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RESEARCH ARTICLE

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The role of biomass energy consumption and economic complexity on environmental sustainability in G7 economies

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Abstract

This paper empirically examines the effect of biomass energy consumption and economic complexity on environmental sustainability in G7 economies. The current study attempts to report a comprehensive analysis of biomass energy and economic complexity on ecological and carbon footprints and carbon emissions. We employ data from 1990 to 2019 and adopt robust panel econometric techniques that account for the analysis's cross-sectional dependence. We conduct cointegration analysis, pooled ordinary least squares (OLS), system generalized method of moments (GMM) and conditional quantile model for our empirical analysis. The empirical findings show that both biomass energy consumption and economic complexity are detrimental to the ecological footprint and carbon footprint. Additionally, we find that globalization positively affects the environment, while we find some evidence that bureaucratic quality improves environmental quality. Finally, in line with other research, we find that economic growth has detrimental effects on the environment. Our results suggest that policymakers should be more cautious in promoting biomass as a clean energy source and that the G7 economies should take advantage of their leading position in innovation to invest more in sustainable practices and investment.

KEYWORDS
biomass energy, carbon footprint, clean energy, ecological footprint, economic complexity, G7 economies

1 | INTRODUCTION

Biological material, or biomass, is organic material such as wood, the organic component of municipal solid waste and crops. Biomass can be used as a source to produce renewable energy in the form of fuels (solid, liquid and gaseous), heat and electricity. Easy access to these materials made them a traditional source of energy in the past and in many developing countries today. In Africa, for example, 63% of households had wood fuel as the main fuel for cooking in 2011. Worldwide, biomass is ranked the fourth largest energy source, following coal, oil and NAT gas (UNEP, 2019). A main advantage of biomass is that it results in lower emissions of greenhouse gases when sustainably used than the top-three energy source (coal, oil and NAT gas). Combined with being a renewable source, it is a promising alternative to mitigate climate change and to contain the ecological footprint (EF). However, when used in an unsustainable way, biomass can be detrimental to the environment.

Biomass originating from wood can lead to losses of biodiversity and climate change (see Smith et al., 2013, for a comprehensive analysis of the potential of greenhouse gas mitigation in the Agriculture, Forestry and Other Land Use Sectors, which consider services provided by land). This occurs when the forest is harvested unsustainable, generating a depletion of forest stocks. Bailis et al. (2015) estimated in 2009 that about 1.9–2.3% of global greenhouse gas emissions originated from unsustainable harvesting and incomplete combustion of traditional wood fuels. When implemented with sustainability considerations, forestry presents a significant potential to mitigate climate change by increasing forest carbon stocks. IPCC (2007) estimates that biomass from forestry has the potential to mitigate about 0.4–4.4 GtCO2 per year, depending on whether biomass replaces coal or gas in power plants.

This article throws valuable insights for policymakers, academics and practitioners on environmental concerns. This research analyses the potential effects of biomass energy on greenhouse gas emissions, on the EF and on the carbon footprint (CF) by focusing on the G7 economies from 1990 to 2019. The current study uses data for G7 economies for a number of reasons. The G7 economies together accounted on average for over 50% of world gross domestic product (GDP) (GDP constant 2010 US$—WDI, 2021) in the period 1990 until 2019, and they were responsible for approximately 30% of world total greenhouse gas emissions (kt of CO_2 equivalent—WDI, 2021) in a similar period (1990–2018). Additionally, some research has analysed the environment-economy nexus for G7 economies with which we can compare our results but that lack an investigation of the effect of biomass energy consumption and economic complexity despite the importance of these two elements in the G7 economies. In the literature review, we discuss the existing gaps in the literature which we intend to fill, in particular, the inclusion of biomass energy consumption and economic complexity to assess the impact on environmental variables. Our paper's novelty is to integrate the empirical literature on environmental sustainability, fill in the gap in the literature by analysing biomass energy consumption and economic complexity and apply state-of-the-art empirical techniques. We add to the empirical seam in the literature by exploring the underlying nexus across biomass energy consumption and economic complexity in the presence of major regressors through the application of second-generation panel estimation techniques. This study takes into account the impact of cross-sectional dependency. It is essential to explore the issues of cross-sectional dependence in the current context of global integration. Global policy changes related to trade and the environment can affect a single country or the panel, alongside added exogenous shocks.

Precisely, after testing the presence of cross-sectional dependence, our paper applies the second-generation panel unit root test procedures postulated by Pesaran (2007) and panel cointegration test by Persyn and Westerlund (2008). The panel cointegration test proposed by Persyn and Westerlund (2008) is robust to cross sectional issues. We further examine the long-run elasticities of the underlying variables by applying relevant recent empirical techniques like ordinary least squares (OLS) with Driscoll–Kraay standard errors and the generalized method of moments (GMM) with fixed effects. In addition to adopting the aforesaid panel estimation methods, our paper also applies the panel quantile regression technique proposed by Canay (2011) for robustness of model specifications. By applying Canay (2011), the current study (*i*) explores the non-linearity in the underlying relations; thereby, the model specification relaxes the 'symmetry' assumption as reported in the earlier literature; and (*ii*) the study models the entire conditional distribution of the dependent variable in the model specifications.

Balat and Ayar (2005) argue that the biomass potential is promising as it offers a renewable source of energy and pollution emissions from the plants are less than from fossil-fuel-based plants. However, the authors also note that emissions from biomass energy systems can occur through more hidden channels, such as forest clearing, and the type of conversion technology. Overall, whether biomass is preferred from an environmental perspective depends among other things on the nature of the biomass resource, on the impact on the demand for energy, the carbon intensity of the replacement, on technical aspects to generate this energy and the sustainability of practices involved. As such, it is an empirical question whether biomass energy has a favorable impact in decreasing greenhouse gas emissions and on the EF. In this paper, we analyse this question for G7 countries. G7 countries consumed in 2018 27% of the world's total energy (IEA, 2020a, 2020b) and have therefore the biggest incentive to look for more sustainable alternative sources. Understanding the environmental impact of biomass consumption is therefore crucial for defining effective policies and is the first focus of our paper.

A second focus is to analyse whether the level of complexity of an economy has an effect on the environment. Developed economies have been the leaders in innovation, green technologies and in establishing more stringent environmental regulations (IEA, 2020b; OECD, 2016; UNCTAD, 2021). In the same line, Stern (2021) calls the G7 for leadership for sustainable growth as an opportunity in rebuilding the economies after the COVID pandemic. G7 economies are not only overall wealthier than the world average, but they also have relatively complex economies. Nonetheless, within these seven countries, there is still significant variability. Whereas Japan remained the number 1 in the Economic Complexity Index at the global level throughout the period 1999 to 2019, Canada fell from the 17th position in 1999 to the 30th in 2019. The on-hand study explores whether there are links between these trends in economic complexity and the environment.

Section 2 reviews the literature review on environmental sustainability by focusing on biomass, economic complexity and the literature on G7 economies. Section 3 presents the materials and methods, where we specify the data and the models, and we discuss the estimation strategy and provide the results and robust analysis. In Section 4, we discuss our findings in three parts; first, we discuss the preliminary analysis, thereafter the panel cointegration analysis and lastly the robustness check. Section 5 presents the detailed discussion. Finally, Section 6 concludes key empirical results and provides some policy implications.

2 | RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

2.1 | Literature review

This paper contributes to the broad literature on the determinants of environmental sustainability. More specifically, our paper is close to three strands in the literature. The first one analyses the case of biomass, a second one focuses on a specific group of countries that are at the frontier of technological progress, the G7 economies, and finally, a third strand analyses the link between economic complexity and the environment. As such, this literature review focuses on papers either analysing the impact of biomass on environmental sustainability and/or analysing the determinants of greenhouse gas emissions in G7 economies and or economic complexity. Our emphasis in this literature review is on empirical papers close to our research and referenced later to discuss our results.

