Environmental Science and Pollution Research
https://doi.org/10.1007/s11356-023-26118-x

RESEARCH ARTICLE

Heterogeneous effects of energy consumption structure on ecological footprint

Emad Kazemzadeh[1] · **Mohammad Reza Lotfalipour**[1] · **Masoud Shirazi**[2,3] · **Ali Sargolzaie**[4]

Received: 22 May 2022 / Accepted: 21 February 2023

Abstract
Attention to environmental sustainability has increased among nations, especially after the Paris Agreement and COP26 of 2021. Considering that fossil fuel consumption is one of the main factors causing environmental degradation, altering the energy consumption patterns of nations toward clean energy can be a suitable solution. For this purpose, this study investigates the impact of energy consumption structure (ECS) on the ecological footprint from 1990 to 2017. This research includes three steps: First, the energy consumption structure is calculated using the Shannon–Wiener index. Second, from 64 countries with middle- and high-income levels, the club convergence method is used to identify countries with similar patterns in an ecological footprint over time. Third, using the method of moments quantile regression (MM-QR), we examined the effects of ECS in different quantiles. The results of club convergence show that the two groups of countries with 23 and 29 members have similar behavior over time. The results of the MM-QR model show that for club 1, the energy consumption structure in quantiles of 10th, 25th, and 50th has positive effects on the ecological footprint, while in 75th and 90th are negative. The results of club 2 indicate that the energy consumption structure has positive effects on the ecological footprint in quantiles 10th and 25th, but negative effects on 75th. Also, the results show that GDP, energy consumption, and population in both clubs have positive effects, and trade openness has negative effects on ecological footprint. Considering that the results indicate that changing the structure of energy consumption from fossil fuels to clean energies improves the environmental quality, so governments should use incentive policies and support packages for the development of clean energy and reduce the costs of installing renewable energy.

Keywords Ecological footprint · Shannon–Wiener index · MM-QR model · Club convergence · Environmental economics · Econometrics

Responsible Editor: Roula Inglesi-Lotz

✉ Mohammad Reza Lotfalipour
lotfalipour@um.ac.ir

Emad Kazemzadeh
Emad.kazemzadeh67@mail.um.ac.ir

Masoud Shirazi
masoud.shirazi@uc.pt

Ali Sargolzaie
ali.sargolzaie73@gmail.com

1 Department of Economics, Faculty of Economics and Administrative Sciences, Ferdowsi University of Mashhad, Mashhad, Iran

2 CeBER and Faculty of Economics, University of Coimbra, Coimbra, Portugal

3 Cyprus Institute of Marketing, Nicosia, Cyprus

4 Department of Economics, University of Sistan and Baluchestan, Zahedan, Iran

Introduction

Human and economic activities have a harmful impact on the environment. Specifically, due to demographic and economic transitions, the pollution mix has shifted from greenhouse gas emissions to solid waste and effluents, indicating that total waste remains high, and per capita pollution may not have declined (Sinha et al. 2020; Nathaniel and Khan 2020). As a very important environmental indicator, the ecological footprint is considered the sole metric for assessing the extent and utilization of nature. The ecological footprint is touted as a powerful tool for enhancing sustainability and well-being among nations; for optimizing public project investments by local leaders; and for individuals to comprehend their effect on the planet (Global Footprint Network 2022). About people's footprint on the planet, there are the differences between carbon footprints vs. ecological

Published online: 11 March 2023

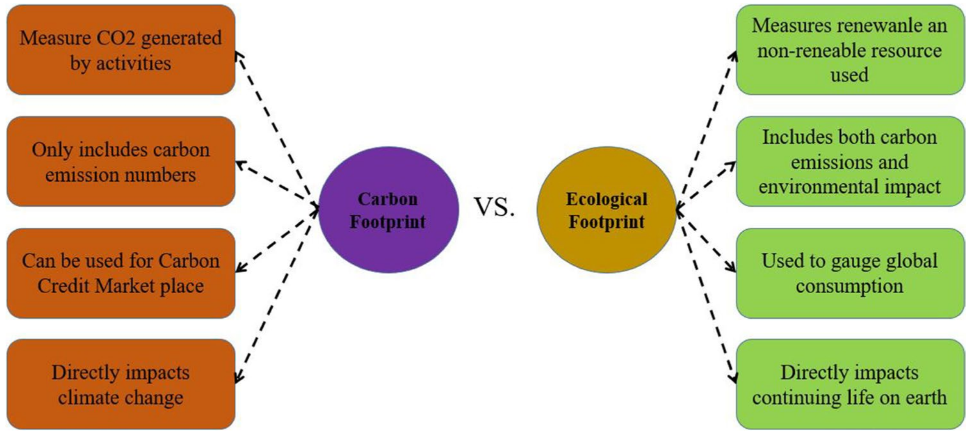


Fig. 1 Carbon footprint vs. ecological footprint (8 Billion Trees™ 2023)

footprints, which are presented in Fig. 1 (8 Billion Trees™ 2023).

In this respect, scholars point out that fossil fuel consumption is an affecting factor in economic growth and, also, a major cause of environmental degradation (Mealy and Teytelboym 2020; Hanif et al. 2019).[1] Besides, the role of new and renewable energy technologies in resource diversity, affordable energies, and ecological footprint (Weiss et al. 2021) has become strengthened in recent years (Sun and Ren 2021; Kazemzadeh et al. 2021; Ebrahimi Salari et al. 2021; Zafar et al. 2019). This process decreases fossil fuel usage and changes the structure of energy consumption (Sun and Ren 2021) and portfolio decisions of primary energy sources (Shirazi and Fuinhas 2023; Shirazi and Šimurina 2022; Shirazi et al. 2021; APERC 2007) throughout the energy systems, lowering environmental degradation.[2]

In order to mitigate environmental degradation and retain sustainability, the utilization of new and renewable energy sources should be enhanced. On the other hand, the countries considerably depend on using traditional energy sources to meet their national development goals and targets, which increases the level of ecological footprint. This issue calls for the need of advanced generation technologies and wide utilization in respect of new and renewable energy sources (Raghutla et al. 2022). However, it is necessary for both environmentalists and policymakers to understand the main determinants of environmental degradation and increasing ecological footprint (Sun and Wang 2022; Kutlar et al. 2021; Ahmed et al. 2021, among others). Therefore, to fill in the knowledge gap found throughout the existing literature, the motivation for a balanced growth of energy trilemma, e.g., energy security, energy equity, and environmental sustainability, can be facilitated through development of energy consumption structure (Shirazi and Fuinhas 2023; Shirazi 2022). Earlier articles have not yet explicitly studied all determinants of ecological footprint, especially through the context of diversification of primary energy demand within the energy systems. Hence, and to the best of the authors' knowledge, this is the first study to investigate the role of energy consumption structure from a broad perspective of environmental quality through concentration on the issue of ecological footprint. Accordingly, exploring the determinants of ecological footprint as a proxy for environmental quality expands the investigation of industrial activities, urbanization, the adverse effects of human activities, and portfolio decisions of primary energy sources through the energy systems (Destek and Sinha 2020; Danish 2019; Ulucak and Lin 2017). Keeping this motivation in mind, this research utilizes the panel method of moments quantile regression and aims to assess the impact of energy consumption structure (ECS) and controlling variables, e.g., gross domestic product (GDP), total energy consumption (TOTAL), industry value added (IND), foreign direct investment (FDI), population (POP), and trade openness (TO) on the conditional quantiles of the ecological footprint (EFP) across multi-groups of economies with similar EFP behaviors throughout 64 middle-income countries over time. The significant findings via diverse quantiles provide different policy instructions that are suggested helping these countries to adopt comprehensive dynamic energy policies, develop their energy systems, and, therefore, cause sustainable economic development. It is worthy to be noted that the world's middle-income economies are a diverse group of countries by income level, size, and population. They are classified as lower middle-income economies—those with a gross national income per capita between $1036

[1] The International Energy Agency (IEA 2018) reports that economic growth-related efforts and carbon-based fuel portfolio have contributed to intensifying ecological footprint in both developing and developed countries.

[2] As a consequence of technological advancements, enforcement of environmental terms, and regulations and environmental sustainability, the level of environmental pollution against economic output has declined in developed countries (Shahzad 2020; Golpîra et al. 2018).

and $4045; and upper middle-income economies—those with a gross national income per capita between $4046 and $12,535 (World Bank 2021). Middle-income economies encompass 75% of the world's population and 62% of the world's poor. Simultaneously, middle-income countries represent about $\frac{1}{3}$ of global gross domestic product and are major driving forces of global growth.

