower levels of economic complexity, but when economic complexity reaches higher levels, it mitigates CO_2 emissions, suggesting an inverted U-shaped relationship between economic complexity and CO_2 emissions. Based on the DOLS estimator, Balsalobre-Lorente et al. (2022) offer support for this finding in PIIGS (Portugal, Ireland, Italy, Greece and Spain) countries from 1990 to 2019. The authors also find an N-shaped relationship, which suggests that when economic complexity grows further above the levels where it diminishes CO_2 emissions, increased CO_2 emissions become attributable to economic complexity. Chu and Le (2021) employ the FMOLS estimator to observe, in G7 countries over the period 1997–2015 that an inverted U-shaped relationship is also evident between economic complexity and ecological footprint. This has been also shown by Pata (2021), who use the case of US for the period 1980–2016 and a vector error correction model.

Few studies have shown that income level (stage of economic development) can influence how economic complexity is associated with environmental degradation. Using data for 118 countries (classified according to income level) over the period 1995–2016, Adedoyin et al. (2021) based on the random effects model estimation show that economic complexity stimulates CO_2 emissions in low-income countries but wields no significant effect on CO_2 emissions in lower-middle-income; however, it reduces CO_2 emissions in upper-middle- and high-income countries. These findings are also confirmed by their fixed effect model estimation except in the low-income countries where the CO_2 emissions-effect of economic complexity is no longer influential. Doğan et al. (2019) consider a quantile regression model to examine how economic complexity relates to CO_2 emissions, utilizing data 55 countries for the 1971–2014 period. They find that economic complexity leads to lower CO_2 emissions across the quantiles for the high-income countries. In the upper-middle- and lower-middle-income countries, economic complexity is largely found to raise CO_2 emissions.

Literature is replete with evidence on the nonlinearity between economic complexity and environmental degradation, especially on heterogeneous environmental degradation-effect of economic complexity and the EKC hypothesis in the context of economic complexity. We supplement the extant literature by examining this nonlinearity in the presence of income. Existing studies (see, e.g., Adedoyin et al., 2021; Doğan et al., 2019) have shown that how economic complexity affects environmental degradation is contingent on the income level by grouping countries into income clusters. This approach does not reveal the inherent role of income in the economic complexity-environmental degradation nexus. We address this limitation observed in literature in twofold. First, we examine the effect of economic complexity on environmental degradation as a non-parametric function of income. Second, we examine the moderating role of income in the economic complexity-environmental degradation nexus, while also controlling for distributional heterogeneity. On a side note, we are able to provide robust evidence considering that we gauge environmental degradation with four notable measures, which include ecological footprint, CO_2 emissions, N_2O emissions and GHG emissions.

3 | METHODOLOGY

3.1 | Model

The empirical model is set with the theoretical support of the EKC hypothesis, Stochastic Impacts by Regression on Population, Affluence and Technology (STIRPAT) model and the pollution haven hypothesis.[1] The EKC hypothesis establishes how income is related to environmental degradation. The STIRPAT model identifies population, affluence or income and technology as drivers of environmental degradation. The pollution haven hypothesis asserts that countries tend to become potential destinations (havens) for firms that engage in pollution-intensive production activities as their borders become more open to the global markets. From the brief expositions of these theories, income, population, technology and openness can be argued to be central to environmental degradation. Therefore, we control for their influence on environmental degradation while examining the effect of economic complexity on environmental degradation. We specify the empirical model as

$$ED_{it} = \gamma EC_{it} + \rho INC_{it} + \sigma POP_{it} + \delta TECH_{it} + \varphi OPEN_{it} + \alpha_i + \varepsilon_{it}, \tag{1}$$

where ED_{it}, EC_{it}, INC_{it}, POP_{it}, $TECH_{it}$ and $OPEN_{it}$, respectively, denote environmental degradation, economic complexity, income, population, technology and openness; α_i is the unobserved time-invariant individual effect (fixed effect); and ε_{it} is the stochastic disturbance term.

To understand the moderating role of income in the economic complexity-environmental degradation nexus, we extend the linear model in Equation (1) by including the interaction term of economic complexity and income ($EC_{it} * INC_{it}$). The extended model is expressed as

$$ED_{it} = \gamma EC_{it} + \rho INC_{it} + \partial EC_{it} * INC_{it} + \sigma POP_{it} + \delta TECH_{it} + \varphi OPEN_{it} + \alpha_i + \varepsilon_{it}. \tag{2}$$

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3.2 | Data

We draw a sample of 35 OECD countries over the period 1998–2017, taking into consideration data availability (refer to Table 1A for the country list).[2] The economic complexity and ecological footprint datasets influenced the start and end years of the sample period, respectively.

Though CO_2 emissions are the widest used proxy for environmental degradation in the literature, in this study, we follow others such as Danish et al. (2019), Nathaniel et al. (2021). Opoku and Boachie (2020) and Opoku et al. (2022) and represent the environment more holistically (employing several proxies) as possible in the literature. The Intergovernmental Panel on Climate Change (IPCC) also emphasizes that gases leading to global warming transcends CO_2, though CO_2 is the major gas (IPCC, 2014). Hence, the dependent variable, which is environmental degradation, is assessed separately with ecological footprint, CO_2 emissions, N_2O emissions and GHG emissions. Ecological footprint is often identified as a broad measure of environmental degradation in the literature (see Aluko et al., 2021, 2022; Ibrahim & Vo, 2021; Opoku & Aluko, 2021). This is because its computation takes into account anthropogenic human activities associated with the demand for land for farming (crop and livestock), production of fibre, regeneration of timber, CO_2 emissions absorption from the burning of fossil fuels and building of physical infrastructures. In this study, ecological footprint is the amount of biologically productive land and sea area consumed by humans, expressed in global hectares. CO_2 emissions represent the CO_2 emitted in the process of burning fossil fuels and cement manufacturing, measured in kilotons (kt). N_2O emissions, measured in thousand metric tons of CO_2 equivalent, are emissions arising from burning of agricultural biomass, industrial activities and livestock management. GHG emissions represent total GHG emissions (total CO_2 emissions excluding short-cycle burning of biomass but including other biomass burning), measured in kt of CO_2 equivalent. With the exception of ecological footprint, which is sourced from the Global Footprint Network database, the remaining measures of environmental degradation are obtained from the World development Indicators (WDI).

Economic complexity, which is the independent variable of interest, is measured by the economic complexity index in the Observatory of Economic Complexity (OEC) provided by Massachusetts Institute of Technology (MIT). This index measures the amount of knowledge held in a country's production structure. The higher the value on the index, the more economically complex the country is. The other independent variables are income, population, technology and openness. Income is measured by the income index, obtained from the United Nations Development Programme (UNDP). According to the UNDP, this index is gross national income (GNI) per capita, which is normalized on a scale of 0–1 using the lowest value of \$100 and highest value of \$75,000. Higher (lower) scores on the index connote higher (lower) income. The index hence ranks countries based on their income per capita, and at a glance one could easily rank countries to ascertain low and high income countries. Population is measured by the midyear estimate of the total number of country's residents irrespective of legal status and citizenship, and this is sourced from WDI. The aggregate of patent applications by residents and non-residents obtained from WDI is used to measure technology. Our use of patent applications to proxy technology is akin to several other studies (see, e.g., Acheampong et al., 2022; Carrión-Flores & Innes, 2010; Cho & Sohn, 2018; Lindman & Söderholm, 2016; Miyamoto & Takeuchi, 2019; Popp et al., 2011). Openness is captured by trade openness, which represents total trade (imports + exports) expressed as a percentage of GDP and it is sourced from WDI.

The summary statistics of the raw data are provided in Table 1, while Table 2 provides their correlations. The correlations indicate that economic complexity, income, population and technology are positively correlated with the measures of environmental degradation (ecological footprint, CO_2 emissions, N_2O emissions and GHG emissions), while openness is negatively correlated with these measures. It is important to test for multicollinearity before proceeding with estimations. The presence of multicollinearity in a regression model may result in misleading conclusions. Multicollinearity arises from a strong linear relationship between the independent variables, which causes standard errors of the regression coefficients to be inflated. We use the variance inflation factor (VIF) test to detect the presence of multicollinearity. The common rule of thumb for the VIF test is that the VIF

TABLE 1 Summary statistics

Variable	Data	Mean	Std. Dev	Minimum	Maximum	Obs.
Ecological footprint	Ecological footprint of consumption (global hectares)	2.12×10^8	4.67×10^8	7,743,798	3.06×10^9	699
CO_2 emissions	CO_2 emissions (kt)	35,9317.1	904,936	4,950	5,776,410	699
N_2O emissions	N_2O emissions (thousand metric tons of CO_2 equivalent)	22,237.74	43,397.85	770	269,930	699
GHG emissions	Total GHG emissions (kt of CO_2 equivalent)	440,741.4	1,075,319	10,490	6,861,150	699
Economic complexity	Economic complexity index	1.042	0.605	−0.290	2.311	699
Income	Income index	0.873	0.068	0.678	0.99	699
Population	Total population (midyear estimate)	3.61×10^7	5.57×10^7	1,314,545	3.25×10^8	699
Technology	Total patent applications	35,587.49	100,108.7	25	606,956	685
Openness	Trade openness (% of GDP)	81.719	36.738	18.126	188.469	699

Note: The natural logarithm transformation data of all the data are used in the regression models except the economic complexity and income indexes.