Within the literature considering biomass energy consumption, few of the recent studies (Aslan, 2016; Bildirici, 2013, 2014; Bilgili & Ozturk, 2015) analysed the impact of biomass on economic growth. Few of the recent studies (Aslan, 2016; Bildirici, 2014; Bilgili & Ozturk, 2015) find that from an economic growth perspective, biomass energy consumption has a positive contribution to growth; however, others find a weaker causal relationship (Bildirici, 2013). In the same line, Bildirici (2013) argued that at an initial level of economic development, traditional biomass is predominant. As countries start to industrialize, they move towards commercial fossil fuels.

Later in the development process, countries start to adopt modern biomass energy, which helps to reduce foreign oil dependency. Meanwhile, Bilgili and Ozturk (2015) show that biomass energy consumption has a positive impact on economic growth in G7 economies. As a policy advice, the authors thus argue for the promotion of biomass energy to promote economic growth. The authors mention the positive contribution of biomass energy to reducing greenhouse gases emissions but do not provide evidence for this effect. From an economic perspective, Doytch (2020) documented the heterogeneous impacts of foreign direct investments on the EF of low-income, middle-income and high-income countries. The empirical findings reported that low-income countries witness production-related ecological effects of foreign direct investments (FDI), while the burden of FDI generated exports EF is more disproportionately related with middle-income and high-income countries. Studying the data of developing economies, Doytch and Ashraf (2021) examined the burden of greenfield investments and merger and acquisition on EFs. The empirical results mentioned that greenfield investments burden is born by foreign activity-related footprints in developing countries, whereas cross-border mergers and acquisitions tend to harm the ecosystems of developing countries. More recently, Ashraf and Doytch (2022) explored the impacts of inward and outward foreign investments on EFs (consumption and production). The empirical results reported positive impacts of outward and inward FDI on the EF of developed economies, while merger and acquisition variable reported mixed effects.

A separate strand in the literature analysed the impact of biomass on carbon dioxide emissions (CO_2) (Ahmed et al., 2016; Danish & Ulucak, 2020; Danish & Wang, 2019; Dogan & Inglesi-Lotz, 2017; Mahmood et al., 2019) or greenhouse gas emissions (Baležentis et al., 2019). In addition to biomass energy as an independent variable, these papers control for different independent variables but do not take into account the potential impact of economic complexity. The main independent variables controlled for are (*i*) GDP per capita (Ahmed et al., 2016; Danish & Wang, 2019; Mahmood et al., 2019), (*ii*) GDP (Baležentis et al., 2019; Dogan & Inglesi-Lotz, 2017), (*iii*) urbanization rate (Danish & Wang, 2019; Dogan & Inglesi-Lotz, 2017), (*iv*) trade openness (Danish & Wang, 2019; Dogan & Inglesi-Lotz, 2017; Mahmood et al., 2019), (*v*) foreign direct investment (Danish & Wang, 2019; Mahmood et al., 2019), (*vi*) environmental institution (Danish & Wang, 2019; Mahmood et al., 2019), (*vii*) other renewable (Baležentis et al., 2019) and (*viii*) technology as measured by the number of patents (Ahmed et al., 2016). Finally, the variable considered for biomass energy also varies per study (see Tables 1 and 2).

Tables 1 and 2 provide an overview of the papers analysing the impact of biomass on greenhouse gases emissions. From these papers analysed, Mahmood et al. (2019) found a positive impact of biomass on greenhouse gases emissions for Pakistan; that is, biomass energy implies an increase in emissions ceteris paribus. Using an autoregressive distributive lag model (ARDL), Mahmood et al. (2019) find that this effect is larger in the long-run than in the short-run. Other papers found the opposite result (Danish & Ulucak, 2020; Danish & Wang, 2019; Baležentis et al., 2019; Dogan & Inglesi-Lotz, 2017). Danish and Ulucak (2020) apply the ARDL for China and find that biomass consumption has a negative and significant impact on CO_2 emissions. Danish and Wang (2019) analyse the case of BRICS economies from 1992 to 2003 and find that biomass energy consumption reduces emissions. Baležentis et al. (2019) find similar results for the EU in the period 1995–2015. Dogan and Inglesi-Lotz (2017) consider data for countries having a biomass contribution in the energy consumption mix, for the period 1985–2012 and find that biomass energy consumption reduces CO_2. Finally, Ahmed et al. (2016) find insignificant results for biomass on CO_2 emissions in a panel of 24 European countries in the period 1980–2010.

The current study also considers alternative environmental dependent variables, specifically EF and CF. In the literature, empirical papers adopting EF (e.g., Al-mulali et al., 2015; Altintas & Karrouri, 2020; Charfeddine, 2017; Destek et al., 2018; Destek & Sarkodie, 2019; Uddin et al., 2019; Ulucak & Bilgili, 2018; Wang et al., 2013) or CF (Charfeddine, 2017) as dependent variable do not consider the potential impact from biomass energy consumption nor economic complexity (see Table 3), a gap which we intend to fill-in in this paper. A few of these papers consider renewable energy consumption (Danish et al., 2020; Destek et al., 2018; Destek & Sinha, 2020). Altintas and Karrouri (2020), Danish et al. (2020), Destek and Sinha (2020) and Destek et al. (2018) find that renewable energy consumption has the expected negative effect on EF.

TABLE 1 Analysis of relevant literature

	Danish and Ulucak (2020)	Baležentis et al. (2019)	Danish and Wang (2019)	Mahmood et al. (2019)	Dogan and Inglesi-Lotz (2017)	Ahmed et al. (2016)
Dependent variable	CO_2 emissions	GHG emissions (in tonnes of CO_2 equivalent)	CO_2 emissions in million tons per capita	CO_2 emission in metric tons per capita	CO_2 emissions in kilotons	CO_2 emissions per capita in metric tons
Biomass energy	Two variables were added simultaneously: biomass energy consumption & biomass energy production	Biomass toe	Biomass extraction	Biomass energy–domestic material consumption per capita	Electricity power generated from biomass and waste in kilowatt-hours	Biomass in 1000 tons of used extraction from agriculture
GDP per capita	x		x	x		x
GDP per capita squared			x	x		x
GDP		x			x	
GDP squared		x			x	
Urbanization rate			x		x	
Trade openness	x		x	x	x	
FDI	x		x	x		
Technology						x
Other renewables (solar, wind, geothermal)		x				
Environmental institution (dummy for Kyoto Protocol)			X	x		

TABLE 2 Analysis of relevant literature

	Ulucak and Bilgili (2018)	Charfeddine (2017)	Destek and Sinha (2020)	Danish et al. (2020)	Destek et al. (2018)	Destek and Sarkodie (2019)
Dependent variable	Ecological footprint per capita	Ecological footprint, ecological carbon footprint and CO_2 emissions	Ecological footprint per capita	Ecological footprint	Ecological footprint per capita	Ecological footprint
GDP per capita			x	x	x	x
GDP per capita squared	x		x	x	x	x
GDP	x	x				
GDP squared						
Urbanization rate				x		
Trade openness	x		x		x	
Credit of private sector to GDP ratio						x
Technology						
Biocapacity	x					
Renewable energy consumption			X	x	x	
Non-renewable energy consumption					x	
Energy consumption						x
Human capital	x					
NAT resource rent				x		

TABLE 2 (Continued)

	Uddin et al. (2019)	Wang et al. (2013)	Ozturk et al. (2016)	Al-mulali et al. (2015)	Bagliani et al. (2008)	Altintas and Karrouri (2020)
Dependent variable	Ecological footprint per capita	Ecological footprint per capita (production and consumption)	Ecological footprint	Ecological footprint	Ecological footprint per capita	Ecological footprint per capita
GDP per capita	x	x			x	x
GDP per capita squared	x	x			x	X
GDP			x (tourism sector)	x		
GDP squared				x		
Urbanization rate			x	x		
Trade openness			x	x		

(Continues)

TABLE 2 (Continued)

	Uddin et al. (2019)	Wang et al. (2013)	Ozturk et al. (2016)	Al-mulali et al. (2015)	Bagliani et al. (2008)	Altintas and Karrouri (2020)
Credit of private sector to GDP ratio						
Technology						
Biocapacity		x			x	
Renewable energy consumption						x
Non-renewable energy consumption						x
Energy consumption			x	x		
Human capital						
NAT resource rent						

2.2 | Hypotheses development

Based on the discussion in the literature review, we test two main hypotheses in Section 4.