Particularly, this study significantly considers ecological footprint (EFP) as a major indicator of environmental quality, which mainly relates to resource utilization. The ecological footprint, presented by Rees (1992), indicates the regeneration of biological capacity, which is required for economic activities including resource consumption and commodity production. EFP is introduced as a comprehensive indicator of environmental quality, which has been widely applied throughout literature, related to pollution and the environment (Nathaniel and Khan 2020; Destek and Sinha 2020; Fakher 2019; Ulucak and Lin 2017, among others).[3]Specifically, the EFP refers to the effects of economic and non-economic activities on environmental quality (Nathaniel and Khan 2020). The EFP provides a wide variety of climate and environment-related information through an indicator and contributes to the comprehensive policy implications to reduce the environmental negative externalities, especially for the developed economies (Danish 2019; Ulucak and Lin 2017).

Generally, the emerging and developed economies use more volumes of natural resources to pursue economic activities in the sort of forest resources, water, minerals, oil, and coal. The large consumption of energy sources further damages the environmental quality and leads to EFP (Destek and Sinha 2020). Although pieces of articles take the ratio of coal consumption as the proxy of ECS to investigate the impact of ECS on environmental quality, the use of the Shannon–Wiener index to measure ECS corrects the deviation created through using the former index. So, it is more rigorous and accurate to use the Shannon–Wiener index in reflecting the nexus between EFP and ECS. This indicator is widely used in the biological literature to measure the diversification of the ecosystem (Sun and Ren 2021). Accordingly, and as a determinant of EFP, the ECS, which refers to a diversification of primary energy demand (DPED), balances the energy mix to satisfy the equitability of energy resources.[4] Specifically, if ECS decreases, the country becomes dependent on one primary energy source. On the other hand, higher values of ECS indicate that the economy's energy consumption sources are equally distributed among the major primary energy sources, which reflects the economy's success in switching from fossil fuels and nuclear energy toward new and renewable energy sources. Thus, a markedly potential offset to lower EFP of the country's energy systems is concluded as a higher indicator's value is assessed. The benefits of DPED can be achieved as the energy sources would be substituted in the energy mix supported through the resource availability and negative correlations among resource prices (Costello 2007). Therefore, the optimization of ECS may be the major measure of environmental quality promotion. In this regard, the contribution of energy system transition toward new and renewable energy sources reduces the usage of fossil fuels and, also, the environmental degradation. Hence, the determining role of the optimized structure of energy consumption can be continued as one of the main driving forces for future sustainable development (Shirazi 2022; Sun and Ren 2021).

Accordingly, this article contributes to environmental literature in respect of resource diversity in multi-fold steps presented as follows:

First, the ECS is introduced in this study as the primary determinant of environmental quality, which balances the energy mix to satisfy the DPED. Based on APERC (2007),[5]the Shannon–Wiener index is modified in this paper to measure the ECS, which exhibits equitability dimension of the resource diversification throughout the energy systems. The existing studies are inconclusive regarding the portfolio decisions of primary energy sources: The present article is the pioneer to provide structural findings regarding the effect of ECS on the issue of EFP. Resource diversification is closely related to structural transformations in the energy sector: diversification from carbon-based resource portfolio and nuclear energy toward new and renewable energy sources (Sun and Ren 2021; Francés et al. 2013). Specifically, this paper reports the environmental externalities in respect of the DPED.

Second, this research shows the nexus among EFP, as the dependent variable, and ECS, and control variables, e.g., GDP, TOTAL, IND, FDI, POP, and TO, that are considered as the explanatory variables. The potential interdependence through the regression reports how the low, medium, and high quantiles of EFP are affected through the changes associated with the explanatory variables. The significant relationship via diverse quantiles provides different policy instructions to environmental scientists and policymakers. Accordingly, the research unveils novel outcomes regarding ECS and climate change.

[3] The productive area, e.g., land- and sea-based surfaces, absorbs the related waste it created through the existing infrastructure and technologies (Shahzad et al. 2021).

[4] ECS also leads to volatility reduction of energy prices, contributes to fuel price stability, and enhances the affordability and availability dimensions of energy security based on the prioritized objectives of the energy systems (Francés et al. 2013).

[5] Asia Pacific Energy Research Centre (2007).

Third, 64 countries across middle-income levels are selected using the club convergence model with a nonlinear time-varying factor proposed by Phillips and Sol (2009, 2007). Club convergence identifies multi-groups of countries with similar EFP behaviors over time. Therefore, the convergence behavior between selected countries is investigated to examine the effects of ECS on EFP over time. The results show that we have 2 main convergent groups with 23 and 29 members, respectively, throughout the applied sample.

In the next step and after exhibiting the abnormal distribution of data, the existence of cross-sectional dependence is analyzed to show the multilinearity of the variables (Belsley et al. 2005). Then, a long-run relationship between EFP and explanatory variables is satisfied to avoid spurious regression (Antonietti and Fontini 2019; Wang et al. 2018; Al-Mulali et al. 2015). In the following, the panel method of moments quantile regression (MM-QR) is applied, which relates to the "conditional heterogeneous covariance effects," to analyze how the explanatory variables affect the low, medium, and high quantiles of EFP (Sun et al. 2022; Wolde-Rufael and Mulat-Weldemeskel 2022; Machado and Silva 2019).

Lastly, this study reports innovative solutions and interesting conclusions related to the overall climate change issues. To do that, the results can lead to assessing major "sustainable development goals," e.g., sustainable economic growth, affordable and clean energy, and climate action. It is worthy to note that the current article seems to be the first research to release the role of ECS in mitigating EFP. The conclusions and empirical implications in respect of resource diversity, affordable energies, and ecological footprint can be contributed to the existing literature, providing road maps for the economies.

The remainder of this paper is organized as follows: The literature review is presented in the second section. The third section provides data and method. The fourth and fifth sections explain results and discussion, respectively. Finally, conclusions and policy implications are covered in the sixth section.

Literature review

A limited body of recent literature has attempted to explain the nexus between resource abundance and the environment. Sun and Ren (2021) use the "Shannon–Wiener diversity index" (SWI) to reflect resource abundance. They apply the "autoregressive distribution lag model" (ARDL) and find out resource abundance slows carbon emissions down from 1985 to 2016. Through the "augmented mean group estimation model," Langnel et al. (2021) show that the abundance of natural resources does not mitigate the environmental degradation in Nigeria and Cameroon. Ali et al. (2021) use the "Driscoll-Kraay algorithm method" and confirm a reduction in EFP due to switching to renewable energy consumption in all countries under consideration. Ahmadov and van der Borg (2019) combine a panel fixed-effects method for the European countries with a comparative qualitative approach of the Belgium and the Netherlands and find that overall resource abundance is conducive to the production of renewable energy within a country, while specified natural resource like petroleum is harmful. Consequently, the impact of ECS on EFP depends on the overall interaction between the sensitivity level of environmental quality to fossil fuels, nuclear energy, as well as new and renewable energy sources, which determines the net effect of ECS on EFP. Specifically, an increase in ECS reduces EFP if the marginal pollution of fossil fuels and nuclear energy is greater than new and renewable energy sources, and, of course, the opposite around is issued (Shirazi and Šimurina 2022; Sun and Ren 2021; Balsalobre-Lorente et al. 2018; Dinda 2004). Accordingly, the nexus among natural resources, e.g., coal, crude oil, natural gas, minerals, and forest, and the environmental quality is not an issue without controversy (Baloch et al. 2019).

Concerning the control variables, Ali et al. (2021) find that the EFP is increased in reaction to a positive change in GDP. Sun and Ren (2021) indicate that the "environment Kuznets curve (EKC) hypothesis" was not issued in China from 1985 to 2016. Hassan et al. (2019) apply the ARDL method with a structural break and reveal that GDP and biocapacity increase the EFP, contributing to environmental degradation. Zafar et al. (2019) employ the ARDL technique and show that higher levels of GDP increase the EFP. Also, urbanization and industrialization require more volume of input that leads to more natural resource usage in both consumption and production activities, which causes more natural resource extraction and more EFP (Sun and Ren 2021; Langnel et al. 2021; Ullah, et al. 2021; Ali et al. 2021; Zafar et al. 2019; Danish 2019).[6]Moreover, some scholars consider the destructive effect of FDI on environmental quality (Naz et al. 2019; Mert et al. 2019; Adams and Acheampong 2019; Waqih et al. 2019; Koçak and Şarkgüneşi 2018). It is noted that during the entire period under consideration, they find the nexus between FDI and environmental pollution has not followed linear and direct. By the initial stages, FDI contributes to

[6] International Resource Panel (2019) reports that the extraction and processing of natural resources account for approximately 50% of the world's greenhouse gas emissions. Further, the report notes that the resource-associated effects on water stress as well as biodiversity loss because of land use are considerable (Baloch et al. 2019).

increasing EFP, whereas the adoption of friendly advanced environmental technologies turns the relationship negative after achieving higher levels of FDI. The suggested non-linear relationship is introduced as the "Pollution Heaven Hypothesis[7]" in the environment-related literature. Furthermore, TO leads to more trade flow, i.e., a sum of import and export, of merchandise, which requires more fossil fuels to consume, produce, and transport that, in turn, causes more environmental degradation (Ben Jebli et al. 2019). In this way, an increase in EFP is reported in response to the higher levels of TO (Sun and Ren 2021; Ali et al. 2021; Irfan and Faisal 2021; Seetanah et al. 2019; Adams and Acheampong 2019; Raza and Shah 2018). Kutlar et al. (2021), in a study for MINT countries (Indonesia, Mexico, Turkey, Nigeria), examined the relationship between per capita income, energy consumption, and ecological footprint from 1976 to 2016. The authors found that, in the long run, higher energy consumption leads to an increased ecological footprint. Sun and Wang (2022), in a study of 17 cities in China's Yellow River Basin from 2005 to 2019, investigated urban development according to ecological constraints. The authors found that ecological well-being performance has a negative correlation with GDP per capita, urbanization rate, and energy consumption.