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TABLE 2 Correlations

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Ecological footprint [1]	1.000								
CO_2 emissions [2]	0.997* (0.000)	1.000							
N_2O emissions [3]	0.945* (0.000)	0.945* (0.000)	1.000						
GHG emissions [4]	0.997* (0.000)	0.999* (0.000)	0.957* (0.000)	1.000					
Economic complexity [5]	0.290* (0.000)	0.285* (0.000)	0.144* (0.000)	0.266* (0.000)	1.000				
Income [6]	0.237* (0.000)	0.240* (0.000)	0.213* (0.000)	0.234* (0.000)	0.656* (0.000)	1.000			
Population [7]	0.941* (0.000)	0.923* (0.000)	0.878* (0.000)	0.923* (0.000)	0.302* (0.000)	0.135* (0.000)	1.000		
Technology [8]	0.811* (0.000)	0.817* (0.000)	0.687* (0.000)	0.804* (0.000)	0.384* (0.000)	0.222* (0.000)	0.829* (0.000)	1.000	
Openness [9]	−0.398* (0.000)	−0.374* (0.000)	−0.432* (0.000)	−0.382* (0.000)	0.150* (0.000)	0.032 (0.396)	−0.504* (0.000)	−0.388* (0.000)	1.000

Note: *p* values are placed in parentheses.
*p value < 0.01.

TABLE 3 VIF test

	VIF	$\sqrt{\text{VIF}}$	Tolerance	R^2
Economic complexity	2.56	1.60	0.391	0.609
Income	1.95	1.40	0.512	0.488
Population	3.40	1.84	0.294	0.706
Technology	4.35	2.09	0.230	0.770
Openness	2.71	1.65	0.368	0.631
Mean VIF	2.99			

value must not exceed 10, and the tolerance value must not be below 0.1 to confirm the absence of severity of the multicollinearity problem (Miles, 2014). However, based on Studenmund (2011), we set the cut-off point for the VIF value as 5. The results of the VIF test reported in Table 3 show that the VIF values are below 5 and the tolerance values are greater than 0.1, thus suggesting that the inclusion of the independent variables together in the regression model do not give rise to multicollinearity.

3.3 | Estimation approaches

We first use the fixed effects model estimator to estimate the models depicted in Equations (1) and (2). Equation (1) considers the direct effect of economic complexity, while Equation (2) aims at showing the effect of economic complexity through the income channel. This estimator observes only the linearity in the economic complexity-environmental degradation nexus. To account for nonlinearity in this nexus, we fit a partially linear functional-coefficient (PLFC) model proposed by Yonghong et al. (2016). The PLFC model is semiparametric in nature and accounts for heterogeneity over individuals and times as well as allows for linearity in some regressors and nonlinearity in other regressors (Du et al., 2020). In this study, we consider the effect of economic complexity on environmental degradation nexus as a nonparametric function of income. Thus, we transform Equation (1) into a PLFC model, and it is expressed as

$$ED_{it} = g(INC_{it})\gamma EC_{it} + \beta X'_{it} + \alpha_i + \varepsilon_{it}. \tag{3}$$

Equation (3) can be divided into the nonparametric and parametric parts. $g(INC_{it})$ is the nonparametric part, which is an unknown function that captures the marginal effect of economic complexity, and X'_{it} is the parametric (linear) part, which controls for the influence of income, population, technology and openness on environmental degradation.

The PLFC model overcomes possible misspecification bias that often occurs in a linear model due to the strict assumptions imposed on its functional form. We implement the PLFC model with fixed effects to deal with bias that may occur as a result of misspecification, following Yan et al. (2020). Due to the presence of fixed effects in the model, the series estimator is used to fit the PLFC model instead of the kernel estimator, which is often used in fitting semiparametric and nonparametric models. The kernel estimator becomes less ideal in the presence of fixed effects. The series estimator possesses some advantages that include computational convenience, ease of imposing restrictions and quicker convergence rate (Yonghong et al., 2016). The series estimator eliminates the fixed effects through first-differencing. After first-differencing Equation (3), it becomes

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$$\Delta ED_{it} = \Delta(g(INC_{it})EC_{it})\gamma + \beta\Delta X'_{it} + \Delta\varepsilon_{it}, \quad (4)$$

where Δ is the first-difference operator. The B-splines sieve method is used for the approximation of the unknown function, $g(INC_{it})$. The performance of the sieve method depends on the number of approximation terms, which is determined by the number of knots (Du et al., 2020). The optimal number of knots required by the sieve method is determined by the least-squares cross-validation method. The PLFC model though quite new has been used in a number of recent studies including Liu et al. (2022), Wang et al. (2021, 2022) and Yan et al. (2020, 2022).

We also account for nonlinearity by controlling for distributional heterogeneity in Equations (1) and (2) through a quantile regression approach. The approach provides more information, and it is not influenced by the presence of outliers (Chernozhukov & Hansen, 2008). Koenker and Bassett (1978) argue that the quantile regression approach provides efficient and consistent estimates in the presence of normal and non-normal error distributions. Koenker and Bassett (1978) develop the quantile regression model and it can be expressed as

$$Y_{it} = U'_{it}\beta_\theta + \varepsilon_{it}; Q_\theta(Y_{it}|U_{it}) = U'_{it}\beta_\theta, \quad (5)$$

where U' is a vector of regressors (independent variables), ε is a vector of residuals and $Q_\theta(Y_{it}|U_{it})$ identifies the θ^{th} conditional quantile of Y given U.

We use the Method of Moments Quantile regression estimator with fixed effects introduced by Machado and Santos Silva (2019) to estimate the quantile regression model. This estimator yields non-crossing estimates of regression quantiles, which many empirical applications do not consider important (Machado & Santos Silva, 2019). It estimates a conditional location-scale model, similar to Koenker and Bassett (1978) approach. The estimation of the conditional quantiles $Q_Y(\epsilon|U_{it})$ for a location-scale model has been given as

$$Y_{it} = \alpha_i + U'_{it}\beta + (\varepsilon_i + Q'_{it})V_{it}, \quad (6)$$

where the probability, $P\{\varepsilon_i + Q'_{it}\omega > 0\} = 1$. $(\alpha, \beta', \varepsilon, \omega')'$ are parameters to be estimated. $(\alpha_i, \varepsilon_i), i = 1, \ldots n$, is the individual i fixed effects and Q is the k-vector of identified components of U, which are differentiable transformations with element m given by

$$Q_m = Q_m(U), m = 1, \ldots, k. \quad (7)$$

U_{it} is independently and identically distributed (*i.i.d*) for any fixed i and is independent across time (t). V_{it} is *i.i.d* across individuals (i) and through t and orthogonal to U_{it} and normalized to meet the moment conditions given by Machado and Santos Silva (2019), which inter alia do not suggest strict exogeneity. The following is implied from Equation (6):

$$Q_Y(\epsilon|U_{it}) = (\alpha_i + \varepsilon_i q(\epsilon)) + U'_{it}\beta + Q'_{it}\omega q(\epsilon). \quad (8)$$

From Equation (8), U'_{it} is a vector consisting of the independent variables. $Q_Y(\epsilon|U_{it})$ is the quantile distribution of Y_{it}, which is conditional on the location of U_{it}. $\alpha_i(\epsilon) = \alpha_i + \varepsilon_i q(\epsilon)$ is the scalar coefficient that is indicative of the quantile ϵ fixed effect for individual i. Unlike the individual fixed effect in the least squares regression, the individual fixed effect in the Method of Moments quantile regression does not represent an intercept shift. They are time-invariant parameters whose heterogeneous effects are allowed to vary across the quantiles of conditional distribution of Y. $q(\epsilon)$ is the ϵth sample quantile, which is estimated by solving this optimization problem:

$$\min_q \sum_i \sum_t \varphi_\epsilon (R_{it} - (\epsilon_i + Q'_{it}\omega)q), \quad (9)$$

where $\varphi_\epsilon(A) = (\epsilon - 1)AI\{A \le 0\} + \epsilon AI\{A > 0\}$ is the check function.

4 | RESULTS AND DISCUSSION

In this section, we present and discuss the results of the study. This paper aims at investigating the effect of economic complexity on

TABLE 4 Estimation results of the linear fixed effects model

	Dependent variable (Environmental degradation)			
	Ecological footprint (I)	CO_2 emissions (II)	N_2O emissions (III)	GHG emissions (IV)
Economic complexity	0.001 (0.060)	0.182** (0.086)	0.013 (0.108)	0.213** (0.079)
Income	2.967*** (0.440)	1.728** (0.734)	0.582 (0.821)	1.068* (0.628)
Population	0.004 (0.154)	0.334 (0.200)	−0.443 (0.347)	0.297 (0.192)
Technology	0.026 (0.020)	0.061** (0.024)	0.013 (0.032)	0.055** (0.021)
Openness	−0.226*** (0.058)	−0.372*** (0.079)	−0.408*** (0.089)	−0.336*** (0.068)
Constant	16.309*** (2.577)	5.449 (3.388)	17.598*** (5.401)	6.797** (3.219)
No. of countries	35	35	35	35

Note: Robust standard errors, computed by clustering across countries, are in parentheses.
*p value < 0.1. **p value < 0.05. ***p value < 0.01.