> **Hypothesis 1.** Biomass energy consumption: If biomass energy consumption is used in a sustainable way, an increase in biomass energy consumption, ceteris paribus, improves environmental variables such as ecological footprint, carbon footprint and carbon dioxide emissions.

Biomass energy consumption is considered a renewable source of energy and, therefore, largely supported by most countries. However, as discussed in the introduction and literature review, when used in an unsustainable way, biomass energy consumption can be detrimental to the environment. Whether biomass energy consumption improves/worsens environmental variables is, therefore, an empirical question, which we test in our models.

> **Hypothesis 2.** Economic complexity: Economic complexity improves, ceteris paribus, environmental variables such as ecological footprint, carbon footprint and carbon dioxide emissions.

Economic complexity goes together with innovation, knowledge embedded in technology and human capital, all of which are needed to combat environmental degradation. Structural changes towards industries that are more intensive in knowledge arise at higher levels of economic complexity. As a consequence, the increase in economic complexity, ceteris paribus, provides the knowledge and, hence, the technology which facilitates the implementation of environmental-friendly practices, methods and technologies (Shahzad et al., 2021).

3 | MATERIALS AND METHODS

3.1 | Data specification and models

This research analyses the potential effect of biomass energy on greenhouse gases emissions and the potential effect of biomass energy on EF and on the CF in the G7 economies during the period 1990–2019. The G7 economies are the United States, Canada, the United Kingdom, France, Italy, Germany and Japan. Table 3 presents the data adopted in the different model specifications, where CO_2, EF and CF are the three alternative dependent variables, and the remaining variables are the independent variables. Notably, the authors have used the EF and CF variables as consumption related indicators. Ecological and CFs capture the biophysical burden imposed by resource consumption, populations and industrial processes on the supportive ecosystems. Ecological and CF are also viewed as human demand for consuming natural resources (Doytch, 2020). The consumption footprint[1] also catches the consumption of biocapacity embedded in

TABLE 3 Data and variables specification

Variables	Specification	Presentation	Source
Carbon emissions	Carbon dioxide emissions (kt)	CO_2	World Bank (2021)
Ecological footprint	Ecological footprint expressed in Global hectare (gha)	EF	Global Footprint Network (2021)
Carbon footprint	Carbon footprint expressed in global hectare (gha)	CF	Global Footprint Network (2021)
Biomass energy	Bio-mass energy use (in tonnes)	BIOMASS	IEA (2020a, 2020b)
Economic complexity	Economic complexity as the diversity of exports	ECI	Observatory of Economic Complexity (2021)
Trade globalization	KOF Globalization Index—captures economic, social and political dimensions of globalization (index ranges from 1 to 100)	GLOB	KOF Swiss Economic Institute—Gygli et al. (2019)
Bureaucratic quality	Index of quality of government	BQ	The International Country Risk Guide (ICRG)-PRS Group and others (2021)
NAT resources	Total NAT resources rents (% of GDP)	NAT	World Bank (2021)
Economic growth	GDP (constant 2010 US$)	GDP	World Bank (2021)

TABLE 4 Descriptive statistics

Variable		Mean	SD	Min	Max	Observations
CO_2	Overall	13.574	0.874	12.622	15.572	$N = 203$
	Between		0.935	12.782	15.485	$n = 7$
	Within		0.107	12.635	13.756	$T = 29$
EF	Overall	20.008	0.758	19.254	21.855	$N = 203$
	Between		0.813	19.419	21.730	$n = 7$
	Within		0.078	19.768	20.227	$T = 29$
CF	Overall	19.583	0.823	18.668	21.528	$N = 203$
	Between		0.880	18.949	21.410	$n = 7$
	Within		0.097	19.302	19.766	$T = 29$
BIOMASS	Overall	19.897	0.735	18.958	21.688	$N = 203$
	Between		0.782	19.126	21.474	$n = 7$
	Within		0.114	19.418	20.110	$T = 29$
ECI	Overall	0.250	0.178	−0.382	0.559	$N = 203$
	Between		0.164	−0.045	0.501	$n = 7$
	Within		0.092	−0.088	0.472	$T = 29$
GLOB	Overall	4.078	0.188	3.497	4.369	$N = 203$
	Between		0.167	3.787	4.252	$n = 7$
	Within		0.107	3.787	4.334	$T = 29$
BQ	Overall	0.037	0.005	0.025	0.040	$N = 203$
	Between		0.005	0.028	0.040	$n = 7$
	Within		0.002	0.034	0.044	$T = 29$
NAT	Overall	0.662	1.001	0.011	5.333	$N = 203$
	Between		0.983	0.021	2.750	$n = 7$
	Within		0.413	−1.315	3.245	$T = 29$
GDP	Overall	28.793	0.718	27.622	30.517	$N = 203$
	Between		0.756	27.944	30.205	$n = 7$
	Within		0.155	28.415	29.125	$T = 29$

human consumption in the form of goods and services (Doytch & Ashraf, 2021). While there are limited studies on consumption EFs, the current study reports some novel findings and implications in this regard. Table 4 reports the descriptive statistics for all studied variables. Figure 1 shows the biomass energy consumption patterns in G7 countries. Figure 2 highlights the EF, and Figure 3[2] documents the

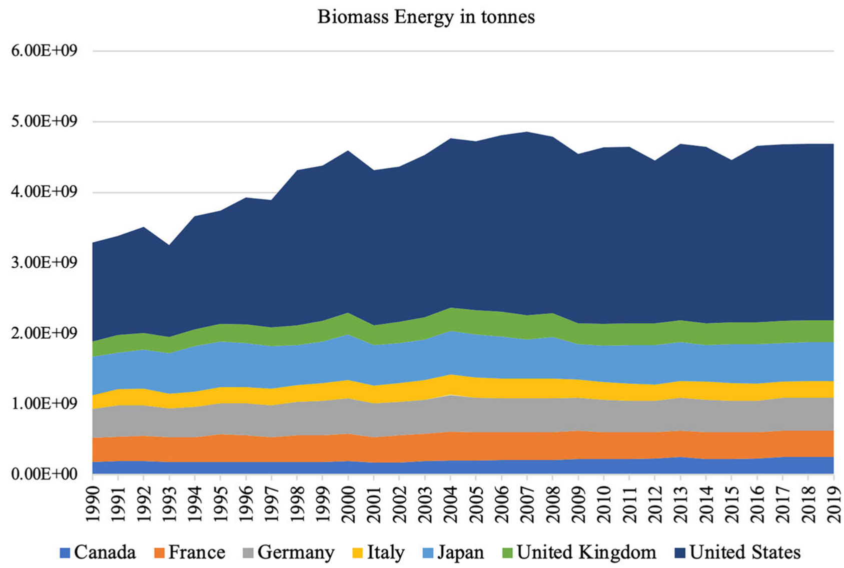

FIGURE 1 Biomass energy in G7 countries

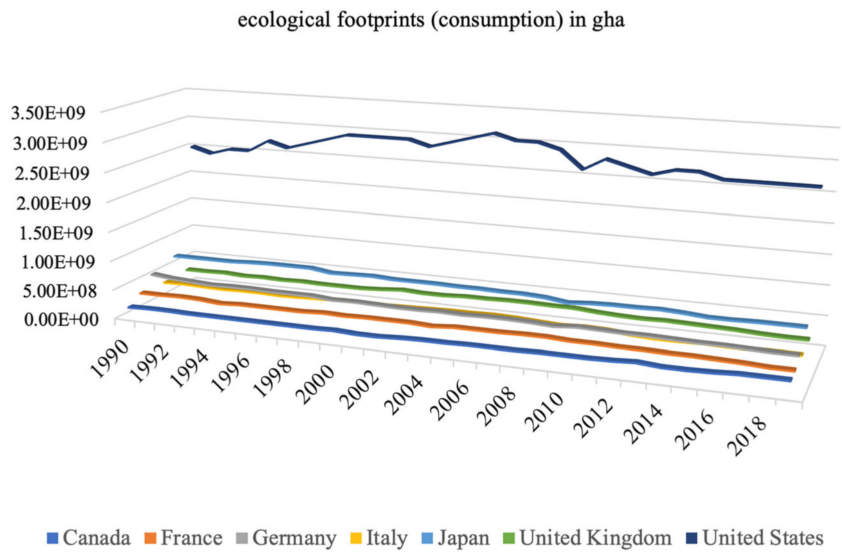

FIGURE 2 Ecological footprint in G7 countries

GDP per capita in G7 economies. The time series plots mention that during the studies period G7 countries witnessed economic bolster, huge biomass energy as well as with the rise in EFs.