Conversely, urbanization is constructive for the environment when it associates with land use through a biological production process and positive externalities (Erdogan et al. 2020; Ulucak and Khan 2020). Urbanization is also related to research and development projects, innovation, and technological development that leads to environment-friendly production processes and techniques across urban areas (Erdogan et al. 2020).[8]Subsequently, a knowledge- and information-intensive society tends to decrease human demands from the environment and lower EFP. In this way, some investigations show that EFP lowers when human capital and urbanization increase (Langnel et al. 2021; Ulucak and Khan 2020; Zafar et al. 2019; Liobikienė and Butkus 2018). Also, Ali et al. (2021) find that urbanization in low-income and upper-middle countries reduces EFP, while it is increased in high-income economies. Moreover, some scholars exhibit that FDI is conducive to reducing concerns regarding EFP since it improves a country's capacity to use new and renewable energy technologies in the sectors of an economy (Yahaya et al. 2020; Zafar et al. 2019; Pan et al. 2019; Cheng et al. 2019; Khan et al. 2019). As the other major determinant, energy consumption can make the transition to EFP, and it has drawn the attention of scholars worldwide. In this regard, most of the studies argue that switching from the carbon-based fuel portfolio to clean sources reduces fossil fuel consumption and, hence, lowers EFP (Langnel et al. 2021; Shahzad et al. 2021; Ullah et al. 2021; Ebrahimi Salari et al. 2021; Nathaniel and Khan 2020; Zafar et al. 2020; Ahmed et al. 2020; Destek and Sinha 2020; Danish 2019; Alola et al. 2019; Ozcan et al. 2019; Li and Sun 2018; Ulucak and Lin 2017). Finally, some articles find that EFP decreases in response to the increase of TO (Ebrahimi Salari et al. 2021; Khan et al. 2019; Liobikienė and Butkus 2018; Destek et al. 2018; Jebli et al. 2016; Al-Mulali et al. 2015). This effect shows that free trade facilitates the technology transfer between countries, and cleaner technologies assessment reduces EFP. Ahmed et al. (2022a), in a study of India from 1984 to 2017, investigated the effects of financial risk and external conflicts on the ecological footprint. The authors found that financial risk reduces ecological footprint levels, while external conflicts have no effect on environmental quality. Ahmed et al. (2022b) found in a study for G7 countries that technological innovations and globalization reduce carbon dioxide emissions and increase the use of renewable energy. Ahmed et al. (2022c) in a study for the G7 countries from 1985 to 2017 found that economic growth increases the ecological footprint, while democracy and renewable energy consumption decrease that. Ahmed et al. (2022d) in a study for Pakistan from 1984 to 2017 evaluated the role of clean energy and democracy in ecological footprint. The authors found that clean energy and democracy reduce the ecological footprint. Ahmed et al. (2021) explored the asymmetric effects of globalization on ecological footprints in the USA. The long-term results showed that globalization has a positive effect on ecological footprint, and 1% positive change in globalization has less effects than 1% negative change on ecological footprint.

In the most recent studies mentioned above, resource abundance, economic growth, industry value added, urbanization, net inflow of foreign direct investment, trade openness, and technological advances have been studied as the factors affecting environmental quality, although the energy consumption structure (ECS) is one of the main factors affecting the environmental quality. To the best of the authors' knowledge, no specific research has directly studied the effect of the energy consumption structure (ECS) on the ecological footprint. This issue is a major gap throughout the energy-related literature, which is

[7] It indicates the existence of a positive short-term and negative long-term relationship between FDI and environmental quality (Waqih et al. 2019).

[8] Urbanization may provide basic human services, e.g., water supply, health services, waste disposal, enhance the economic return, and develop environment-friendly infrastructure that facilitates building, operating, and sustaining urban environments. Urbanization creates opportunities for residents to acquire higher and qualified education, which leads to greater awareness as well as an environmentally friendly attitude. The urban population also uses energy-efficient appliances and environment-friendly commodities, caused by relatively higher levels of income (Erdogan et al. 2020; Ulucak et al. 2020).

Table 1 Variable acronyms, descriptions, and sources

Variable acronyms	Variable description	Sources
Dependent variables		
EFP	Ecological Footprint (global hectares)	Global Footprint Network (GFN)* (2022)
Independent variables		
ECS	Energy consumption structure	Calculated by Shannon-Winer index
GDP	Gross domestic product (GDP) (constant = 2010 $)	World Bank Data (WBD)** (2022)
FDI	Foreign direct investment, net inflows (% GDP)	World Bank Data (WBD) ** (2022)
IND	Industry (including construction), value added (% GDP)	World Bank Data (WBD) ** (2022)
TO	Trade openness = (import + export)/GDP	World Bank Data (WBD) ** (2022)
POP	Total population	World Bank Data (WBD) ** (2022)
TOTAL	Total energy consumption (TWH)	Our World in Data*** (2022)

* https://data.footprintnetwork.org/

** https://data.worldbank.org/

*** https://ourworldindata.org/

discussed in this research. This study is also innovative in some other aspects: First, the Shannon–Wiener index has been applied to calculate ECS. Second, the convergence club method has been used to find convergent countries among 64 countries during the time period. Third, after finding converging countries, the new MM-QR econometric method has been applied to examine the ECS in low, medium, and high quantiles on the ecological footprint. In the next section, the data, variables, and methods used in this research are presented.

Data and method

This section consists of two subsections: the first subsection introduces the data/variables, and the second subsection presents the methods used in the research.

Data

The study was conducted in 64 countries with middle and upper-middle income levels during the period 1990 to 2017. Before estimating the MM-QR model, first, using club convergence, countries that behave similarly in the ecological footprint over time are selected in the same groups, and then a separate estimate is made for each of these groups. For some of the 64 countries, data for other years was not available, or it was incomplete for some countries. Therefore, we decided to study the period from 1990 to 2017. Table 1 shows the data/variables and sources.

In this research, the variables EFP, ECS, GDP, FDI, IND, TO, POP, and TOTAL have been used, where EFP is the dependent variable and the rest are independent variables. In this study, the Shannon–Wiener index was used to calculate ECS. After introducing the variables, the next section describes the methodologies.

Method

This section consists of three main subsections: The first subsection includes the Shannon–Wiener index. The second section indicates the club convergence method. Finally, the third section presents the method of moments quantile regression (MM-QR).

Shannon-Winer index

The Shannon–Wiener index (SWI) is derived from the Second Law of Thermodynamics' idea of entropy. Entropy is a physics term that describes the degree of disorder in a system; the more chaotic the system is, the higher the degree of entropy (Chuang and Ma 2013). Shannon (1948) established the SWI by using entropy to explain informational uncertainty. The SWI places a stronger focus on uncommon species in terms of relative abundance (Izsák 2007). The SWI is used to calculate diversity in the domains of biology, ecology, and economics (Hickey et al. 2010). In some of studies, this index has been used to calculate energy diversity and security (Jansen et al. 2004; Costantini et al. 2007; Van Vliet et al. 2012). The formula for the SWI is

$$SWI = -\sum_{i=1}^{N} p_i \ln(p_i) \tag{1}$$

where *i:* the type of the primary energy; *j:* p_i: the share of primary energy *i*; *N:* the number of primary energy types. Greater system variety is related with higher SWI values.

The SWI will be at its greatest when all alternatives have an equal proportion (Chuang and Ma 2013).

Club convergence

Convergence is one of the most prominent topics in macroeconomic theories (Solow 1956). The convergence hypothesis is examined for many economic indicators in a wide range of domains (Ulucak and Apergis 2018). The club convergence method takes into account the presence of numerous steady-state pathways and assumes that an economy would eventually achieve its steady-state path, which is determined by its beginning position or another country-specific attribute. As a result, countries with similar characteristics on different topics such as economic structure, income level, factor endowments, etc., will converge to similar equilibria (Islam 2003).