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TABLE 5 Linear fixed effects model with interaction term estimation results

	Dependent variable (Environmental degradation)			
	Ecological footprint (I)	CO_2 emissions (II)	N_2O emissions (III)	GHG emissions (IV)
Economic complexity	0.031 (0.426)	1.644*** (0.578)	1.999*** (0.560)	1.330** (0.543)
Income	2.977*** (0.443)	2.177*** (0.775)	1.191 (0.743)	1.411** (0.646)
Economic complexity*Income	−0.035 (0.476)	−1.700** (0.683)	−2.308*** (0.627)	−1.298** (0.634)
Population	0.006 (0.163)	0.416** (0.200)	−0.333 (0.322)	0.359* (0.191)
Technology	0.026 (0.021)	0.050* (0.025)	−0.002 (0.031)	0.047** (0.022)
Openness	−0.225*** (0.063)	−0.303*** (0.083)	−0.314*** (0.092)	−0.283*** (0.072)
Constant	16.270*** (2.791)	3.566 (3.290)	15.041*** (4.965)	5.359* (3.157)

Note: Robust standard errors, computed by clustering across countries, are in parentheses.
**p* value < 0.1. ***p* value < 0.05. ****p* value < 0.01.

environmental degradation, and how this effect is moderated by income in the OECD countries. We start the discussion by first reporting the results estimated by the fixed effects model. The estimation results are reported in Tables 4 and 5. While Table 4 only considers the direct effect of economic complexity on the environment, Table 5 accounts for the moderating effect of income. Each table contains four models, distinguished by the dependent variable used: ecological footprint CO_2, N_2O and GHG emissions.

In Table 4, the results show the coefficients of economic complexity to be positive in all the estimated models, however statistically significant (5% level) when CO_2 and GHG emissions are the dependent variables. This implies that, all other things being equal, as countries' (in our sample) economic complexity increases environmental degradation increases by way of increasing CO_2 and GHG emissions. Specifically, as economic complexity rises by 1 unit, CO_2 and GHG emissions are expected to rise on the average by about 1.19 and 1.24 units, respectively.[3] The results suggest that as the various productive structures of countries become more complex, environmental degradation increases. Economic complexity is associated with increase in production and trade, and these may explain the associated increase in emissions. This finding is similar to those of Boleti et al. (2021), Abbasi et al. (2021), and Neagu and Teodoru (2019). However, our finding contrasts with Can and Gozgor (2017), Swart and Brinkmann (2020) and Ahmed et al. (2021).

In Table 5, which accounts for the interaction between economic complexity and income, the results suggest economic complexity to have positive effect and statistically significant (1–5% levels) coefficients for all the dependent variables but ecological footprint. The results of the income variable remain akin to those of Table 4. The interaction term (between economic complexity and income) however registers negative coefficients and statistically significant (1–5% level) except in the case where ecological footprint is the dependent variable. The results therefore suggest that, largely, economic complexity and income separately exert direct negative impact on environmental degradation. The interactive results suggest that the moderating effect of income on the effect of economic complexity on environmental degradation is negative. The results suggest that while economic complexity works to deteriorate the environment, environmental performance improves in the presence of increasing income. This can be explained by the role of high income on environmental sustainability and economic complexity. At high levels of income or as income increases, countries are able to afford cleaner technologies and technologies that do not cause much harm to the environment. Also, with increasing incomes citizens agitate for cleaner environments, and this puts pressure on the government to legislate economic activities to ensure that economic transformation does not happen at the expense of the environment. In the era of championing sustainable development and environmental sustainability, high-income countries relative to low-income countries feel the pressure to show leadership by example.

Regarding the other independent (control) variables (in both Tables 4 and 5), we observe that the coefficients of trade openness are negative and statistically significant (1% level). This implies that all other things being equal, openness to trade in the sampled countries improves environmental quality. The income variable registers positive and statistically significant coefficients except in using N_2O emissions as the dependent variable. This implies that, generally, rise in income is associated with increase in environmental degradation. Technology is found to be positive and statistically significant (5–10%) only when CO_2 and GHG emissions are the dependent variables. This suggests that ceteris paribus, increase in technology increases environmental degradation by way of increasing CO_2 (and GHG) emissions. The coefficients of population though generally positive are only found to be statistically significant in Table 5 (when CO_2 and GHG emissions are used as the dependent variables). Hence, the results suggest that ceteris paribus, population exerts pressure on the environment by increasing CO_2 (and generally GHG) emissions.

4.1 | Results of the partially linear functional-coefficient (PLFC) model

Due to the limitations of incorporating interaction terms that may lead to biassed estimation and model misspecification, we use the partial

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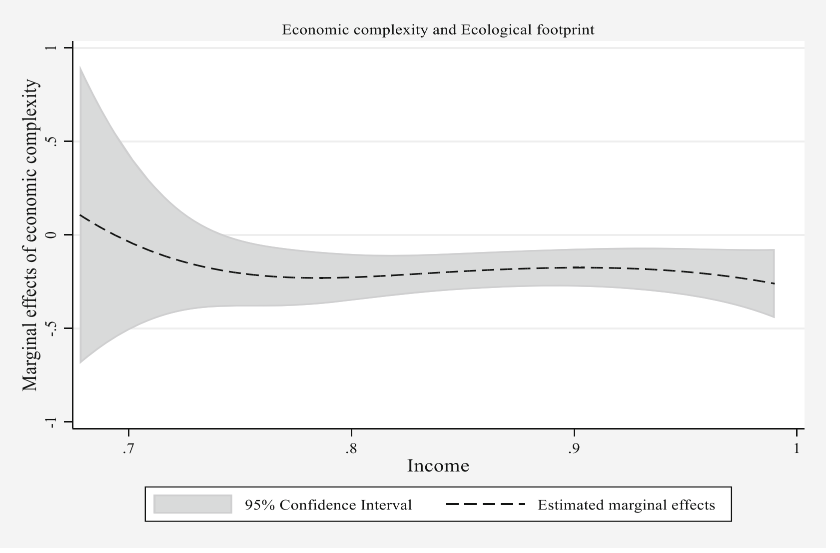

FIGURE 1 Estimated marginal effects (functional coefficients) of economic complexity on ecological footprint. *Note*: The estimated functional coefficients are represented by the broken line, and the 95% confidence interval is the grey-shaded area.

linear functional-coefficient (PLFC) model to estimate the economic complexity response function of environmental degradation, by considering the heterogeneity of different income levels. The prior estimation method employed assumes a hypothesized linear pattern, such as a unique impact parameter across all countries, homogeneous impact parameters within groups of countries and a uniquely marginal increment of impact with rise in income (Yan et al., 2020). The PLFC model is flexible and capable of accommodating the nonlinear structure and the heterogeneity across cross-sections and time (Du et al., 2020). The PLFC model allows for linearity in some regressors and nonlinearity in others (Du et al., 2020).

We present the estimated functional coefficients of economic complexity in Figures 1–4 (with ecological footprint, CO_2, N_2O, GHG emissions, respectively, as the dependent variables) with 95% confidence interval. It can be observed from Figure 1 that the estimated functional coefficients of economic complexity are positive when income is below the index of 0.7. However, above the index of 0.7, the estimated coefficients show economic complexity to be negative. This implies that at higher levels of income, the effect of economic complexity on ecological footprint is negative, and positive at lower levels of income. Regarding the CO_2 emissions estimations (Figure 2), the results reveal that at income levels of (about) less than the index of 0.81 the impact of economic complexity is positive and however becomes slightly negative after the index of 0.81. Figure 3 reveals that when income level is below the index of about 0.72 the effect of economic complexity on N_2O emission is positive and at income levels greater than 0.72 the effect becomes negative. With respect to the GHG emissions estimation, Figure 4 shows that at about an income level less than the index of 0.8 the effect of economic complexity on GHG emissions is positive and turns slightly statistically insignificant between the income indices of 0.8 and 0.9 as the estimated coefficients within this range almost lies on the zero line. However, when income is greater than the index of 0.9, the effect of economic complexity on GHG emissions is negative. The results in Figures 1–4 show that the impact of economic complexity on the environment depends on the level of income. Generally, at higher levels of income, economic complexity is seen to improve environmental quality by having a negative effect on environmental degradation. The figures show more information than the conventional panel data models (such as provided in Table 5).