3.2 | Estimation strategy

This empirical study explores the two key potential effects of whether biomass energy reduces (*i*) emanations of carbon dioxide, (*ii*) the EF and (*iii*) the CF and whether economic complexity reduces emanations and ecological and CF in the presence of other crucial regressors for the G7 countries. With this aim, our study applies an array of panel methods, with a gradual rise in the intricacies of the methods to capture the unobserved heterogeneity in the underlying observations. A usual underlying assumption concerning the panel data techniques is that the dissimilarities in the cross-section specifications can be summarized through the fixed constant terms so that the underlying heterogeneous behaviour is encapsulated. Arguably, divergences may exist at the individual country levels owing to dissimilarities in economic structuring. It is important to address the underlying dissimilarities otherwise the estimation may generate spurious results. Accordingly, our study proceeds as a first step by checking for cross-section-based dependencies among individual units. Second, the nature of stability of the data sets is examined through panel unit root test methods. Third, in case the variables are integrated in higher order, for example, I(1) or I(2), we consider subsequently applying the panel cointegration techniques to scrutinize the long-run relationship amid the underlying observations. Finally, OLS with Driscoll and Kraay (1998) standard errors and system generalized method of moments (SGMM) are utilized to explore the long-run elasticities between the explained variables and the explanatory variables (after to obtaining the co-integrating nature of the variables).

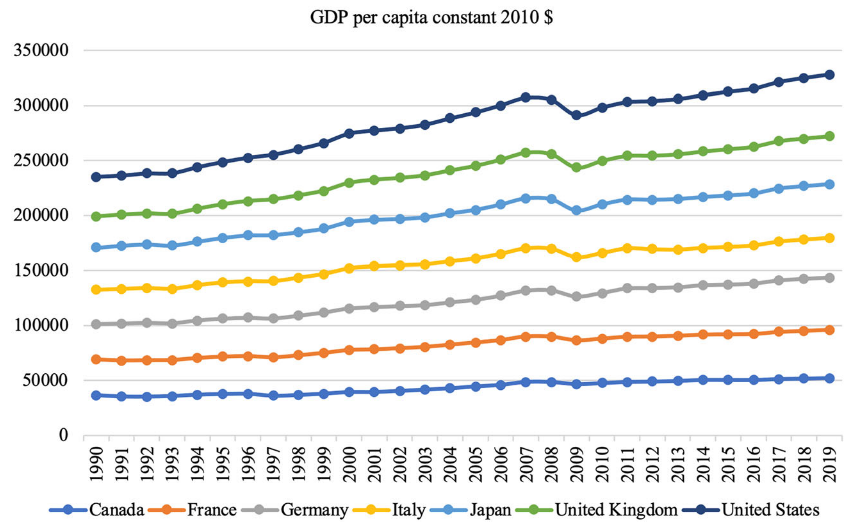

FIGURE 3 GDP per capita of G7 countries

The advantage of using the Driscoll–Kraay standard error method is twofold: (*i*) This method can take into account the problems of cross-sectional dependence and heteroscedasticity in panel data; and (*ii*) this method counters the problems associated with serial dependence and missing data in the panel set of observations (Pei et al., 2017). Unlike ordinary least squares, the OLS with Driscoll–Kraay standard error produces reliable and robust estimates. By using the SGMM, we try to address the issue related to endogeneity in the regressors. Further, the SGMM methodology is based on the application of a set of instruments, and it contains the lagged variables in the difference of the endogenous variables and further exogenous variables (Arellano & Bond, 1991; Rafique et al., 2021).

3.2.1 | Cross-sectional dependence test

We apply the cross-sectional dependence test to scrutinize the underlying cross-section nature of the variables. We apply three tests often used when the panel time dimension is larger than the cross-sectional dimensions, as the case for our data. First, the Pesaran (2015) CD test is applied; see Equation (1).

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=j+1}^{N}\hat{\rho_{ij}}\right) \sim N(0,1)i,j \quad (1)$$

Here, CD denotes the statistic to be tested under the null hypothesis. The null hypothesis following Wang and Dong (2019) under Pesaran (2015) CD test states the absence of cross-sectional-based dependence. According to Pesaran (2015), the CD test is based on pairwise correlations. Pesaran (2015) argues it is indispensable to apply a cross-section-based dependency test for a panel set of observations owing to unobserved discrepancies and exogenous shocks.

Second, we applied Friedman (1937) cross-section dependence test based on the averaging of Spearman's rank correlation coefficient; see Equation (2) for the robustness of the analysis.

$$R_{av} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r_{ij}} \quad (2)$$

Here, r_{ij} depicts the sample of rank correlation-related coefficient based on residuals.

Third, we applied the Frees (1995) cross-section dependence test which improves the Friedman (1937) test procedure, based on the summation of the squared rank order of correlations on the residual; see Equation (3).

$$R_{av}{}^2 = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r_{ij}}^2 \quad (3)$$

3.2.2 | Panel unit root tests

Pesaran (2007) extended the conventional Dickey–Fuller test or the augmented Dickey–Fuller test techniques to develop the panel unit root test techniques based on cross-sectional dependencies. The new CADF test statistics as proposed by Pesaran (2007) is defined as follows; see Equation (4).

$$y_{it} = (1-\emptyset_i)\mu_i + \emptyset_i y_{i,t-1} + u_{it};\ i = 1,2.........N\ \&\ t = 1.2..........T \quad (4)$$

Here, the initial value y_{i0} is expected to have a density function based on a finite order in mean and variance. Again, the error term u_{it} is with a single-based factor structure defined under Equation (5).

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \quad (5)$$

Here, f_{it} explains the observed common based effects, and ε_{it} explains the individual-based error.

Pesaran (2007) further develops Equations (4) and (5); see Equations (6) and (7), respectively, to build the hypothesis test on the unit root:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \tag{6}$$

Here, $\alpha_i = (1-\emptyset_i)\,\mu_i$; $\beta_i = -(1-\emptyset_i)$, and Δy_{it} denotes $y_{it} - y_{it-1}$.

The null hypothesis is denoted as

H_0: $\beta_i = 0$ in case of all i.

Additionall, Pesaran (2007) develops the Pesaran cross-section-based augmented level of unit root test following Pesaran and Shin (CIPS) for the panel; see Equation (7).

$$\text{CIPS} = N^{-1}\sum_{i=1}^{N} t_i(\text{N,T}) \tag{7}$$

where t_i(N,T) examines the t statistics in CADF-based regression.

3.2.3 | Panel cointegration test

The empirical discussion in the extant literature has applied a different set of panel cointegration methods, for example, the popularly used Pedroni method on cointegration. Nevertheless, this study applies the Westerlund method of cointegration postulated by Persyn and Westerlund (2008). There are distinct advantages in the application of this method of cointegration in panel estimation. The Westerlund method describes four tests on structural cointegration which are based on the normal distribution. Across these four tests, two exhibit error correction in the individual specification, and the other two exhibit error correction in the entire panel. Distinct from the earlier cointegration tests, Persyn and Westerlund (2008) take into consideration the problems associated with cross-sectional related dependencies. The null hypothesis under Westerlund cointegration assumes the existence of no cointegration amid cross-section specification and across the whole panel. Thus, the null hypothesis surmises under the conditional based error term reduces to zero. Equation (8) describes the Westerlund error correction-based panel cointegration technique as specified by Persyn and Westerlund (2008):

$$\Delta y_{it} = \delta_i' d_t + \alpha_i y_{i,t-1} + \lambda_i' x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij}\Delta y_{i,t-j} + \sum_{j=q_i}^{p_i} \gamma_{ij}\Delta x_{i,t-j} + \varepsilon_{it} \tag{8}$$

Here, y denotes the dependent variable and x the explanatory variables for i = 1,2 …N (cross-section units) and t = 1,2 …T (time); d_t is the deterministic component; ε is the usual error related term. According to the specification by Persyn and Westerlund (2008), y_{it} *and* $x_{i,t}$ have cointegrating behaviour if $\alpha_i < 0$; this explains the conditionality related to the error correction; if $\alpha_i = 0$, then the underlying observations shows no cointegration.