In this research, in order to evaluate the concept of club convergence, the Phillips and Sul's technique has been used, and, finally, the effect of energy consumption structure on the ecological footprint has been evaluated (Phillips and Sul 2007a, b). It can detect panel cross-sections that tend to have similar convergence even if there is complete panel convergence between cross-sections. In this process, the presence of clusters is revealed while enabling certain cross-sections to diverge at the same time. Furthermore, the group clustering procedure is based on data attributes rather than a priori assumptions, and it takes into account heterogeneity among the time series in the panel. Whether the data are trend stationary or not, the Phillips and Sul (2007a, b) technique is reliable. It offers the benefit of providing a framework for modeling both transitional and long-run behavior using a nonlinear time-varying component model. Phillips and Sul (2007a, b) used the time-varying common factor form of Eq. (2) for the set of observable y_{it} series.

$$y_{it} = \delta_{it}\mu_t \tag{2}$$

In Eq. (2) μ_t denotes a single common trend, and δ_{it} is a time-varying idiosyncratic element that records state i's divergence from the common trend route. In this way, all N states (either the full sample or within the cluster) will converge to a steady state (at some point in the future), If $\lim_{k\to\infty}\delta_{it+k} = \delta$ for all $i = 1,2, \ldots, N$, regardless of whether ecological footprint across countries is near to the steady state or in transition. Given that routes to steady state(s) in the ecological footprint across countries might be quite different. In estimatingδ_{it}, Phillips and Sul (2007a, b) adjust Eq. (2) in order to remove the trend component by rescaling the panel average as follows:

$$h_{it} = \frac{y_{it}}{(\frac{1}{N})\sum_{i=1}^{N} y_{it}} = \frac{\delta_{it}}{(\frac{1}{N})\sum_{i=1}^{N} \delta_{it}} \tag{3}$$

The transition route with regard to the panel average is captured by h_{it} in Eq. (3). This method takes into account the semi-parametric form of δ_{it}, which gives an empirical methodology for identifying clubs, as well as an econometric test of convergence:

$$\delta_{it} = \delta_i + \sigma_{it}\xi_{it} \tag{4}$$

where $\sigma_{it} = \frac{\sigma_i}{L(t)t^{\alpha}}, \sigma_i > 0, t \geq 0$, and ξ_{it} is weakly reliant over t, but (0,1) across i.

As t approaches infinity, the function (t), which is equal to $\log(t)$, increases in t and becomes divergent. $H_0 : \delta_i = \delta, \alpha \geq 0$ is the null hypothesis of convergence for δ_{it}, as opposed to the alternative hypothesis of non-convergence for some $i : H_A : \delta_i \neq \delta, \alpha < 0$.

The function (t), which is equal to log(t), is increasing in t and divergent as t tends to infinity. The null hypothesis of convergence for δ_{it} is $H_0 : \delta_i = \delta, \alpha \geq 0$, against the alternative hypothesis for non-convergence for some $i : H_A : \delta_i \neq \delta, \alpha < 0$. To test the null hypothesis, the following regression is estimated:

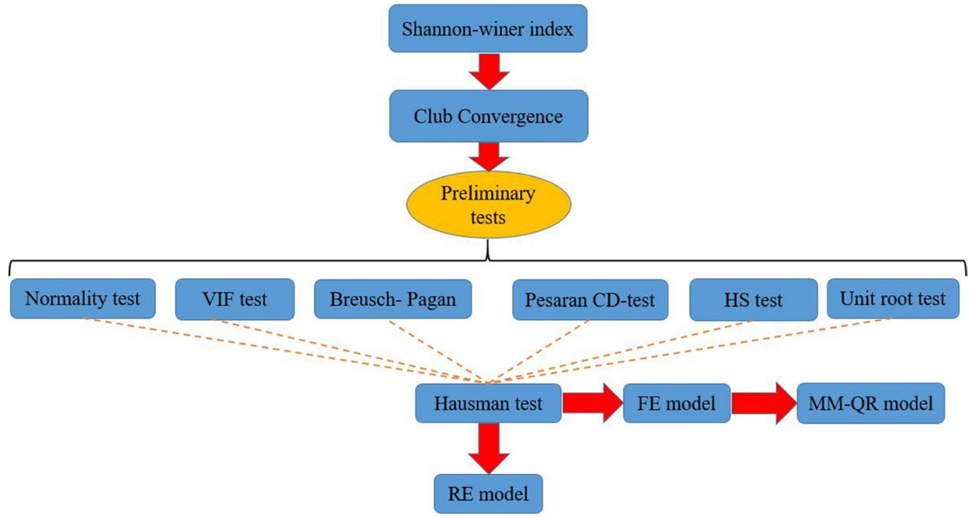
$$\log\left(\frac{H_1}{H_t}\right) - 2\log[\log(t)] = \hat{c} + \hat{b}\log(t) + \hat{u}_t \tag{5}$$

where $H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2$ is the relative transition coefficients for square cross-sectional distance according to Phillips and Sul (2007a, b), Eq. (5) is estimated for $t = [rt], [rT] + 1, \ldots, T$ where $r > 0$ is put on the [0.2, 0.3] range. Also, note that null hypothesis for $\hat{b} = 2\hat{\alpha}$ can be formulated as a one-sided test of $\hat{b} \geq 0$ versus the alternative of $\hat{b} < 0$. $t_{\hat{b}} < -1.65$ results in a rejection of the null hypothesis at the 5% level of significance.

The robust clustering algorithm approach introduced by Phillips and Sul (2007a, b) is used to identify clubs in a panel and is implemented as follows:

1. Arrange the N states according of their most recent observation.
2. We add nearby states from our sorted lists starting with the highest-order state. We use Eq. (5) to calculate the $\log(t)$ regression for each formation. Then, using the following cut-off point criterion, we choose a core group: $K^* = ArgMax_K\{t_{\hat{b}K}\}$ subject to $Min_K\{t_{\hat{b}k}\} > -1.65$ for $k = 2,3,.., N$.
3. One state at a time is added to the core group, and the $\log(t)$ regression is re-estimated in Eq. (5). The sign criterion $\hat{b} \leq 0$ is used to determine whether a state or territory should join the core group; and

Fig. 2 Summary of research stages (based on the authors' findings)



4. We repeat steps (2)-(3) for the remaining sectors/states until we can no longer establish clubs, at which point each club will have its unique convergence route. If the algorithm's last group fails to converge, these states/territories form a diverging club.

According to Phillips and Sul (2007a, b), adopting a sign requirement in step (2) might result in an overestimation of the number of clubs. As a result, after running the method in Eq. (5), Phillips and Sul (2007a, b) recommend undertaking club-merging tests.

Method of moments quantile regression (MM-QR)

In this research, we investigated the impact of ECS on ecological footprint using panel quantile regression, as developed by Koenker and Bassett (1978). This method permits line slopes in regression to differ across quantiles of the dependent variable, making it more powerful than classic regression techniques like OLS, which focus on mean effects. This approach is more accurate when outliers are present and the random error term is not regularly distributed (Zhu et al. 2018). Quantile regression with individual effects, on the other hand, has several flaws, such as failing to account for unobserved variation between people. As a result, we used Machado and Silva's latest approach of moments quantile regression with fixed effect (Machado and Silva 2019; Koengkan et al. 2022). This approach, which is based on conditional means, allows for the estimation of conditional quantiles using combined estimations of the location and scale functions. Indeed, unlike Koenker (2004) and Canay (2011), the MM-QR allows individual effects to influence both the position and scale of the dependent variable Y (EFP) and to impact the whole distribution rather than simply altering location.

The MM-QR calculates the conditional quantiles of a dependent variable Y (EFP) whose distribution is dependent on a k-vector of covariate X and is used in location-scale variant models. The following is the definition of Y:

$$Y_{it} = \alpha_i + \acute{X}_{it}\beta + (\delta_i + \acute{Z}_{it}\gamma)U_{it} \tag{6}$$

where the probability, $P\{\delta_i + \acute{Z}_{it}\gamma > 0\} = 1.(\alpha, \acute{\beta}, \acute{\gamma})$ are unknown parameters to be estimated. Individual i fixed effects are represented by $(\alpha_i, \delta_i), i = 1, \ldots, n$, and Z comprises k-vector of defined components of X. These are differentiable transformations with the element l as follows:

$$Zl = Zl(X), l = 1, \ldots, k \tag{7}$$

For every fixed i and throughout time (t), X_{it} and U_{it} are i.i.d. According to Machado and Silva (2019), U_{it} are orthogonal to X_{it} and standardized to fulfill the moment criteria that do not involve rigorous exogeneity. The conditional quantile $Q_y(\tau|x)$ of the dependent variable Y is stated as follows using Eq. (6):

$$Q_y(\tau|X_{it}) = (\alpha_i + \delta_i q(\tau)) + \acute{X}_{it}\beta + \acute{Z}_{it}\gamma q(\tau) \tag{8}$$

where $\acute{X}_{it}$ includes the independent variables (ECS, GDP, FDI, IND, TO, POP, TOTAL). The quantile distribution of the dependent variable Y_{it} (EFP) is denoted by $Q_y(\tau|X_{it})$, which is conditional on the position of explanatory variables X_{it}. The scalar coefficient $\alpha_i(\tau);(\alpha_i(\tau) \equiv \alpha_i + \delta_i q(\tau))$ defines the fixed effect of quantile τ for individual i. Individual effects do not exhibit intercept shift, unlike the standard least-square fixed effect. Their diverse affects are permitted to change across the quantiles of the dependent variable Y