Table 6 presents the results of the linear part of the PLFC model. Regarding the control variables, unlike the fixed effects model estimation results in Tables 4 and 5, the coefficients of the trade openness variable are positive and statistically significant at the 1% level, suggesting that ceteris paribus increase in trade openness increases ecological footprint and the emissions of CO_2, N_2O and GHG in general (see Table 6). Specially, the results suggest that all things being equal, 1% increase in trade openness will likely lead to about 0.12%, 0.10%, 0.13% and 0.09%, respectively, in ecological footprint, CO_2, N_2O and total GHG emissions. Trade is considered one of the major drivers of environmental degradation. However, considering that the sample is mainly developed countries, and following the assertion of Copeland and Taylor (2004) one would have expected trade openness improving environmental quality. Copeland and Taylor (2004) postulates that trade enhances comparative advantage in production, and as developed countries have comparative advantage in clean industries, emissions would reduce in these countries. Besides, environmental regulations are more stringent in developed countries, and this would push polluting industries to relocate to developing countries where environmental regulations are relatively lax (Balsalobre-Lorente et al., 2022; Cole, 2004; Eskeland & Harrison, 2003). Hence, this would work to reduce emissions in developed countries. However, trade expansion comes with enormous utilization of energy and resources (Shahbaz et al., 2017), and hence, international trade may increase emissions and generally environmental degradation through energy consumption and utilization of natural resources. This may possibly drive the results.

Similar to the results reported in Tables 4 and 5, the results in Table 6 show the direct effect of the income variable to be positive

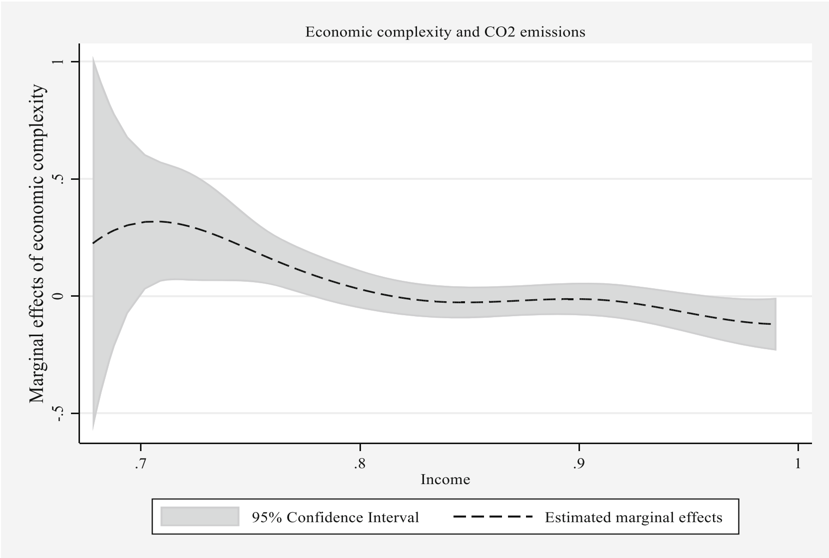

FIGURE 2 Estimated marginal effects (functional coefficients) of economic complexity on CO_2 emissions. *Note*: The estimated functional coefficients are represented by the broken line and the 95% confidence interval is the grey-shaded area.

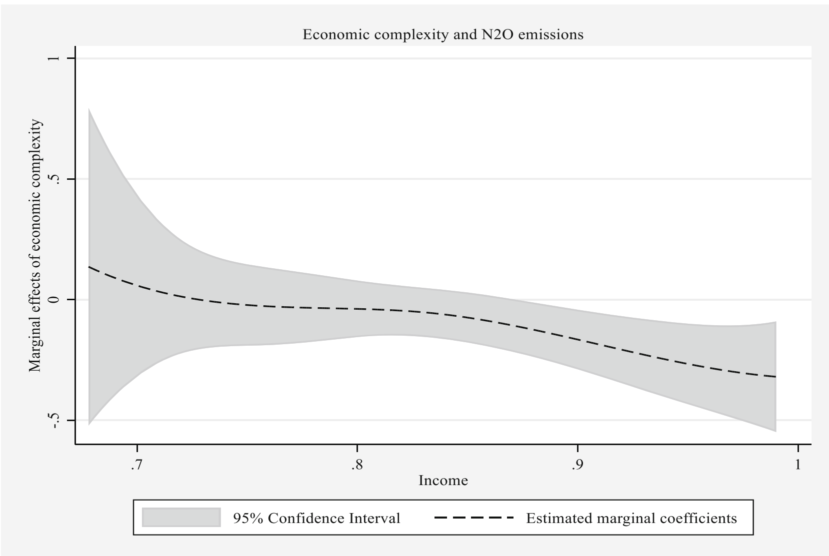

FIGURE 3 Estimated marginal effects (functional coefficients) of economic complexity on N_2O emissions. *Note*: The estimated functional coefficients are represented by the broken line, and the 95% confidence interval is the grey-shaded area.

and statistically significant in all the estimated models. Hence, the results suggest that increase in income or economic activities exert pressure on the environment leading to increase in environmental degradation. Specifically, the results indicate that ceteris paribus, 1% increase in income levels lead to about 4.7%, 2.9%, 1.9% and 2.5% increase in ecological footprint, CO_2, N_2O and total GHG emissions, respectively. Increase in income increases economic activities, demand, production and consumption. These activities result from the consumption of energy (mainly fossil fuels). Besides, increasing production and consumption increases resource exploitation. Theoretically, the outcome of the income variable supports the assertion of the STIRPAT model, which argues that increasing affluence results in environmental degradation (York et al., 2003). Empirically, our results buttress that of Liddle (2013), He et al. (2021), Aluko et al. (2021), Opoku and Aluko (2021), Opoku et al. (2022) and Leitão et al. (2021). Regarding the technology variable, akin to the results in Tables 4 and 5, technology is found to have an increasing effect on CO_2 and total GHG emissions. However, it is found to have statistically insignificant effect on ecological footprint (negative coefficient) and N_2O emissions (positive coefficient). Specifically, the results indicate that a 1% increase in technology results in 0.022% and 0.017% increase in emissions, respectively. Ideally, it would be expected that increase and improvement in technology would improve environmental sustainability especially if the technology is driven towards renewable energy production/consumption and issues of sustainability in general. However, unsustainable technologies can increase the consumption if energy, and this may be the driving force behind technology increasing emissions. It must be added that our results may be influenced by the proxy of technology use (aggregate of patent applications). This does not tell us exactly the kind of technology it is. Opoku et al. (2022) also find technology to be positive for the CO_2 and GHG emissions estimations.

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FIGURE 4 Estimated marginal effects (functional coefficients) of economic complexity on GHG emissions. *Note*: The estimated functional coefficients are represented by the broken line, and the 95% confidence interval is the grey-shaded area.

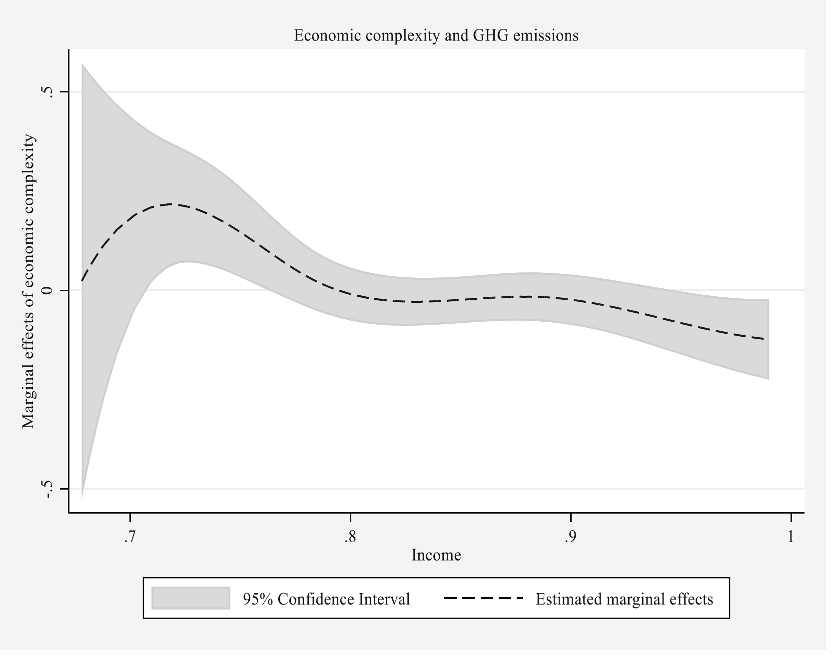

TABLE 6 Estimation results of the parametric (linear) part of the PLFC model

	Dependent variable (Environmental degradation)			
	Ecological footprint (I)	CO_2 emissions (II)	N_2O emissions (III)	GHG emissions (IV)
Income	4.741*** (0.550)	2.944*** (0.442)	1.928*** (0.608)	2.459*** (0.378)
Population	−0.172 (0.210)	0.222 (0.228)	−0.426 (0.264)	0.185 (0.213)
Technology	−0.007 (0.012)	0.022** (0.009)	−0.001 (0.014)	0.017** (0.008)
Openness	0.115*** (0.040)	0.098*** (0.027)	0.128*** (0.047)	0.093*** (0.023)
No. of countries	35	35	35	35

Note: Bootstrapped standard errors, computed with 1,000 bootstrapping replications, are in parentheses.
**p value < 0.05. ***p value < 0.01.