3.2.4 | Long-run elasticities estimation

After obtaining cointegrating association across the variables, the subsequent step is to estimate the long-run relations. This study applies two methodologies, specifically the OLS with Driscoll–Kraay standard errors, and SGMM. These methods take into consideration problems of serial correlation and endogeneity through various approaches.

Our study uses the GMM estimation technique (Arellano & Bond, 1991; Blundell & Bond, 1998) to explore the impact of biomass energy and economic complexity in the presence of major controls on the concerned dependent pollution variables. The SGMM has wide-ranging application in the related literature on environment studies (Nguyen et al., 2021; Ullah et al., 2018). Equation (9) makes a brief exposition of the SGMM specification:

$$Y_{it} = \gamma_1 \Lambda_{it} + \gamma_2 \Theta_{it} + \vartheta_i + \varepsilon_{it} \tag{9}$$

Here, i = 1,2 …N; specifies the cross-section units; t = 1,2 …T is the time dimension; Y_{it} is the dependent variable; Θ explains the predetermined covariates; Λ describes the exogenous covariates, respectively; ϑ stands for the unobserved group effect, and ε is the usual error term. The SGMM is unique in addressing major sources of endogeneity including dynamic endogeneity, simultaneity and the un-observed related heterogeneity (Nguyen et al., 2021; Ullah et al., 2018). Precisely, the use of instruments corrects the endogeneity suitably. Based on diagnostic tests, for example, the first- and second-order AR (1) and AR (2), respectively, our study validates the robustness of the approach.

3.3 | Robustness of estimation

Our study is pioneering the use of the Canay (2011) technique for studying the environment-innovation nexus. It is the appropriate technique for our question for two main reasons. First, it uses a fixed effect and therefore captures the unobserved heterogeneities among the provinces and the sectors. Second, it uses a two-stage regression, which mitigates endogeneity. The quantile regression technique was introduced in the seminal paper by Koenker and Bassett (1978). The conditional quantile model presented by Canay (2011) can be summarized as follows:

$$Y_{it} = X_{it}'\beta(\tau) + \alpha_{i\tau} + \varepsilon_{it\tau}, \tag{10}$$

where

$$\varepsilon_{it\tau} = X_{it}'(\beta(U_{it}) - \beta(\tau)) \text{ and} \tag{11}$$

$$\varepsilon_{it\tau} = X_{it}'(\beta(U_{it}) - \beta(\tau)). \tag{12}$$

Then,

$$Y_{it} = X_{it}'\beta(U_{it}) + \alpha_i, \tag{13}$$

where Y_{it} is an observable explained variable, X_{it}' is a vector of explanatory variables for country i at time t; t = 1 …, T; i = 1, …, n, the vector

X'_{it} is supposed to contain a constant term, (U_{it}, α_i) are unobservable, and $U_{it} \rightsquigarrow U[0,1]$. is an unknown parameter; the function $\tau \mapsto X'\beta(\tau)$ is assumed to be strictly increasing in $\tau \in (0.1)$, and the parameter of interest is presumed to be $\beta(\tau)$.

4 | EMPIRICAL RESULTS AND DISCUSSION

4.1 | Preliminary tests

With macroeconomic variables and panel data, the cross-sectional dependence could be an issue and could mislead our empirical results. Therefore, Table 5 reports the results of the cross-sectional dependence. Based on Pesaran (2015), the null hypothesis is that there is no cross-sectional dependence. It is clear that we reject the null hypothesis (Table 5). For further robustness, we apply several CD tests. The results of these tests are reported in Table 6.

We perform panel root unit tests (second generation) to avoid producing spurious regressions. The second generation-panel root test (Pesaran, 2007), also known as the CIPS test, is reported in Table 7. The second-generation unit root test is best suitable in comparison to traditional unit root tests because it considers cross-sectional dependence and heterogeneity among the series. Table 7 confirmed the stationarity of the variables at the first difference, and no variable is stationary at second difference.

TABLE 7 Panel unit root test results

Variables	CIPS test	CADF test
CO_2	−4.191***	−3.417***
ΔCO_2	−6.080***	−6.768***
EF	−2.670***	−3.847***
ΔEF	−5.240***	−5.493***
CF	−1.968	−1.339*
ΔCF	−5.233***	−5.167***
BIOMASS	−2.533	−2.997***
Δ BIOMASS	−5.589***	−5.340***
ECI	−1.875	2.080
ΔECI	−5.031***	−3.607***
GLOB	−2.728***	−1.780***
ΔGLOB	−5.326***	−5.193***
BQ	0.383	6.656
ΔBQ	−0.684*	4.950*
NAT	−2.349	−0.790
ΔNAT	−4.521***	−4.240***
GDP	−1.748	0.721
ΔGDP	−3.927***	−2.203***

***Denotes statistical significance at 1%.
**Denotes statistical significance a 5%.
*Denotes statistical significance at 10%.

TABLE 5 Cross-sectional dependence empirics (Pesaran, 2015)

Variable	CD test	*p* value	Average joint	Mean ρ	Mean abs(ρ)
CO_2	8.478***	.000	29.000	0.340	0.400
EF	6.968***	.000	29.000	0.280	0.420
CF	7.822***	.000	29.000	0.320	0.450
BIOMASS	11.538***	.000	29.000	0.470	0.530
ECI	19.187***	.000	29.000	0.780	0.780
GLOB	22.464***	.000	29.000	0.910	0.910
BQ	0.251	.802	29	0.01	0.08
NAT	9.420***	.000	29.000	0.380	0.430
GDP	23.204***	.000	29.000	0.940	0.940

Note: Under the null hypothesis of cross-section independence CD ∼ $N(0,1)$.
****p* < .01. ***p* < .05. **p* < .1.

TABLE 6 Cross-sectional dependence findings

	CD-test on preferred models					
	Model-1		Model-2		Model-3	
CD tests	CD statistic	*p* value	CD statistic	*P* value	CD statistic	*p* value
Pesaran (2004)	4.018***	.001	3.36***	.000	3.060**	.002
Frees (1995)	1.036*	.081	0.501*	.089	0.988*	.089
Friedman (1937)	58.42***	.000	45.58***	.000	51.054***	.000

Note: Under the null hypothesis of cross-section independence CD ∼ $N(0,1)$.
****p* < .01. ***p* < .05. **p* < .1.

The Pedroni Cointegration (1999) test is unsuitable as many crucial matters such as heteroscedasticity, serial correlation, systemic disruptions and cross-sector dependency of the countries or cross-sectional units are not discussed, whereas Westerlund (2007) is an advanced test of cointegration as all of these problems are resolved. The previous studies ignore the serious issue of cross-sectional dependence and structural breaks that leads to bias in the findings. Westerlund (2007) introduced the cointegration test that covers the aforesaid issues.

To check the cointegration among the variables, we employed the xtwest command on STATA for Westerlund cointegration. The results of Table 8 confirm the evidence of long-run cointegration among the variables which is used in the study because the probability values of Gt, Ga, Pt and Pa of the (Persyn & Westerlund, 2008) cointegration tests are lower than 0.05. This allows us to reject the null hypothesis of no cointegration.

4.2 | Panel regression analysis

4.2.1 | Core estimations

Effect of biomass on environmental degradation: G7 countries

We obtain the long-run estimation of the underlying coefficients after validating the cointegration results. Both pooled OLS with Driscoll–Kraay standard errors estimation and SGMM methods estimation are used. Table 9 presents the long-run estimation of coefficients under both the estimation procedures. In general, the two methods yield consistent estimation.