Table 2 Results of the ecological footprint (gha) based on club convergence (64 countries)

Panel A: Club convergence tests		$\hat{b}$ coef	$t_{\hat{b}}$
Full sample convergence		−0.6368	−56.8617**
1st club	Brazil, Japan, Saudi Arabia, South Korea, Turkey, United Arab Emirates	0.285	6.284
2nd club	Canada, France, Germany, Iraq, Malaysia, Mexico, South Africa, Thailand, UK	0.117	1.887
3rd club	Argentina, Australia, Chile, Colombia, Italy, Peru, Poland, Spain	0.094	1.402
4th club	Austria, Belgium, Guatemala, Israel, Jordan, Singapore, Sweden	0.053	2.279
5th club	Bahrain, Czech Republic, Ecuador, Gabon, Lebanon, Romania	0.030	0.849
6th club	Denmark, Finland, Greece, Hungary, Norway, Oman, Portugal, Qatar, Switzerland	0.239	2.022
7th club	Bulgaria, Costa Rica, Cuba, Ireland, New Zealand, Panama, Paraguay	0.086	1.612
8th club	Albania, Luxembourg	1.022	14.708
9th club	Cyprus, Fiji, Jamaica	0.213	2.388
10th club	Barbados, Tonga, Trinidad and Tobago	0.002	0.031
Not-convergent group 11	China, Malta, the Netherlands, USA	−0.872	−622.632***
Panel B: Club merging analysis		$\hat{b}$ coef	$t_{\hat{b}}$
New club **I**	Merging club1 + 2	0.1427	2.8093
New club **II**	Merging club 2 + 3	−0.0228	−0.4144
New club **III**	Merging club 3 + 4	−0.1903	−6.918***
New club **IV**	Merging club 4 + 5	−0.0064	−0.1897
New club **V**	Merging club 5 + 6	0.1105	2.2999
New club **VI**	Merging club 6 + 7	−0.1728	−3.4020***
New club **VII**	Merging club 7 + 8	−0.1915	−6.2815***
New club **VIII**	Merging club 8 + 9	−0.3952	−11.8779***
New club **IX**	Merging club 9 + 10	−0.3952	−11.2933***
New club **X**	Merging club 10 + 11	−0.7254	−77.3507***
Panel C: Final club classifications		$\hat{b}$ coef	$t_{\hat{b}}$
Club 1	Argentina, Australia, Brazil, Canada, Chile, Colombia, France, Germany, Iraq, Italy, Japan, Malaysia, Mexico, Peru, Poland, Saudi Arabia, South Africa, South Korea, Spain, Thailand, Turkey, United Arab Emirates, UK	−0.047	−1.073
Club 2	Austria, Bahrain, Belgium, Bulgaria, Costa Rica, Cuba, Czech Republic, Denmark, Ecuador, Finland, Gabon, Greece, Guatemala, Hungary, Ireland, Israel, Jordan, Lebanon, New Zealand, Norway, Oman, Panama, Paraguay, Portugal, Qatar, Romania, Singapore, Sweden, Switzerland	−0.031	−0.825
Club 3	Albania, Luxembourg	1.022	14.708
Club 4	Cyprus, Fiji, Jamaica	0.213	2.388
Club 5	Barbados, Tonga, Trinidad and Tobago	0.002	0.031
Not convergent group 6	China, Malta, the Netherlands, USA	−0.872	622.632***

Notes: For testing the one-sided null hypothesis: $b \geq 0$ against $b < 0$, we use the critical value: $t_{0.05} = -1.651$ in all cases; statistical significance at the 5% level is denoted by **, rejecting the null hypothesis of convergence

since they are time-invariant factors. $q(\tau)$ is estimated from the following optimization problem:

$$Min_q = \sum_i \sum_t \rho_\tau(R_{it} - (\delta_i + \acute{Z}_{it}\gamma)q) \quad (9)$$

where $R_{it} = Y_{it} - (\alpha_i + \acute{X}_{it}\beta)$ and $\rho_\tau(A) = (\tau - 1)AI\{A \leq 0\} + TAI\{A > 0\}$ denotes the check function. Figure 2 summarizes the steps of this research.

Empirical results

This section consists of three parts: the first part presents the results of club convergence, the second part deals with the review of preliminary tests, and the last part presents the MM-QR estimation results.

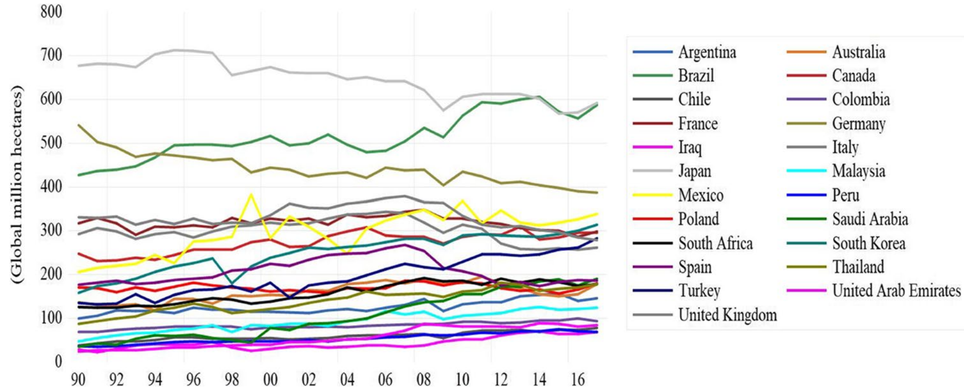


Fig. 3 Ecological footprint of club I (23 selected countries)

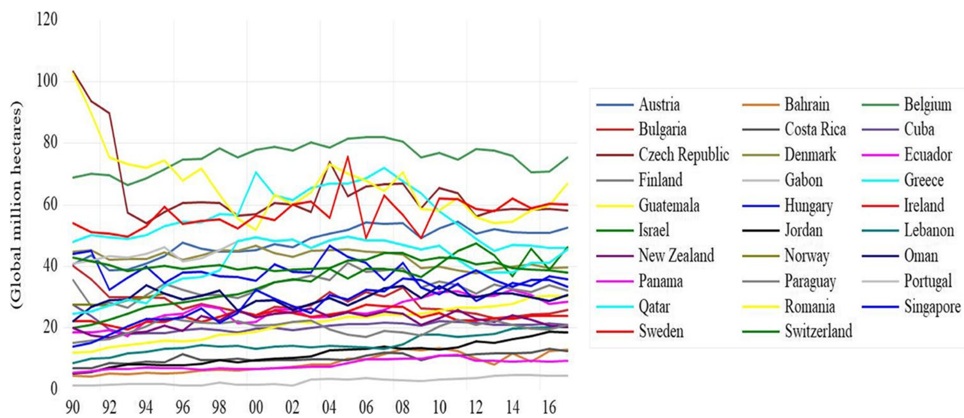


Fig. 4 Ecological footprint of club II (29 selected countries)

Club convergence results

This section examines the convergence between countries. The club convergence model is utilized for this purpose, which groups countries based on similar behavior over time. In this study, we examined the convergence of ecological footprints in 64 countries. This model first groups countries based on their initial convergence with similar behavior in a club (panel A, Table 2), and then, in the next step, it examines the merger of clubs (panel B, Table 2). If the clubs have the ability to merge, it will merge the clubs; otherwise, the results will be presented in their initial club grouping in the final panel (panel C, Table 2). As shown in Table 2, panel A, if the t-statistic is less than ($t_{\hat{b}} < -1.651$), it means that there is no convergence. The full sample's convergence results show a t-statistic of − 56.8617, which is less than the threshold ($t_{\hat{b}}$), so there is no full sample convergence in all countries. The lack of general convergence does not mean the absence of convergence in subgroups, so we will continue to examine the convergence in subgroups. The initial results of these subgroups (panel A) show 10 convergent clubs and one non-convergent club.