The population variable is found to have statistically insignificant effect on the dependent variables employed. This implies that on the average, population increase does not have effect on the proxies of environmental degradation that we have employed in the sampled countries. Growing population is however noted to be associated with increasing environmental degradation as population growth comes with rise in economic activities, energy consumption, resource utilization, deforestation, construction and transportation (Martínez-Zarzoso et al., 2007; Opoku & Boachie, 2020). The results might be driven by the sampled countries; our sample is OECD countries that have very slow population growth rates. Overall, between the years 2000 and 2019, the population of regions across OECD countries grew annually at an average rate of 0.4%, while substantial share of the regions in Asia and Europe is witnessing decline in population (OECD, 2020). Since the population is not growing much and even decreasing in some OECD countries, the effect of population growth on the environment may be insignificant.

4.2 | Further results: Method of Moments Quantile Regression

In Tables 7–10 (without the interaction term), we report results based on the Method of Moment Quantile regression, which accounts for nonlinearity by controlling for distributional heterogeneity (Machado & Santos Silva, 2019). Table 7 uses ecological footprint as the dependent variable and shows that the effect of economic complexity on ecological footprint is negative and statistically significant (1–10% levels) across all quantiles (0.1–0.9) of the dependent variable. Similarly, Table 8 (using CO_2 emissions as the dependent variable), Table 9 (using N_2O emissions as the dependent variable) and Table 10 (using GHG emissions as the dependent variable) show economic complexity to have statistically significant effect on CO_2, NO_2 and GHG emissions, respectively, in all quantiles. Unlike the fixed effects model estimation results reported in Tables 4 and 5, which show the effect of the covariates at the conditional mean distribution of the

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TABLE 7 Method of Moments quantile regression model estimation results (economic complexity and ecological footprint)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	−0.096*** (0.022)	−0.027* (0.014)	−0.052* (0.028)	−0.066*** (0.024)	−0.080*** (0.022)	−0.087*** (0.021)	−0.093*** (0.022)	−0.101*** (0.023)	−0.112*** (0.025)	−0.124*** (0.029)	−0.139*** (0.034)
Income	3.784*** (0.163)	0.267*** (0.101)	3.346*** (0.208)	3.488*** (0.179)	3.625*** (0.163)	3.696*** (0.159)	3.753*** (0.161)	3.841*** (0.169)	3.953*** (0.188)	4.066*** (0.213)	4.220*** (0.255)
Population	0.900*** (0.011)	−0.007 (0.007)	0.911*** (0.014)	0.907*** (0.012)	0.904*** (0.011)	0.902*** (0.011)	0.901*** (0.011)	0.899*** (0.012)	0.896*** (0.013)	0.893*** (0.015)	0.889*** (0.018)
Technology	0.067*** (0.008)	−0.001 (0.005)	0.068*** (0.010)	0.068*** (0.009)	0.068*** (0.008)	0.067*** (0.008)	0.067*** (0.008)	0.067*** (0.008)	0.067*** (0.009)	0.067*** (0.010)	0.066*** (0.012)
Openness	0.075*** (0.027)	−0.020 (0.017)	0.108*** (0.034)	0.098*** (0.030)	0.087*** (0.027)	0.082*** (0.026)	0.078*** (0.027)	0.071** (0.028)	0.063** (0.031)	0.054 (0.035)	0.042 (0.042)
Constant	−0.782*** (0.290)	0.156 (0.180)	−1.037*** (0.370)	−0.955*** (0.317)	−0.874*** (0.288)	−0.833*** (0.284)	−0.800*** (0.286)	−0.749** (0.300)	−0.683 (0.332)	−0.617 (0.376)	−0.527 (0.453)

Note: Standard errors are in parentheses.
*p value < 0.1. **p value < 0.05. ***p value < 0.01.

TABLE 8 Method of Moments quantile regression model estimation results (economic complexity and CO_2 emissions)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	−0.137*** (0.039)	−0.000 (0.024)	−0.137*** (0.050)	−0.137*** (0.042)	−0.137*** (0.039)	−0.137*** (0.038)	−0.137*** (0.039)	−0.138*** (0.041)	−0.138*** (0.044)	−0.138*** (0.050)	−0.138** (0.062)
Income	4.471*** (0.314)	0.126 (0.189)	4.264*** (0.397)	4.341*** (0.336)	4.389*** (0.315)	4.423*** (0.308)	4.459*** (0.311)	4.502*** (0.326)	4.549*** (0.355)	4.605*** (0.403)	4.695*** (0.499)
Population	0.896*** (0.022)	−0.047*** (0.013)	0.973*** (0.028)	0.944*** (0.024)	0.927*** (0.022)	0.914*** (0.022)	0.901*** (0.022)	0.885*** (0.023)	0.867*** (0.025)	0.847*** (0.029)	0.814*** (0.036)
Technology	0.177*** (0.015)	−0.024*** (0.009)	0.217*** (0.019)	0.202*** (0.016)	0.193*** (0.015)	0.186*** (0.015)	0.180*** (0.015)	0.171*** (0.016)	0.163*** (0.017)	0.152*** (0.019)	0.135*** (0.024)
Openness	0.291*** (0.049)	−0.120*** (0.030)	0.487*** (0.063)	0.414*** (0.054)	0.370*** (0.050)	0.337*** (0.049)	0.302*** (0.049)	0.261*** (0.052)	0.217*** (0.056)	0.164** (0.064)	0.080 (0.313)
Constant	−9.726*** (0.569)	1.685*** (0.342)	−12.490*** (0.727)	−11.461*** (0.622)	−10.833*** (0.572)	−10.369*** (0.560)	−9.883*** (0.569)	−9.307*** (0.597)	−8.686*** (0.650)	−7.938*** (0.739)	−6.745*** (0.909)

Note: Standard errors are in parentheses.
*p value < 0.1. **p value < 0.05. ***p value < 0.01.

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TABLE 9 Method of Moments Quantile regression model estimation results (economic complexity and N_2O emissions)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	−0.715*** (0.067)	−0.121*** (0.036)	−0.533*** (0.087)	−0.572*** (0.080)	−0.621*** (0.074)	−0.688*** (0.069)	−0.727*** (0.068)	−0.781*** (0.070)	−0.812*** (0.072)	−0.850*** (0.077)	−0.906*** (0.086)
Income	4.309*** (0.453)	0.355 (0.240)	3.774*** (0.586)	3.888*** (0.541)	4.031*** (0.496)	4.227*** (0.459)	4.343*** (0.453)	4.501*** (0.468)	4.593*** (0.487)	4.702*** (0.518)	4.866*** (0.581)
Population	0.753*** (0.033)	−0.151*** (0.017)	0.981*** (0.041)	0.933*** (0.039)	0.872*** (0.038)	0.788*** (0.035)	0.739*** (0.034)	0.672*** (0.035)	0.632*** (0.035)	0.586*** (0.037)	0.516*** (0.041)
Technology	0.137*** (0.024)	0.093*** (0.013)	−0.003 (0.030)	0.027 (0.028)	0.064** (0.027)	0.115*** (0.025)	0.146*** (0.024)	0.187*** (0.025)	0.211*** (0.025)	0.240*** (0.027)	0.282*** (0.030)
Openness	0.016 (0.074)	−0.120*** (0.039)	0.196** (0.096)	0.158* (0.088)	0.110 (0.081)	0.043 (0.075)	0.004 (0.074)	−0.049 (0.077)	−0.081 (0.080)	−0.117 (0.085)	−0.173* (0.095)
Constant	−7.561*** (0.806)	2.510*** (0.427)	−11.341*** (1.039)	−10.536*** (0.965)	−9.524*** (0.904)	−8.140*** (0.838)	−7.320*** (0.821)	−6.209*** (0.844)	−5.554*** (0.866)	−4.784*** (0.925)	−3.624*** (1.031)

Note: Standard errors are in parentheses.
**p* value < 0.1. ***p* value < 0.05. ****p* value < 0.01.

TABLE 10 Method of Moments Quantile regression model estimation results (economic complexity and GHG emissions)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	−0.254*** (0.038)	−0.061*** (0.023)	−0.162*** (0.045)	−0.196*** (0.039)	−0.213*** (0.037)	−0.227*** (0.037)	−0.248*** (0.037)	−0.270*** (0.040)	−0.292*** (0.043)	−0.315*** (0.049)	−0.355*** (0.060)
Income	3.817*** (0.280)	0.487*** (0.169)	3.073*** (0.334)	3.346*** (0.289)	3.484*** (0.276)	3.596*** (0.273)	3.765*** (0.278)	3.942*** (0.295)	4.121*** (0.323)	4.301*** (0.361)	4.625*** (0.444)
Population	0.832*** (0.020)	−0.052*** (0.012)	0.912*** (0.024)	0.882*** (0.021)	0.868*** (0.020)	0.855*** (0.019)	0.837*** (0.020)	0.818*** (0.021)	0.799*** (0.023)	0.780*** (0.026)	0.745*** (0.032)
Technology	0.192*** (0.014)	0.009 (0.008)	0.177*** (0.016)	0.183*** (0.014)	0.185*** (0.014)	0.188*** (0.013)	0.191*** (0.014)	0.194*** (0.014)	0.198*** (0.016)	0.201*** (0.018)	0.207*** (0.022)
Openness	0.152*** (0.044)	−0.041 (0.026)	0.215*** (0.052)	0.192*** (0.045)	0.180*** (0.043)	0.171*** (0.043)	0.156*** (0.043)	0.141*** (0.046)	0.126** (0.050)	0.111** (0.056)	0.083 (0.069)
Constant	−7.192*** (0.497)	0.883*** (0.299)	−8.541*** (0.591)	−8.046*** (0.512)	−7.797*** (0.489)	−7.594*** (0.483)	−7.287*** (0.492)	−6.967*** (0.522)	−6.641*** (0.572)	−6.315*** (0.639)	−5.728*** (0.787)

Note: Standard errors are in parentheses.
**p* value < 0.1. ***p* value < 0.05. ****p* value < 0.01.