A 1% rise in biomass leads to a rise in the carbon emissions by 0.59% (Model 1) (Driscoll–Kraay Estimation), and as per the SGMM method, the levels of carbon emission is 0.71% (Model 1), respectively. A 1% rise in biomass leads to a rise in the EF by 0.86% (Driscoll–Kraay estimation) and 0.95% (SGMM method), respectively (Model 2). Again, a 1% rise in biomass leads to a rise in the CF by 0.66% (Driscoll–Kraay estimation) and 0.74% (SGMM) (Model 3). According to out Hypothesis 1, these findings indicate that biomass is not being used sustainably in the G7 economies.

The results are consistently significant to 1% level under all model specifications. Our findings conform to the study by Mahmood et al. (2019) but are contrary to the works by (Danish & Ulucak, 2020; Danish & Wang, 2019). The rise in use of biomass-based energy can eventually lead to the replacement of energy based on fossil fuels (Danish & Ulucak, 2020). However, our study describes that the favorable impact of the use of biomass energy is not enough to offset the negative effects on the environment for the G7 countries. Thus, the results add to the empirical literature that the impact of biomass energy use on the environment continues to be debatable (Danish & Ulucak, 2020; Danish & Wang, 2019) and caution is needed in stimulating their use. The empirical outcome of the current research describes that energy based on biomass is degrading the environment for the G7 countries. The studies by Destek et al. (2018) and Shahbaz et al. (2019) argue that farming of energy-based crops creates major environmental complications like deforestation, loss of soil quality and competition for land on alternate uses. Further, the combustion practices from the harvest of biomass have a detrimental impact on the environment. So, there is an urgent need to reduce biomass energy use for the G7 countries to augment the environment's welfare (Bilgili & Ozturk, 2015; Destek et al., 2018).

Effect of economic complexity on environmental degradation: G7 countries

The impact of Economic Complexity Index is positive and significant under both the estimation process, which is not in line with our Hypothesis 2. In particular, a 1% rise in ECI leads to a rise in carbon emissions by 0.52% (Driscoll–Kraay estimation) and 0.22% (SGMM estimation) (Model 1). Again, a 1% rise in ECI leads to a rise in the EF by 0.25% (Driscoll–Kraay estimation) and 0.17% (SGMM methods of estimation) (Model 2). Further, under Model 3, a 1% rise in ECI leads to a rise in the CF by 0.36% (Driscoll–Kraay estimation) and 0.20% (SGMM method), respectively. Precisely, based on the empirical outcomes of this study, a positive relationship is obtained between economic complexity and carbon emissions, EF and the CF across the three model specifications. Our results are in conformity with the study by Shahzad et al. (2021) and Yilanci & Pata (2020). Our findings indicate that the complexity of export/import product specialization has led to a degradation of the environment explained through the varying proxies.

As described by the study by Neagu (2019), economic complexity depicts a country's production specialization and the structure of the

TABLE 8 Panel cointegration empirics

Westerlund test	Model-1 (Z-statistic)	Model-2 (Z-statistic)	Model-3 (Z-statistic)
Gt	−3.134***	0.534*	0.769*
Ga	3.125	3.741*	4.421*
Pt	−70.502***	1.370**	3.342***
Pa	−31.426***	1.616	0.908

Note: Models are employed as per our three specified specifications. Gt and Ga denote long-term association, while Pt and Pa denote short-term cointegrations. Cointegration is tested with 6 covariates, as constant and trend.

***Denotes statistical significance at 1%.

**Denotes statistical significance at 5%.

*Denotes statistical significance at 10%.

TABLE 9 Empirics for Driscoll–Kraay estimation and SGMM methods

	Pooled OLS with Driscoll–Kraay standard errors			GMM with fixed effects		
Variables	Model-1	Model-2	Model-3	Model-1	Model-2	Model-3
BIOMASS	0.599*** (0.214)	0.868*** (0.098)	0.665*** (0.130)	0.719*** (−19.57)	0.955*** (−48.260)	0.748*** (−33.91)
ECI	0.520* (0.295)	0.259* (0.135)	0.364** (0.179)	0.226*** (−4.49)	0.171*** (−6.300)	0.203*** (−6.700)
GLOB	−0.417* (0.222)	−0.363*** (0.102)	−0.280** (0.135)	−0.527*** (−13.59)	−0.435*** (−20.84)	−0.409*** (−17.58)
BQ	6.912 (8.671)	−7.279* (3.980)	−2.281 (5.255)	11.66*** (−7.88)	−5.589*** (−7.01)	−0.0144 (−0.02)
NAT	0.263*** (0.056)	0.134*** (0.026)	0.163*** (0.034)	0.201*** -20.96	0.116*** (−22.51)	0.134*** (−23.320)
GDP	0.528** (0.226)	0.149 (0.104)	0.439*** (0.137)	0.391*** (−10.12)	0.0543** (−2.610)	0.348*** (−15.02)
Constant	−12.401*** (2.978)	0.047 (1.367)	−5.272*** (1.805)	−10.45*** (−20.71)	1.316*** (−4.84)	−3.789*** (−12.51)
Observations	203	203	203	203	203	203
R^2/Wald Chi^2	0.828	0.766	0.799	1694.93	1683.30	1764.44
AR2	-	-	-	0.061	0.327	0.063
Sargan test	-	-	-	0.677	0.512	0.061

Note: Model-1 is estimated with carbon emissions, Model-2 shows the ecological footprint and Model-3 is for carbon footprint. AR1 *p values* for the Arellano–Bond test for first-order serial autocorrelation. The system GMM is applied as forwarding different instrumental variables with country fixed effects and year fixed effects. *Z*-statistic values are shown in parentheses.

***Shows the significance level at 1%.

**Shows the significance level at 5%.

*Shows the significance level at 10%.

manufacturing sector to earn competitiveness in the international trade sector. The results from this empirical exercise corroborate the description that in specific stages, the complexity of economic structure is harmful to the environment (Destek & Sinha, 2020). Specific levels of product structure led to specific energy consumption, which affects biomass and NAT resources and has the ultimate influence on the environment through emissions and EF. To understand our findings, in light of our Hypothesis 2, we need to consider that the G7 economies are the innovation leaders in the world. Thus, within these highly economic complex groups of counties, being more complex can be detrimental to the environment. The results suggest that the set of G7 economies need to transfer the processes of economic complexity to a level of efficiency in resource use where complexity in production is embedded in technological sophistication. Such structural shifts may lead to innovations and efficiency in resource use, generating climate benefits.

Effect of additional control variables: G7 countries

For the coefficients of globalization, the findings reveal a negative relationship for both the estimation processes namely the Driscoll–Kraay estimation and SGMM estimation across all three model specifications. Table 9 shows the pooled OLS and system GMM empirical findings. The results describe the environment welfare augmenting impact of globalization for the G7 countries. The findings of the current study confirm the results obtained by Destek and Sinha (2020) for the OECD countries but are contrary to the study by Danish (2019) for the group of BRICS nations and Danish U (2020) for China. Our results from the empirical estimation lend support to the 'Pollution Haven Hypothesis' for the G7 nations from the perspective of globalization.

As far as the impact of bureaucratic quality on the environment level is concerned, it is positive for carbon emissions under the GMM estimation, but insignificant under the Driscoll–Kraay estimation process. The impact of bureaucratic quality is significant and negative on EF under the two estimation techniques. A 1% rise in bureaucratic quality leads to a decline in the EF by 7.27% (Driscoll–Kraay estimation) and 5.58% (SGMM estimation), respectively. Our findings imply that bureaucratic quality improves the environment for the G7 nations proxied through the indicator on EF. This empirical evidence is similar to that of Shahbaz et al. (2019). The discussion in the earlier literature reports that enhanced bureaucratic quality and institutions help develop stringent laws that reduce the exploitation of the NAT resources and enhance the quality of the environment.