In the next step, we will examine the merging of these subgroups (panel B). The results of the club's merger (panel B) show that, according to t-statistics, clubs 1 + 2,

Table 3 Descriptive statistics (club I: 23 countries)

Variables	Descriptive statistics				
	Obs	Mean	Std. dev	Min	Max
FTP	644	2.18e + 08	1.56e + 08	2.17e + 07	7.12e + 08
GDP	644	1.13e + 12	1.28e + 12	2.56e + 10	6.15e + 12
TOTAL	644	1729.518	1360.978	101.798	6205.568
IND	644	32.67409	11.08145	17.24115	84.79598
FDI	644	2.380191	2.22176	− 4.541592	12.76319
POP	644	5.38e + 07	3.93e + 07	1,828,437	2.08e + 08
TO	644	62.25021	37.6827	0.0209992	220.4068
ECS	644	0.7226206	0.185245	0	1

Notes: Obs. is the number of observations in the model, Std.-Dev. is the standard deviation, Min and Max are the minimum and maximum, respectively

Table 4 Descriptive statistics (club II: 29 countries)

Variables	Descriptive statistics				
	Obs	Mean	Std. dev	Min	Max
FTP	812	3.27e+07	1.91e+07	1,216,662	1.03e+08
GDP	812	1.64e+11	1.53e+11	8.43e+09	6.84e+11
TOTAL	812	268.431	194.1102	11.378	996.808
IND	812	28.92	10.26895	13.7614	73.46916
FDI	812	4.9597	7.629841	−15.74502	81.31815
POP	812	7,165,339	4,437,036	476,275	2.32e+07
TO	812	98.06749	60.46602	24.72931	437.3267
ECS	812	0.570086	0.265192	0	1

Notes: Obs. is the number of observations in the model, Std. dev. is the standard deviation, Min and Max are the minimum and maximum, respectively

slope (HS) test. In the fifth step, we use the panel unit root test to check the stationary of the variables. And, finally, the Hausman test is used to examine panels with fixed or random effects. Tables 3 and 4 show the statistical characteristics of both clubs. As can be seen, club I contains 23 countries, and the total number of observations is 644, and club 2 has 29 countries, with 822 total observations. The energy consumption structure (ECS) is between 0 and 1. The ECS mean in the first club is 0.72, and it is 0.57 in the second club.

In the second step, we check the normality of the data. For this purpose, in this research, we use Shapiro–Wilk tests presented by Shapiro and Wilk (1965) and Shapiro-France tests introduced by Shapiro and Francia (1972). Table 5 shows the normality test results of both clubs. As can be seen, all variables in both clubs reject the null hypothesis that the data are normal. Due to the anomaly of the data, the MM-QR method can be used to investigate the heterogeneous effects of the ECS on the ecological footprint.

Table 5 Normal distribution test

Variables	Club I				Club II				Obs
	Shapiro–Wilk		Shapiro-Francia		Shapiro–Wilk		Shapiro-Francia		
LFTP	0.97567	***	0.97710	***	0.91892	***	0.91917	***	644
LGDP	0.97767	***	0.97890	***	0.94286	***	0.94442	***	644
LTOTAL	0.96956	***	0.97090	***	0.94384	***	0.94478	***	644
LIND	0.95894	***	0.95965	***	0.95627	***	0.95682	***	644
LFDI	0.85302	***	0.85176	***	0.92665	***	0.92372	***	644
LPOP	0.94280	***	0.94282	***	0.91810	***	0.91879	***	644
LTO	0.70751	***	0.70291	***	0.96365	***	0.96382	***	644
ECS	0.92451	***	0.92513	***	0.93436	***	0.93641	***	644

Notes: The prefix "L" denotes variables in the natural logarithms; *** denotes statistical significance at the 1% level

2 + 3, 4 + 5, and 5 + 6 can be merged, but other clubs cannot. Finally, panel C shows the final results of the countries' convergence after the merger of the clubs; as can be seen, we have 5 converging clubs and one non-converging group, given that a large number of countries are located in clubs 1 and 2. In this study, we examined the effect of ECS on the ecological footprint in both these two groups.

Club 1 has 23 countries, and club 2 has 29 converging countries based on the ecological footprint. Figures 3 and 4 show the ecological footprint of each club (1, 2) during the period 1990 to 2017.

Pre-estimation tests

Before estimating the models, preliminary tests need to be performed. In this section, first, the statistical specifications of both clubs are given. Second, we check the data normality, because the basic condition for using the MM-QR model is non-normality of data. Third, we evaluate the existence of multicollinearity between variables in both models. Fourth, we check the cross-sectional dependence and homogeneity

Table 6 VIF test

Variables	VIF test (club I)		Variables	VIF test (club II)	
	VIF	Mean VIF		VIF	Mean VIF
LFTP	N.A	2.41	LFTP	N.A	2.17
LGDP	3.95		LGDP	3.38	
LTOTAL	3.1		LTOTAL	3.25	
LIND	2.68		LIND	1.31	
LFDI	1.32		LFDI	1.43	
LPOP	1.88		LPOP	1.97	
LTO	1.60		LTO	1.90	
ECS	2.38		ECS	1.95	

Notes: *** denotes statistically significant at 1% levels; n.a. denotes not available

Table 7 Breusch-Pagan (LM test), Pesaran CD-test, and HS test

Breusch-Pagan (LM test) (club I)		Variables	Pesaran CD test (club II)		
χ^2- statistic	Prob		CD-test	*p*-value	
376.805	0.000***	LFTP	19.72	0.000	***
		LGDP	84.72	0.000	***
		LTOTAL	15.91	0.000	***
		LIND	12.33	0.000	***
		LFDI	16.93	0.000	***
		LPOP	51.48	0.000	***
		LTO	27.26	0.000	***
		ECS	16.49	0.000	***
Homogeneity slope test					
Models	Delta		Adjusted delta		
Club I	22.342***		28.475***		
Club II	20.241***		25.451***		

Notes: *** denotes statistically significant at the 1% level

Table 8 Panel unit root test (CIPS) (club I)

CIPS			CIPS		
Variables	Lags	(Zt-bar)	Variables	Lags	(Zt-bar)
FTP	1	− 0.069	LFTP	1	− 3.381***
GDP	1	0.775	LGDP	1	− 3.162***
TOTAL	1	1.013	LTOTAL	1	− 2.422***
IND	1	0.809	LIND	1	− 2.613***
FDI	1	− 0.691	LFDI	1	− 3.782***
POP	1	0.756	LPOP	1	− 2.124***
TO	1	− 0.127	LTO	1	− 3.603***
ECS	1	− 2.231***	LECS	1	− 5.854***

Notes: ***, **, * denote statistically significant at 1%, 5%, and 10% levels

Table 9 Panel unit root test (CIPS) (club II)

CIPS			CIPS		
Variables	Lags	(Zt-bar)	Variables	Lags	(Zt-bar)
FTP	1	− 1.021	LFTP	1	− 3.945***
GDP	1	0.685	LGDP	1	− 2.435***
TOTAL	1	1.013	LTOTAL	1	− 2.422***
IND	1	1.176	LIND	1	− 2.108***
FDI	1	− 1.345	LFDI	1	− 3.967***
POP	1	0.554	LPOP	1	− 2.874***
TO	1	− 0.174	LTO	1	− 2.899***
ECS	1	− 2.542***	LECS	1	− 6.154***

Notes: ***, **, * denote statistically significant at 1%, 5%, and 10% levels

Table 10 Hausman test for club I and club II

Model	Chi-sq. statistic	Chi-sq. d.f
Club I	14.63 **	7
Club II	15.49 **	7

Notes: ** denotes statistically significant at 5% level

In the third step, we evaluate the multicollinearity between the variables. In this study, the variance inflation factor (VIF) test was used (Belsley et al. 2005). The results of this test for both clubs are given in Table 6. In this test, there is no multicollinearity problem when the VIF value of each variable is less than the standard 10, and, also, the average VIF value is less than 6. As can be seen, both clubs have no particular multicollinearity problem.

In the fourth step, the cross-sectional dependence is evaluated. Normally, two of Pesaran CD-test (Pesaran 2004) and Breusch-Pagan (LM test) (Breusch and Pagan 1980) tests are used to examine cross-sectional dependence. The Pesaran CD-test is applied when the number of sections is larger than the time series (N > T), and, when the N is smaller (N < T), we can use the Breusch-Pagan (the LM test). According to this definition, the Breusch-Pagan test is used for club I, and the Pesaran CD-test is used for club II. Null hypothesis in both tests is the absence of cross-sectional dependence. As shown in Table 7, the null hypothesis is rejected for both clubs. This indicates the existence of cross-sectional dependency. In addition, the Homogeneity Slope (HS) test (Pesaran and Yamagata 2008) was used to examine the HS of the models. The null hypothesis in this test is the existence of an HS. According to the results of Table 7, it can be stated that the null hypothesis is rejected, and both models have a heterogeneous slope.

Considering the confirmation of the cross-sectional dependence and heterogeneous slope in both clubs, in the following, we apply the CIPS-test provided by Pesaran (2007) to check the panel unit root. Null hypothesis in this test is the existence of the panel unit root. Table 8 shows the results of club I, as except for ECS, which is stationary at 1%; none of the variables FTP, GDP, TOTAL, IND, FDI, POP, and TO are stationary at the level. But by converting them to natural logarithms, all variables are stationary at the 1% level.