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TABLE 11 Method of Moments Quantile regression model with interaction term estimation results (economic complexity and ecological footprint)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	1.269***	−0.106	1.440***	1.385***	1.338***	1.307***	1.278***	1.248***	1.201***	1.163***	1.094***
	(0.180)	(0.115)	(0.224)	(0.192)	(0.177)	(0.174)	(0.178)	(0.187)	(0.210)	(0.236)	(0.291)
Income	4.889***	0.146	4.655***	4.729***	4.794***	4.837***	4.877***	4.917***	4.981***	5.034***	5.128***
	(0.228)	(0.146)	(0.284)	(0.244)	(0.225)	(0.221)	(0.226)	(0.237)	(0.266)	(0.299)	(0.369)
Economic complexity*Income	−1.533***	0.084	−1.667***	−1.624***	−1.587***	−1.562***	−1.539***	−1.516***	−1.480***	−1.449***	−1.395***
	(0.202)	(0.129)	(0.252)	(0.217)	(0.199)	(0.196)	(0.200)	(0.210)	(0.236)	(0.266)	(0.328)
Population	0.904***	−0.008	0.918***	0.914***	0.910***	0.907***	0.905***	0.903***	0.899***	0.896***	0.891***
	(0.011)	(0.007)	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)	(0.014)	(0.018)
Technology	0.057***	0.006	0.047***	0.050***	0.053***	0.055***	0.056***	0.058***	0.060***	0.062***	0.066***
	(0.008)	(0.005)	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.010)	(0.013)
Openness	0.028	−0.011	0.045	0.040	0.035	0.032	0.029	0.026	0.021	0.017	0.010
	(0.027)	(0.018)	(0.034)	(0.029)	(0.027)	(0.027)	(0.027)	(0.029)	(0.032)	(0.036)	(0.044)
Constant	−1.513***	0.197	−1.828***	−1.729***	−1.640***	−1.583***	−1.528***	−1.474***	−1.388***	−1.316***	−1.189**
	(0.298)	(0.190)	(0.371)	(0.319)	(0.293)	(0.289)	(0.295)	(0.309)	(0.348)	(0.391)	(0.482)
Marginal effects of economic complexity											
Mean	−0.070***	−0.033**	−0.016	−0.033	−0.048**	−0.058***	−0.067***	−0.076***	−0.091***	−0.103***	−0.124***
	(0.022)	(0.023)	(0.027)	(0.023)	(0.021)	(0.021)	(0.021)	(0.022)	(0.025)	(0.028)	(0.035)
Percentiles											
1%	0.215***	−0.049*	0.293***	0.268***	0.246***	0.232***	0.218***	0.205***	0.184***	0.166***	0.134*
	(0.045)	(0.029)	(0.056)	(0.048)	(0.044)	(0.043)	(0.044)	(0.046)	(0.052)	(0.059)	(0.072)
5%	0.124***	−0.044**	0.195***	0.172***	0.153***	0.140***	0.128***	0.116***	0.096**	0.080*	0.052
	(0.035)	(0.022)	(0.043)	(0.037)	(0.034)	(0.034)	(0.034)	(0.036)	(0.040)	(0.045)	(0.056)
25%	−0.005	−0.037**	0.055*	0.036	0.019	0.009	−0.002	−0.012	−0.028	−0.041	−0.065*
	(0.024)	(0.016)	(0.030)	(0.026)	(0.023)	(0.023)	(0.023)	(0.025)	(0.028)	(0.031)	(0.038)
50%	−0.092***	−0.032**	−0.041	−0.057**	−0.071***	−0.081***	−0.089***	−0.098***	−0.112***	−0.124***	−0.145***
	(0.022)	(0.014)	(0.027)	(0.023)	(0.021)	(0.021)	(0.021)	(0.022)	(0.026)	(0.028)	(0.035)
75%	−0.149***	−0.029*	−0.102***	−0.117***	−0.130***	−0.139***	−0.146***	−0.154***	−0.167***	−0.178***	−0.196***
	(0.023)	(0.015)	(0.029)	(0.025)	(0.023)	(0.023)	(0.023)	(0.024)	(0.027)	(0.031)	(0.038)
95%	−0.212***	−0.026	−0.171***	−0.184***	−0.195***	−0.202***	−0.210***	−0.217***	−0.228***	−0.237***	−0.254***
	(0.028)	(0.018)	(0.034)	(0.030)	(0.027)	(0.027)	(0.027)	(0.029)	(0.032)	(0.036)	(0.045)
99%	−0.241***	−0.024	−0.202***	−0.214***	−0.225***	−0.232***	−0.239***	−0.245***	−0.256***	−0.265***	−0.280***
	(0.030)	(0.019)	(0.037)	(0.032)	(0.030)	(0.029)	(0.030)	(0.031)	(0.035)	(0.039)	(0.049)

Note: Standard errors are in parentheses.
*p value < 0.1. **p value < 0.05. ***p value < 0.01.

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TABLE 12 Method of Moments Quantile regression model with interaction term estimation results (economic complexity and CO_2 emissions)

	Location	Scale	0.10	0.20	0.30	0.40
Economic complexity	4.617*** (0.308)	0.411** (0.190)	3.976*** (0.393)	4.157*** (0.347)	4.317*** (0.319)	4.487*** (0.306)
Income	8.319*** (0.390)	0.224 (0.240)	7.969*** (0.499)	8.068*** (0.440)	8.155*** (0.404)	8.248*** (0.387)
Economic complexity*Income	−5.340*** (0.344)	−0.457** (0.212)	−4.628*** (0.440)	−4.828*** (0.388)	−5.007*** (0.357)	−5.196*** (0.342)
Population	0.912*** (0.020)	−0.025** (0.012)	0.951*** (0.025)	0.940*** (0.022)	0.930*** (0.021)	0.920*** (0.019)
Technology	0.140*** (0.014)	−0.015* (0.008)	0.163*** (0.017)	0.157*** (0.015)	0.151*** (0.014)	0.145*** (0.013)
Openness	0.125*** (0.046)	−0.086*** (0.028)	0.259*** (0.058)	0.222*** (0.052)	0.188*** (0.048)	0.152*** (0.046)
Constant	−12.272*** (0.529)	0.981*** (0.326)	−13.801*** (0.676)	−13.371*** (0.596)	−12.988*** (0.550)	−12.581*** (0.527)
Marginal effects of economic complexity						
Mean	−0.047 (0.035)	0.012 (0.022)	−0.066 (0.045)	−0.060 (0.040)	−0.056 (0.036)	−0.051 (0.035)
Percentiles						
1%	0.943*** (0.077)	0.097** (0.048)	0.793*** (0.099)	0.835*** (0.087)	0.873*** (0.080)	0.913*** (0.077)
5%	0.628*** (0.060)	0.070* (0.037)	0.520*** (0.077)	0.550*** (0.068)	0.577*** (0.062)	0.606*** (0.060)
25%	0.179*** (0.040)	0.031 (0.025)	0.131** (0.051)	0.144*** (0.045)	0.157*** (0.041)	0.170*** (0.040)
50%	−0.125*** (0.035)	0.005 (0.021)	−0.133*** (0.044)	−0.131*** (0.039)	−0.129*** (0.036)	−0.127*** (0.034)
75%	−0.323*** (0.037)	−0.012 (0.023)	−0.304*** (0.047)	−0.309*** (0.041)	−0.314*** (0.038)	−0.319*** (0.036)
95%	−0.542*** (0.044)	−0.031 (0.027)	−0.494*** (0.056)	−0.507*** (0.049)	−0.519*** (0.045)	−0.532*** (0.043)
99%	−0.643*** (0.048)	−0.039 (0.029)	−0.582*** (0.061)	−0.599*** (0.054)	−0.614*** (0.050)	−0.631*** (0.047)

Note: Standard errors are in parentheses.
***p value < 0.01.
**p value < 0.05.
*p value < 0.1.