Economic growth expressed by GDP significantly raises the carbon emissions, EF (under SGMM method) and CF under the three alternative model specifications. We conclude that growth of the economy would augment the degradation of the environment for the G7 nations, which is also described in the extant literature, for example Danish and Wang (2019) and Mahmood et al. (2019). Finally, our results report a significant positive impact of NAT resource use on the levels of environmental degradation under three model specifications. These results imply that the extraction of the NAT resources for the G7 nations leads to the rise in CO_2 and degradation of the ecosystem. Danish and Wang (2019) and Wang et al. (2019) also confirmed similar findings. The rise in the levels of extraction may expand economic growth, but it is detrimental for the environment. Precisely, our results suggest that NAT resources and biomass loss are the major reasons for EF and carbon emissions for the G7 nations.

4.2.2 | Robustness check

To make sure that our empirical results are robust, we have applied the panel quantile regression. Fixed-effect panel quantile was developed by Canay (2011). The quantile estimations are robust to the outlying observations of the dependent variable and are more effective than the OLS regression, especially when the error term is not normally distributed. The robust results would aid policymakers in formulating more precise energy demand management and environmental protection policies. Canay (2011) proposed the two-step quantile regression. The key advantage of a quantile estimation to the OLS estimator is that the quantile regression estimates are robust in the presence of outliers and heavy-tailed distributions. Standard OLS regression estimators are not robust even for modest departures from the normal distribution. Another advantage is that while a conventional regression focuses on the mean, quantile regressions can describe the entire conditional distribution of the dependent variable (Albulescu et al., 2019).

The main results of PQFE regression are reported in Tables 10–12. These tables provide support for the above estimations. It is noted that biomass energy consumption has a significant and positive effect on the measures of environmental degradation (CO_2 emissions, EF, CF). It is worth mentioning that the impact of biomass is high on pollution when it is measured by carbon emission compared with other proxies. The CO_2 emission increase by about 0.6% when biomass energy consumption increases by 1%. The magnitude of biomass coefficient increases at higher quantiles for all used proxies.

5 | DISCUSSION OF FINDINGS

The key result of this study is that biomass consumption leads to more CO_2 emissions in the G7 economies. These empirical results are contrary to the common outcomes of past papers about the positive impact of bioenergy on the environment (improving the quality of the environment). Only a few studies found that the consumption of bioenergy leads to higher CO_2 emissions and environmental degradation. Our study is in line with Adewuyi and Awodumi (2017), Sinha et al. (2017) and Shahbaz et al. (2019).

The European region, in particular, in the United Kingdom (one of the G7 countries), depends mainly on burning wood as a key source of the electricity sector. It is also the main renewable source of energy in the United Kingdom. Despite being considered a renewable resource, our findings indicate that caution needs to be taken by using

TABLE 10 Canay (2011) panel quantile regression: Pollution proxied by CO_2

	(1)	(2)	(3)	(4)	(5)
VARIABLES	0.10	0.20	0.30	0.40	0.5
Ln (BIOMASS)	0.5779*** (0.0263)	0.5480*** (0.0333)	0.5001*** (0.0277)	0.5168*** (0.0302)	0.5211*** (0.0264)
ECI	0.4158*** (0.0541)	0.2483** (0.1120)	0.1446 (0.0945)	0.1537* (0.0817)	0.0737 (0.0707)
GLOB	0.3050*** (0.0220)	0.2771*** (0.0420)	0.2517*** (0.0432)	0.2335*** (0.0425)	0.1694*** (0.0315)
BQ	2.0442 (3.9917)	2.4602 (3.4770)	1.5423 (2.4594)	1.7292 (1.8754)	2.5691 (1.7023)
NAT	0.0481*** (0.0150)	0.0424*** (0.0148)	0.0357** (0.0168)	0.0461*** (0.0147)	0.0377*** (0.0102)
GDP	−0.4105*** (0.0293)	−0.4107*** (0.0327)	−0.3681*** (0.0299)	−0.3974*** (0.0326)	−0.4163*** (0.0282)
Constant	12.3410*** (0.3717)	13.1320*** (0.4348)	13.0483*** (0.4706)	13.6383*** (0.4824)	14.3756*** (0.3812)
Observations	203	203	203	203	203

Note: Robust standard errors in parentheses.
***$p < .01$.
**$p < .05$.
*$p < .1$.

TABLE 10 (Continued)

	(6)	(7)	(8)	(9)	(10)
VARIABLES	0.60	0.70	0.80	0.90	0.95
Ln (BIOMASS)	0.4955*** (0.0271)	0.5022*** (0.0382)	0.5540*** (0.0340)	0.5525*** (0.0164)	0.5831*** (0.0176)
ECI	0.0263 (0.0654)	−0.0196 (0.0748)	−0.0284 (0.0453)	−0.0102 (0.0127)	0.0032 (0.0337)
GLOB	0.1773*** (0.0306)	0.1752*** (0.0528)	0.1103** (0.0510)	−0.0111 (0.0410)	−0.0676*** (0.0225)
BQ	2.2325 (1.6590)	2.5345* (1.4630)	4.4049*** (0.9384)	5.4149*** (0.6921)	6.1302*** (0.7103)
NAT	0.0327*** (0.0069)	0.0256*** (0.0090)	0.0161 (0.0104)	0.0077 (0.0068)	0.0098 (0.0081)
GDP	−0.3918*** (0.0297)	−0.4023*** (0.0433)	−0.4766*** (0.0382)	−0.4928*** (0.0232)	−0.5398*** (0.0213)
Constant	14.1874*** (0.3856)	14.3872*** (0.6185)	15.7219*** (0.5814)	16.7060*** (0.5037)	17.6633*** (0.3017)
Observations	203	203	203	203	203

Note: Robust standard errors in parentheses.
***$p < .01$.
**$p < .05$.
*$p < .1$.

TABLE 11 Canay (2011) panel quantile regression: Pollution proxied by CF

	(1)	(2)	(3)	(4)	(5)
VARIABLES	0.10	0.20	0.30	0.40	0.5
Ln (BIOMASS)	0.4918*** (0.0396)	0.4750*** (0.0380)	0.4371*** (0.0298)	0.4245*** (0.0328)	0.3944*** (0.0382)
ECI	0.3466*** (0.0949)	0.2092* (0.1145)	0.1372 (0.1169)	−0.0092 (0.1183)	−0.1772 (0.1256)
GLOB	0.0246 (0.0448)	−0.0198 (0.0511)	−0.0634 (0.0439)	−0.1007*** (0.0358)	−0.1240*** (0.0319)
BQ	−7.0647** (2.7580)	−6.7886** (3.3699)	−7.8291** (3.4068)	−6.8835** (2.7784)	−5.5285** (2.5316)
NAT	0.0828*** (0.0167)	0.0749*** (0.0214)	0.0853*** (0.0218)	0.0755*** (0.0195)	0.0661*** (0.0165)
GDP	−0.1664*** (0.0435)	−0.1747*** (0.0359)	−0.1536*** (0.0308)	−0.1523*** (0.0288)	−0.1228*** (0.0352)
Constant	14.4949*** (0.5705)	15.3219*** (0.5020)	15.7254*** (0.4837)	16.1266*** (0.4164)	15.9946*** (0.4187)
Observations	203	203	203	203	203

Note: Robust standard errors in parentheses.
***$p < .01$.
**$p < .05$.
*$p < 0.1$.

TABLE 11 (Continued)

	(6)	(7)	(8)	(9)	(10)
VARIABLES	0.60	0.70	0.80	0.90	0.95
Ln (BIOMASS)	0.3784*** (0.0385)	0.3755*** (0.0322)	0.4192*** (0.0306)	0.4602*** (0.0413)	0.5396*** (0.0378)
ECI	−0.1793** (0.0800)	−0.2184*** (0.0562)	−0.2083*** (0.0433)	−0.2161*** (0.0515)	−0.1837*** (0.0396)
GLOB	−0.0748** (0.0315)	−0.0551** (0.0253)	−0.0312 (0.0240)	−0.0059 (0.0438)	0.0156 (0.0334)
BQ	−5.2875*** (1.5942)	−4.5915*** (1.6703)	−2.9044** (1.4436)	−1.6910 (1.7173)	−0.3950 (1.8809)
NAT	0.0694*** (0.0129)	0.0670*** (0.0084)	0.0612*** (0.0055)	0.0473*** (0.0095)	0.0377*** (0.0075)
GDP	−0.0898** (0.0386)	−0.0858** (0.0346)	−0.1415*** (0.0358)	−0.2002*** (0.0502)	−0.3010*** (0.0403)
Constant	15.1720*** (0.4619)	15.0379*** (0.4105)	15.6325*** (0.4165)	16.3971*** (0.6183)	17.6163*** (0.5291)
Observations	203	203	203	203	203

Note: Robust standard errors in parentheses.
***$p < .01$.
**$p < .05$.
*$p < 0.1$.