The results of the CIPS unit root test for club II also indicate that only the ECS variable is stationary at level, but by converting the variables to the natural logarithm form, they all will be stationary at the 1% level (Table 9).

Finally, before estimating the OLS with fixed effects and MM-QR model, the fixed effects or random effects of the model should be investigated using the Hausman test. The null hypothesis of this test is the existence of random effects.

Table 11 Estimation results from the MM-QR regression model and OLS with fixed effects (club I)

Independent variables	Main method										Robustness check	
	MM-QR										OLS	
	Club I-dependent variable (LEFP)											
	Quantiles										Fixed effects	
	10th		25th		50th		75th		90th			
LGDP	0.00544		0.0546	*	0.16517	***	0.19113	***	0.19181	***	0.1247	***
LTOTAL	0.5196	***	0.4861	***	0.39243	***	0.38889	***	0.38957	***	0.4239	***
LIND	−0.1752	**	−0.1172	**	−0.1021	***	−0.0202		0.03760		−0.2026	***
LFDI	0.0185		0.0047		0.00829		0.01883	**	0.01704	**	0.0141	**
LPOP	0.4272	***	0.3628	***	0.31839	***	0.33343	***	0.34119	***	0.3564	***
LTO	−0.03996		−0.0641	***	−0.0542	***	−0.0659	***	−0.0722	***	−0.0102	
ECS	0.68037	***	0.3717	***	0.01239	***	−0.1902	***	−0.3458	***	0.1951	***
Constant	7.9784	***	0.79489	***	6.6490		0.43773	***	5.5198	***	6.8679	***
Pseudo R^2	0.8141		0.8357		0.8430		0.8451		0.8532		0.9409	

Notes: ***, **, * denote statistically significant at the 1%, 5%, and 10% levels, respectively

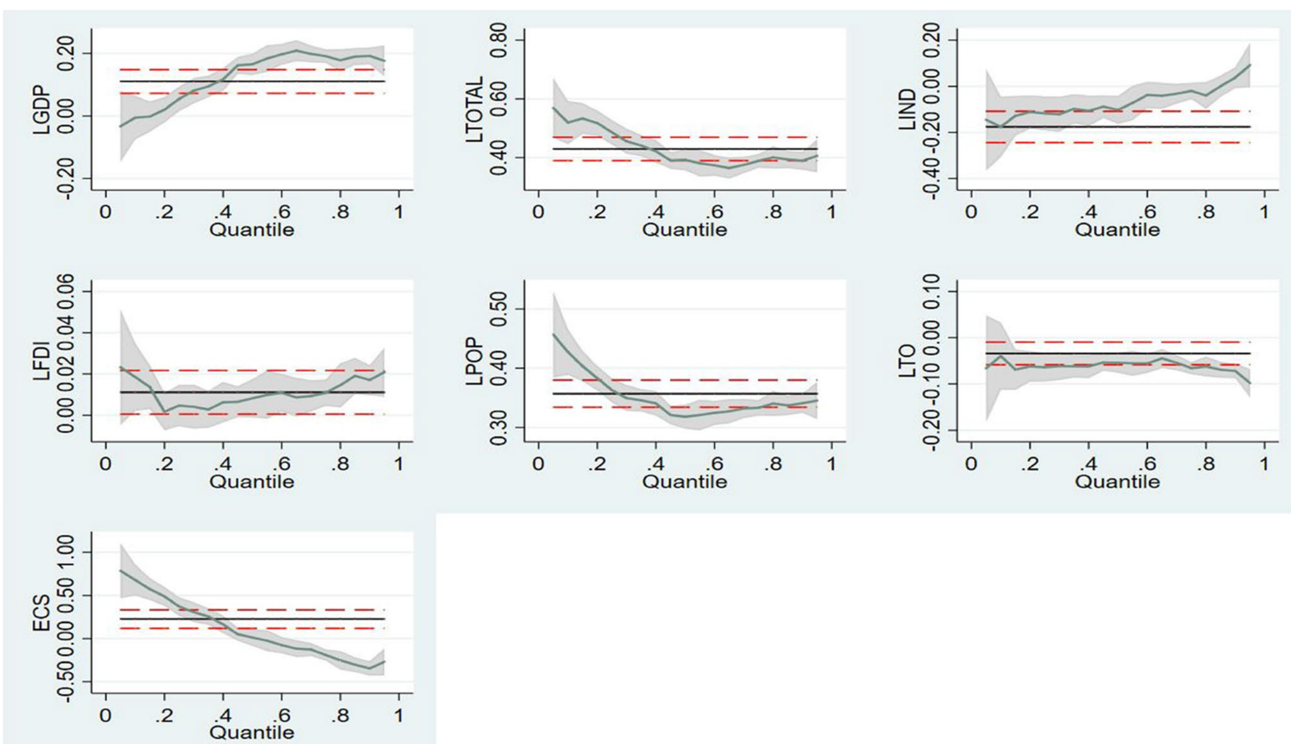


Fig. 5 Quantile estimate: shaded areas are 95% confidence band for the quantile regression estimates

As shown in Table 10, both clubs reject the null hypothesis. So, we can continue to apply the model with fixed effects.

Given that both clubs passed the preliminary tests well, we can continue to use the OLS with fixed effects and MM-QR model to investigate the effects of ECS on the ecological footprint.

Method of moments quantile regression (MM-QR) results

In this section, the estimation results of both clubs using the MM-QR model are given. For this purpose, 10th, 25th, 50th, 75th, and 90th quantiles have been used. OLS with

Table 12 Estimation results from the MM-QR regression model and OLS with fixed effects (club II)

Independent variables	Main method										Robustness check	
	MM-QR										OLS	
	Club II-dependent variable (LFTP)											
	Quantiles										Fixed effects	
	10th		25th		50th		75th		90th			
LGDP	0.13036	***	0.14017	***	0.15630	***	0.19040	***	0.24742	***	0.13368	***
LTOTAL	0.36858	***	0.36627	***	0.38826	***	0.35178	***	0.30143	***	0.05656	***
LIND	−0.13357	**	−0.0421		0.04102		0.20027	***	0.33128	***	0.23036	***
LFDI	−0.01660		−0.0165	**	−0.0191	*	−0.0139		−0.0079		0.000186	
LPOP	0.51373	***	0.48459	***	0.42746	***	0.41078	***	0.25711	***	0.626313	***
LTO	−0.03992		−0.0184		−0.0976	***	−0.0789	*	−0.1193	***	−0.05964	**
ECS	0.27927	***	0.2086	***	0.00711		−0.1493	**	−0.0496		0.08213	
Constant	4.05424	***	0.47645	***	4.7146	***	3.9309	***	4.9858	***	3.08945	***
Pseudo R^2	0.7811		0.7555		0.6879		0.6365		0.5937		0.8616	

Notes: ***, **, * denote statistically significant at the 1%, 5%, and 10% levels, respectively

fixed effects has also been applied to evaluate the model robustness. Table 11 shows the club I results.

As can be seen in Table 11, LGDP has positive effects on ecological footprint (LFTP) at all quantiles except the 10th. The results also showed that LGDP has higher effect on LFTP in the high quantile (such as 90th). LTOTAL and LPOP have positive and significant effects on LFTP in all quantiles. Industrialization (LIND) in quantities 10th, 25th, and 50th has significant negative effects on LFTP, and these effects are greater at low levels so that 1% increase in LIND causes −0.175% decrease in ecological footprint. In contrast, foreign direct investment (LFDI) has positive and significant effects on ecological footprint only in 75th and 90th. While trade openness (LTO) at all levels except 10th has negative effects on LFTP. The results for the energy structure (LECS) show that the effects of this variable on ecological footprint (LFTP) are positive in quantiles 50th and below, and negative in quantiles 75th and 90th. These results show that increasing the diversity of energy consumption and the use of clean energy help to improve the environment. Finally, to evaluate the model robustness, we compared the results of the MM-QR model in quantile 50th with the OLS with fixed-effect results. As can be seen, the OLS with fixed effect also confirms that LGDP, LTOTAL, LFDI, LPOP, and LECS have positive effects on the ecological footprint, while LIND and LTO have negative effects. Figure 5 shows the effects of independent variables on the ecological footprint in different quantiles for club I.

After analyzing the club I results, Table 12 shows the estimation results of MM-QR model and OLS with fixed effects for club II.