TABLE 12 (Continued)

	0.50	0.60	0.70	0.80	0.90
Economic complexity	4.621*** (0.308)	4.739*** (0.321)	4.845*** (0.340)	5.038*** (0.389)	5.285*** (0.468)
Income	8.321*** (0.391)	8.385*** (0.407)	8.443*** (0.431)	8.548*** (0.492)	8.683*** (0.592)
Economic complexity*Income	−5.344*** (0.345)	−5.476*** (0.359)	−5.594*** (0.380)	−5.808*** (0.434)	−6.083*** (0.523)
Population	0.911*** (0.020)	0.904*** (0.020)	0.898*** (0.022)	0.886*** (0.025)	0.871*** (0.030)
Technology	0.140*** (0.014)	0.136*** (0.014)	0.132*** (0.015)	0.125*** (0.017)	0.116*** (0.021)
Openness	0.124*** (0.046)	0.100** (0.048)	0.078 (0.051)	0.037 (0.058)	−0.015 (0.070)
Constant	−12.263*** (0.530)	−11.981*** (0.551)	−11.728*** (0.586)	−11.267*** (0.669)	−10.677*** (0.807)

(Continues)

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TABLE 12 (Continued)

	0.50	0.60	0.70	0.80	0.90
Marginal effects of economic complexity					
Mean	−0.047 (0.035)	−0.044 (0.037)	−0.041 (0.039)	−0.035 (0.425)	−0.028 (0.053)
Percentiles					
1%	0.944*** (0.078)	0.972*** (0.081)	0.997*** (0.086)	1.042*** (0.098)	1.100*** (0.118)
5%	0.629*** (0.060)	0.649*** (0.063)	0.666*** (0.066)	0.699*** (0.076)	0.741*** (0.091)
25%	0.180*** (0.040)	0.189*** (0.042)	0.197*** (0.044)	0.211*** (0.050)	0.230*** (0.061)
50%	−0.125*** (0.034)	−0.123*** (0.036)	−0.122*** (0.038)	−0.120*** (0.044)	−0.117** (0.053)
75%	−0.323*** (0.037)	−0.326*** (0.038)	−0.329*** (0.041)	−0.335*** (0.046)	−0.342*** (0.056)
95%	−0.542*** (0.044)	−0.551*** (0.045)	−0.559*** (0.048)	−0.573*** (0.055)	−0.488*** (0.061)
99%	−0.644*** (0.048)	−0.655*** (0.050)	−0.665*** (0.053)	−0.683*** (0.060)	−0.591*** (0.066)

Note: Standard errors are in parentheses.
***p value < 0.01. **p value < 0.05. *p value < 0.1.

dependent variable, the Method of Moments Quantile regression results show that rising economic complexity is associated with decreasing environmental degradation all other things being equal. Hence, at the varying conditional distributions (quantiles) of the dependent variables, the effect of economic complexity is negative. Also, unlike in Tables 4 and 5, the economic complexity is statistically significant in all the estimated models.

In Table 11 (using ecological footprint as the dependent variable), Table 12 (using CO_2 emissions as the dependent variable), Table 13 (using N_2O emissions as the dependent variable) and Table 14 (using GHG emissions as the dependent variable), we repeat the results in Tables 7–10; however, we include the interactive term of economic complexity and income in each table. Table 11 shows that the coefficient of the interactive term (between economic complexity and income) is negative and statistically significant in all the quantiles. Similarly, Tables 12–14 also show negative and statistically significant coefficients for the interactive term in all the quantiles. This outcome buttresses the results in Table 5. Next, we consider the marginal effects of economic complexity at the mean and percentile levels (lower parts of Tables 11–14). The results indicate the marginal effect of economic complexity at the mean levels of income is negative for all the dependent variables. Except where the N_2O emissions is the dependent variable, at the percentile levels of income, the results show varying outcomes, however, generally positive at the lower percentiles (1%–5%) and negative effect at higher percentiles (50%–99%). At all the percentile levels except 1%, marginal effect of economic complexity is negative and statistically significant when N_2O emissions are the dependent variables. The interaction results together with their marginal effects generally indicate that income levels moderate the effect of economic complexity on environmental degradation. Largely, at higher levels of income, economic complexity reduces environmental degradation all other things being equal.

Regarding the control variables, the income, population and technology variables have similar results as those reported in Tables 4 and 5. All the coefficients are generally positive and statistically significant at varying quantiles. Unlike the fixed effects model estimation results showing trade openness to have a negative coefficient, the quantile regression results show a similar outcome as the PLFC model (linear part in Table 6) for the trade openness variable. The coefficients of the trade openness variable are largely negative and statistically significant.

5 | CONCLUSION AND POLICY IMPLICATIONS

In this study, we employ data from 35 OECD countries over the period 1998–2017 and examine the effect of economic complexity on environmental degradation. To broadly capture the environment, we measure environmental degradation with ecological footprint, carbon dioxide, nitrous oxide and total greenhouse gas emissions. From the fixed effects model estimations, we show that increasing economic complexity is associated with increasing environmental degradation.

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TABLE 13 Method of Moments Quantile regression model with interaction term estimation results (economic complexity and N_2O emissions)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	1.859***	0.376	1.291**	1.426***	1.549***	1.771***	1.884***	2.057***	2.158***	2.274***	2.445***
	(0.431)	(0.232)	(0.564)	(0.515)	(0.479)	(0.438)	(0.432)	(0.445)	(0.463)	(0.494)	(0.553)
Income	6.392***	0.640*	5.427***	5.655***	5.866***	6.242***	6.435***	6.730***	6.902***	7.100***	7.391***
	(0.621)	(0.334)	(0.812)	(0.741)	(0.691)	(0.632)	(0.623)	(0.641)	(0.667)	(0.712)	(0.797)
Economic complexity*Income	−2.891***	−0.511*	−2.120***	−2.302***	−2.470***	−2.771***	−2.926***	−3.161***	−3.299***	−3.457***	−3.689***
	(0.491)	(0.264)	(0.641)	(0.586)	(0.546)	(0.500)	(0.492)	(0.507)	(0.527)	(0.562)	(0.630)
Population	0.762***	−0.145***	0.980***	0.928***	0.881***	0.796***	0.752***	0.686***	0.647***	0.602***	0.536***
	(0.032)	(0.017)	(0.041)	(0.038)	(0.038)	(0.035)	(0.034)	(0.034)	(0.034)	(0.037)	(0.041)
Technology	0.762***	0.073***	0.007	0.033	0.057**	0.100***	0.122***	0.155***	0.175***	0.197***	0.230***
	(0.022)	(0.012)	(0.029)	(0.027)	(0.026)	(0.024)	(0.023)	(0.024)	(0.024)	(0.026)	(0.029)
Openness	−0.074	−0.246***	0.297***	0.209**	0.128	−0.017	−0.091	−0.204**	−0.270***	−0.346***	−0.458***
	(0.078)	(0.042)	(0.101)	(0.093)	(0.089)	(0.082)	(0.080)	(0.082)	(0.084)	(0.090)	(0.095)
Constant	−8.940***	2.800***	−13.166***	−12.165***	−11.245***	−9.596***	−8.751***	−7.464***	−6.707***	−5.841***	−4.567***
	(0.806)	(0.447)	(1.076)	(0.988)	(0.946)	(0.873)	(0.849)	(0.870)	(0.892)	(0.954)	(1.065)
Marginal effects of economic complexity											
Mean	−0.667***	−0.071*	−0.560***	−0.585***	−0.609***	−0.650***	−0.671***	−0.704***	−0.723***	−0.745***	−0.777***
	(0.067)	(0.036)	(0.088)	(0.080)	(0.075)	(0.069)	(0.068)	(0.070)	(0.072)	(0.077)	(0.086)
Percentiles											
1%	−0.131	0.024	−0.167	−0.158***	−0.150	−0.136	−0.129	−0.118	−0.111	−0.104	−0.093
	(0.111)	(0.060)	(0.146)	(0.133)	(0.123)	(0.113)	(0.111)	(0.114)	(0.119)	(0.127)	(0.143)
5%	−0.301***	−0.006	−0.292**	−0.294***	−0.296***	−0.300***	−0.302***	−0.304***	−0.306***	−0.308***	−0.311***
	(0.090)	(0.048)	(0.118)	(0.107)	(0.099)	(0.091)	(0.090)	(0.093)	(0.097)	(0.103)	(0.115)
25%	−0.544***	−0.049	−0.470***	−0.488***	−0.504***	−0.533***	−0.547***	−0.570***	−0.583***	−0.598***	0.621***
	(0.070)	(0.038)	(0.091)	(0.083)	(0.077)	(0.071)	(0.070)	(0.072)	(0.075)	(0.080)	(0.090)
50%	−0.709***	−0.078**	−0.591***	−0.619***	−0.645***	−0.691***	−0.714***	−0.750***	−0.771***	−0.795***	−0.831***
	(0.068)	(0.037)	(0.089)	(0.081)	(0.076)	(0.069)	(0.068)	(0.070)	(0.073)	(0.078)	(0.087)
75%	−0.816***	−0.097**	−0.669***	−0.704***	−0.736***	−0.793***	−0.822***	−0.867***	−0.893***	−0.923***	−0.967***
	(0.073)	(0.039)	(0.095)	(0.087)	(0.081)	(0.074)	(0.073)	(0.075)	(0.078)	(0.083)	(0.093)
95%	−0.934***	−0.118***	−0.756***	−0.798***	−0.837***	−0.907***	−0.942***	−0.997***	−1.028***	−1.065***	−1.119***
	(0.083)	(0.045)	(0.108)	(0.099)	(0.092)	(0.085)	(0.083)	(0.086)	(0.089)	(0.095)	(0.106)
99%	−0.989***	−0.128***	−0.797***	−0.842***	−0.884***	−0.959***	−0.998***	−1.057***	−1.091***	−1.131***	−1.189***
	(0.088)	(0.048)	(0.115)	(0.105)	(0.099)	(0.090)	(0.089)	(0.091)	(0.095)	(0.101)	(0.113)

Note: Standard errors are in parentheses.
*p value < 0.1. **p value < 0.05. ***p value < 0.01.