TABLE 12 Canay (2011) panel quantile regression: Pollution proxied by EF

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	0.10	0.20	0.30	0.40	0.5	0.60	0.70	0.80	0.90	0.95
Ln	0.4986***	0.4461***	0.4746***	0.4544***	0.4372***	0.4729***	0.5007***	0.4873***	0.4868***	0.4969***
(BIOMASS)	(0.0314)	(0.0259)	(0.0210)	(0.0216)	(0.0277)	(0.0288)	(0.0216)	(0.0190)	(0.0286)	(0.0510)
ECI	0.2561***	0.1467*	0.1000	−0.0023	−0.0429	−0.0616	−0.0678**	−0.0593**	−0.0877**	−0.0930*
	(0.0930)	(0.0783)	(0.0821)	(0.0698)	(0.0670)	(0.0558)	(0.0331)	(0.0288)	(0.0413)	(0.0559)
GLOB	−0.1578***	−0.1697***	−0.2153***	−0.2351***	−0.2278***	−0.2400***	−0.2317***	−0.2063***	−0.1828***	−0.1647**
	(0.0379)	(0.0398)	(0.0302)	(0.0184)	(0.0269)	(0.0273)	(0.0198)	(0.0124)	(0.0250)	(0.0671)
BQ	−2.8162	−2.8761	−3.2109	−5.4485**	−5.0210***	−4.1842***	−3.6964***	−2.6057***	−1.9260	−1.3667
	(1.7657)	(2.2809)	(3.0561)	(2.1076)	(1.3573)	(1.0423)	(0.7469)	(0.8868)	(1.4240)	(1.6844)
NAT	0.0563***	0.0569***	0.0578***	0.0563***	0.0530***	0.0532***	0.0500***	0.0458***	0.0407***	0.0392***
	(0.0171)	(0.0150)	(0.0136)	(0.0097)	(0.0105)	(0.0084)	(0.0039)	(0.0038)	(0.0056)	(0.0100)
GDP	−0.1842***	−0.1510***	−0.1969***	−0.1750***	−0.1619***	−0.1971***	−0.2226***	−0.2128***	−0.2093***	−0.2290***
	(0.0310)	(0.0289)	(0.0198)	(0.0188)	(0.0273)	(0.0299)	(0.0232)	(0.0185)	(0.0332)	(0.0696)
Constant	15.9494***	16.1509***	17.1414***	17.1245***	17.0665***	17.4151***	17.5571***	17.4122***	17.2256***	17.5142***
	(0.4836)	(0.4395)	(0.2845)	(0.2374)	(0.3271)	(0.3886)	(0.2915)	(0.1774)	(0.3912)	(1.0970)
Observations	203	203	203	203	203	203	203	203	203	203

Note: Robust standard errors in parentheses.
***$p < .01$. **$p < .05$. *$p < .1$.

biomass energy. BEIS Provisional UK greenhouse gas emissions national statistics (2021) shows a declining trend in greenhouse gas emissions in the United Kingdom since the 1990s. Part of it is attributed to the increase in renewable energy. This contradicts our findings, and more research is needed to understand the different channels through which biomass energy could be having a negative impact on the environment.

In general, the G7 nations have made considerable progress as far as the attainment of sustainable development goals is concerned. However, our empirical outcomes demonstrate that these countries are still unable to cope with the environmental problems of poor air quality, rising emissions and decline in the ecological balance. All G7 countries have a negative EF except for Canada (Nathaniel et al., 2021). The G7 countries must mitigate the problems of environmental degradation associated with biomass production by applying advanced environmental-friendly technology. The thrust of emphasis should be towards research and development in biomass and energy conservation.

6 | CONCLUDING REMARKS AND IMPLICATIONS FOR SUSTAINABILITY

The current empirical research scrutinizes the interrelationships between biomass energy use and environmental degradation for the G7 nations from 1990 to 2019 in the presence of major regressors like economic complexity, natural resource rent, GDP, bureaucratic quality and globalization. This study has used three major indicators of environmental degradation: (i) carbon emissions; (ii) EF (consumption); and (iii) CF (consumption). In doing so, we employed second-generation panel estimation methods to explore the underlying nexus amid environment degradation and biomass energy use like cross sectional dependence test, second generation panel unit root tests and Westerlund panel cointegration. For the estimation of long run elasticities, the study has applied the OLS with Driscoll–Kraay standard errors and the SGMM. Further, the robustness of model specification is explored by applying the panel quantile methods (Canay, 2011). The results report the positive impact of biomass on carbon emissions, EF and CF. This implies that biomass energy production has detrimental environmental impact for the G7 nations. In addition, our empirical results demonstrate that NAT resources, economic growth and economic complexity dilapidate the environment; however, the impact of globalization is environment welfare augmenting.

Based on our empirical outcomes, this study suggests some policy implications for sustainability in the context of the G7 countries. Although, biomass energy sources are considered as cleaner and renewable; however, the findings of the current study are in contrast and novel. The empirical findings allow us to conclude that biomass energy sources may not always act as greener energy sources, and it might depend on the process of bioenergy generation. Though biomass is the driver for expansion of energy use in these countries, it is destroying the environment. Therefore, these countries urgently need to devise strategies to reduce biomass energy use which in the long run will augment the quality of the environment. The governments in the G7 countries should increasingly focus attention on research and development towards alternative sources of energy which augment the welfare of the environment based on the use of renewables. Since globalization in the G7 countries is environment welfare augmenting, these countries can mitigate the problems of carbon emissions by imports instead of relying on biomass for domestic energy uses. Arguably, economic complexity has resulted in environmental degradation for the G7 countries. These countries need to encourage more innovation towards product specialization and structural transformation that would produce sophisticated products that are environment friendly. Economic complexity helps in product transformation which are energy efficient and less damaging for the environment. Research and innovation on product transformation to raise the complexity of the production process may accelerate the country's trajectory towards achieving sustainable development goals on clean climate change. The administrative machinery in these countries should devise strategies to support investment in the renewable sector. In this context, improvements in governance are a major factor because the results show that governance reduces the levels of environmental degradation.

A caveat of the present study is that our research does not include different forms of biomass energy use that may affect the environment and policies on energy structure and sustainable development. Future studies may explore the impacts of different forms of biomass energy use, particularly for other economies like the OECD or developing countries. Second future research direction could explore biomass energy use at household levels and the extent of environmental degradation associated with it. Indoor air pollution from biomass extraction has a harmful impact on air quality levels. These extensions of future research will suggest important climate welfare policies, particularly in the household context.

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CONFLICT OF INTEREST

Authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Umer Shahzad performed the data curation, methods, analysis, investigation and revision. Mohamed Elheddad performed the supervision, software, validation and discussion. Julia Swart performed the literature review, hypothesis, methodology and writing—original draft preparation. Sudeshna Ghosh performed the analysis, writing—reviewing and editing and Visualization. Buhari Dogan performed the conceptualization, results and discussion, writing draft and editing.

DATA AVAILABILITY STATEMENT

Data are available upon request from the corresponding author. Data can also be accessed from data sourced mentioned in manuscript.

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ENDNOTES

[1] This biophysical burden is quantified by adding the energy, the material consumption, the waste generation and the ecosystem productivity to estimate a total ecosystem area required to support economic activities.

[2] We plot GDP per capita to show the economic progress, as the economic complexity is an index data, which does not show many fluctuations.

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