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TABLE 14 Method of Moments Quantile regression model with interaction term estimation results (economic complexity and GHG emissions)

	Location	Scale	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
Economic complexity	3.760***	0.085	3.631***	3.665***	3.696***	3.726***	3.756***	3.779***	3.809***	3.852***	3.906***
	(0.268)	(0.159)	(0.320)	(0.288)	(0.269)	(0.262)	(0.267)	(0.278)	(0.303)	(0.350)	(0.425)
Income	7.066***	0.072	6.956***	6.985***	7.011***	7.037***	7.062***	7.082***	7.108***	7.144***	7.190***
	(0.334)	(0.199)	(0.399)	(0.358)	(0.335)	(0.326)	(0.332)	(0.346)	(0.377)	(0.436)	(0.529)
Economic complexity*Income	−4.509***	−0.097	−4.361***	−4.400***	−4.435***	−4.470***	−4.504***	−4.530***	−4.565***	−4.615***	−4.677***
	(0.301)	(0.179)	(0.359)	(0.322)	(0.302)	(0.293)	(0.299)	(0.312)	(0.339)	(0.393)	(0.476)
Population	0.845***	−0.024**	0.882***	0.872***	0.863***	0.854***	0.846***	0.839***	0.831***	0.818***	0.803***
	(0.017)	(0.010)	(0.020)	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)	(0.019)	(0.022)	(0.027)
Technology	0.160***	0.005	0.153***	0.155***	0.156***	0.158***	0.160***	0.161***	0.163***	0.166***	0.169***
	(0.012)	(0.007)	(0.014)	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.015)	(0.019)
Openness	0.012	−0.062**	0.107**	0.081*	0.059	0.037	0.015	−0.002	−0.024	−0.055	−0.095
	(0.042)	(0.025)	(0.050)	(0.045)	(0.042)	(0.041)	(0.042)	(0.044)	(0.048)	(0.055)	(0.067)
Constant	−9.343***	0.811***	−10.587***	−10.254***	−9.964***	−9.668***	−9.387***	−9.168***	−8.875***	−8.462***	−7.942***
	(0.461)	(0.299)	(0.549)	(0.495)	(0.463)	(0.451)	(0.458)	(0.478)	(0.522)	(0.603)	(0.731)
Marginal effects of economic complexity											
Mean	−0.178***	−0.000	−0.178***	−0.178***	−0.178***	−0.178***	−0.178***	−0.178***	−0.178***	−0.178***	−0.179***
	(0.032)	(0.019)	(0.039)	(0.035)	(0.033)	(0.032)	(0.032)	(0.034)	(0.037)	(0.042)	(0.051)
Percentiles											
1%	0.658***	0.018	0.631***	0.638***	0.644***	0.651***	0.657***	0.662***	0.668***	0.677***	0.689***
	(0.068)	(0.040)	(0.081)	(0.073)	(0.068)	(0.066)	(0.067)	(0.070)	(0.076)	(0.088)	(0.107)
5%	0.392***	0.012	0.373***	0.378***	0.383***	0.387***	0.391***	0.395***	0.399***	0.405***	0.413***
	(0.053)	(0.031)	(0.063)	(0.057)	(0.052)	(0.051)	(0.052)	(0.055)	(0.059)	(0.069)	(0.084)
25%	0.013	0.004	0.007	0.008	0.010	0.012	0.013	0.014	0.015	0.017	0.020
	(0.036)	(0.022)	(0.043)	(0.039)	(0.036)	(0.035)	(0.036)	(0.037)	(0.041)	(0.047)	(0.057)
50%	−0.244***	−0.002	−0.242***	−0.242***	−0.243***	−0.243***	−0.244***	−0.244***	−0.245***	−0.246***	−0.247***
	(0.032)	(0.019)	(0.038)	(0.035)	(0.032)	(0.031)	(0.032)	(0.033)	(0.036)	(0.042)	(0.051)
75%	−0.411***	−0.005	−0.403***	−0.405***	−0.409***	−0.409***	−0.411***	−0.412***	−0.414***	−0.416***	−0.420***
	(0.034)	(0.020)	(0.041)	(0.037)	(0.034)	(0.033)	(0.034)	(0.036)	(0.039)	(0.045)	(0.054)
95%	−0.596***	−0.009	−0.582***	−0.585***	−0.589***	−0.592***	−0.595***	−0.598***	−0.601***	−0.606***	−0.611***
	(0.040)	(0.024)	(0.048)	(0.043)	(0.040)	(0.039)	(0.040)	(0.042)	(0.045)	(0.053)	(0.064)
99%	−0.681***	−0.011	−0.665***	−0.669***	−0.673***	−0.677***	−0.681***	−0.684***	−0.688***	−0.693***	−0.700***
	(0.044)	(0.026)	(0.052)	(0.047)	(0.044)	(0.043)	(0.040)	(0.045)	(0.049)	(0.057)	(0.070)

Note: Standard errors are in parentheses.
**p* value < 0.1. ***p* value < 0.05. ****p* value < 0.01.

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We also examine how income levels moderate the effect of economic complexity on environmental degradation. The introduction of nonlinearity motivates us to employ the partial linear functional-coefficient model, which is flexible and permits nonlinearity and heterogeneity across cross-sections and time. We show that income moderates the effect of economic complexity on the environment; specifically in the presence of high income, increase in economic complexity reduces environmental degradation. To further substantiate the results, we also employ the Method of Moment Quantile regression, which accounts for nonlinearity by controlling for distributional heterogeneity. We largely show that economic complexity decreases environmental degradation in all quantiles. The findings from the interaction of income and economic complexity in the quantile regression estimations buttress those of the partial linear functional-coefficient model, which suggests that, at higher income levels, increasing economic complexity generally reduces environmental degradation.

Considering that the effects of climate change is ravaging all over the world and countries are racing to achieve the Sustainable Development Goals, issues of environmental sustainability are top priorities for developed countries. Based on the results, we recommend that policies to promote green initiatives such as the use of renewable energy and adherence to environmental sustainability regulations be enhanced. Strict measures to cut emissions have to be put in place so that increasing economic complexities and economic growth do not come at the expense of the environment. Some of these measures could include compelling firms to report their emission targets and reductions, and those firms that do not meet the targets face strict penalties. Policymakers can also assess firms' commitments to environmental sustainability and those that pollute the environment without remedial measures penalized.

As common in empirical research, our paper is not free from limitations. Due to data limitations, we were unable to cover the whole of the OECD countries and also to expand the years (beyond 1998–2017). With access to data, future studies can expand the sample size to ascertain the impact of economic complexity on environmental degradation for more constructive conclusions. The results from our study may have been influenced by the measurements (proxies) of the variables used and the estimations methods used. We have tried to cater for this as much as possible by employing four different environmental degradation proxies and a battery of estimation methods. Future studies may employ other proxies and estimation methods to re-examine the issue addressed in this paper.

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CONFLICT OF INTEREST

The authors declare no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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ENDNOTES

[1] We take a cue from Opoku and Aluko (2021) and Opoku et al. (2022) for the model building.

[2] We desire to consider all countries with OECD membership; however, three countries (Iceland, Ireland and Luxembourg) were dropped due to data-related issues.

[3] Note that the dependent variables are logged and economic complexity is not; hence, we find the antilog of the economic complexity coefficients.

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APPENDIX A

TABLE 1A List of OECD countries in the sample and ranking based on economic complexity

Country	Rank	Country	Rank	Country	Rank	Country	Rank	Country	Rank
Australia	79	Czech Republic	7	Hungary	14	Mexico	21	Slovenia	12
Austria	9	Denmark	25	Israel	20	Netherlands	22	Spain	36
Belgium	18	Estonia	27	Italy	17	New Zealand	50	Sweden	8
Canada	30	Finland	11	Japan	1	Norway	38	Switzerland	3
Chile	77	France	16	Korea Republic	5	Poland	23	Turkey	40
Colombia	56	Germany	4	Latvia	35	Portugal	48	United Kingdom	13
Costa Rica	53	Greece	52	Lithuania	32	Slovak Republic	15	United States	10

Note: The countries are ranked based on the latest (2019) economic complexity ranking in OEC (https://oec.world/en/rankings).

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