The results of MM-QR model show that economic growth (LGDP), energy consumption (LTOTAL), and population (LPOP) in all quantiles have positive and significant effects on ecological footprint (LEFP). However, economic growth in the upper quantities (75th and 90th) will further increase the LEFP while the greatest impact of LTOTAL is in the middle quantile (50th). A 1% increase in LTOTAL causes 0.39% increase in LEFP. But the trade openness (LTO) in all quantiles has negative and significant effects on the LEFP. Increasing in LTO further reduces the ecological footprint. Industrialization (LIND) in quantile 10th has significant negative effects on the LEFP. While, in high quantiles (75th and 90th), it increases the LEFP. Foreign investment (LFDI) only in quantiles 25th and 50th has significant negative effects on the LEFP. Finally, the energy consumption structure (LECS) in quantiles 10th, 25th, and 75th has significant effects on LEFP. These results show that LECS in quantiles 10th and 25th has positive and significant effects on LEFP, while, in quantile 75th, it is negative. The results confirm that changing the energy consumption structure reduces the ecological footprint. Finally, the OLS with fixed effects has been used to evaluate the robustness of the MM-QR model. The OLS results are compared with quantile 50th. As OLS results with fixed effects show LGDP, LTOTAL, LIND, and LPOP have positive effects on the ecological footprint, LTO has negative effects. Comparison of these results with quantile 50th confirms the model robustness. Figure 6 shows the results of the MM-QR model for club II.

Discussions

This section discusses the results of Tables 11 and 12. Economic growth (LGDP) has significant positive effects on the ecological footprint. These effects are greater in

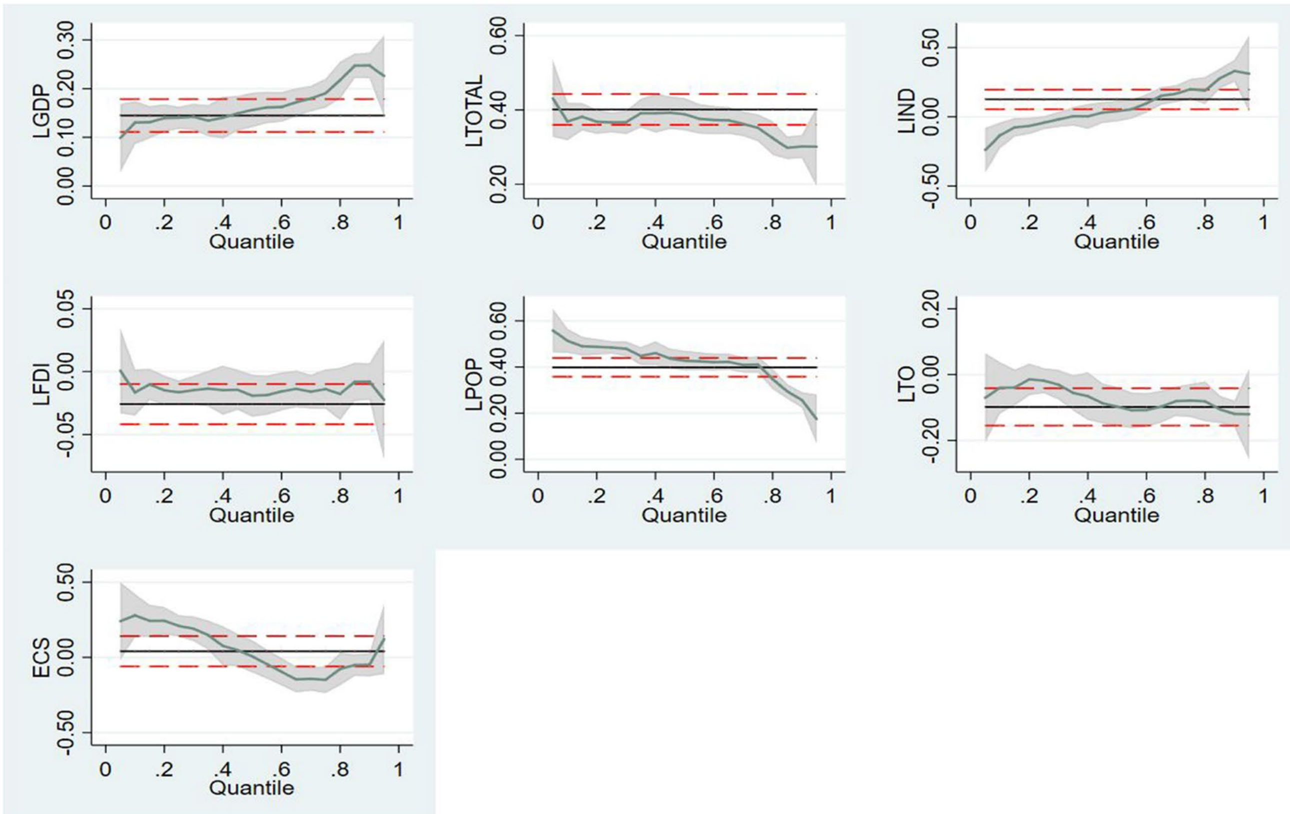


Fig. 6 Quantile estimate: Shaded areas are 95% confidence band for the quantile regression estimates

higher quantiles. It can be said that increasing economic growth requires a larger volume of inputs, which leads to more use of natural resources. Countries pay less attention to the environment in the early stages of industrialization (Ahmad et al. 2020a; Zafar et al. 2019; Banday and Aneja 2019). The results also showed that energy consumption (LTOTAL) destroys the environment and increases the ecological footprint. Khan and Hou (2021), in a study for 38 countries in the International Energy Agency (IEA); Ozturk et al. (2016a, b), in a study of 144 countries; Nathaniel et al. (2019), in a study for South Africa; Shahzad et al. (2021), in a study for the USA; and Baz et al. (2020) confirm the research findings.

In club I, industrialization (LIND) in the middle and lower quantiles has negative and significant effects on the ecological footprint, while, in club II, in quantile 10th, it has negative effects, and, in high quantiles, it has positive effects on ecological footprint. The results indicate that the industrialization process in countries means moving from the agricultural economy to industrial production and the conversion of raw materials into manufactured products. This process is associated with more fossil fuel consumption and causes environmental degradation. On the other hand, it leads to the rapid expansion of secondary industries with high energy consumption and pollution. Yang and Usman (2021), in a study for 10 countries with the highest health care costs; Lee (2019), in a study for Southeast Asian countries; Zafar et al. (2020), in a study for 46 countries; Usman and Balsalobre-Lorente (2022), in a study for newly industrialized countries; and Destek (2021), in a study for Turkey, stated that industrialization has a positive effect on increasing the ecological footprint (LFTP).

In club I, foreign direct investment (LFDI) has positive and significant effects in high quantiles on the ecological footprint (LFTP), while, in club II, these effects are negative and significant in the middle quantiles. According to the "pollution paradise" hypothesis, the flow of foreign direct investment (LFDI) is from developed countries to countries with poorly regulated environments. Therefore, companies bring high-pollution industries from more developed countries to less-developed countries, which leads to environmental degradation in these countries. Solarin and Al-Mulali (2018), in a study of 20 countries stated that FDI causes environmental degradation in developing countries and reduces pollution in developed countries. Some of the studies such as Naz et al. (2019), Mert et al. (2019), and Adams and Acheampong (2019) confirm the destructive effect of foreign direct investment on environmental quality, while some other researchers have stated that foreign direct investment improves the use of renewable energy capacity, and it increases environmental quality (Zafar et al. 2019; Pan et al. 2019; Cheng et al. 2019; Khan et al. 2019). Increasing trade openness (LTO) in both clubs reduces the ecological footprint (LFTP). It can be said that trade openness leads to the transfer of technology between countries, which results in the replacement of old technologies with new high-energy efficiency green energy technologies. These advancements will result in improvements in environmental quality. Kazemzadeh et al. (2022), in a study for emerging countries; Kazemzadeh et al. (2021), in a separate study of 25 countries confirmed the research results. In a study of 144 countries, Ozturk et al. (2022) found that there is a negative relationship between trade openness and ecological footprint in countries with middle- and high-income levels. The results of this study are also consistent with some other studies (Salari et al. 2021; Khan et al. 2019; Liobikienė and Butkus 2018; Destek and Sinha 2020; Jebli et al. 2016; Al-Mulali et al. 2015). While Nathaniel and Khan (2020) stated for the ASEAN country that trade openness results in increased destruction of the environment. In a study for Azerbaijan from 1996 to 2014, Mikayilov et al. (2019) also confirmed the positive impact of trade openness on reducing the ecological footprint. Sabir and Gorus (2019) confirmed the positive effect of trade openness on the EFT in South Asian countries from 1975 to 2017.

The energy consumption structure (LECS) in both clubs shows that this variable has positive effects on the ecological footprint (LFTP) in the lower quantiles, while, in the upper quantiles, these effects are negative. In the lower levels of quantile, due to the fact that the diversity of energy consumption is low and the main energy consumption is fossil fuels, the increase in pollution and environmental degradation is more. With the technological advancement and the use of less-polluted energy (natural gas) and clean energy, the environmental quality also increases. Xu et al. (2022) stated in a study of 7 emerging countries that change in energy structure can reduce ecological footprint. In this regard, most studies argue that the energy transition from the carbon-based fuel basket to clean sources reduces fossil fuel consumption and, thus, leads to an increase in environmental quality (Langnel et al. 2021; Shahzad et al. 2021; Ullah et al. 2021; Salari et al. 2021; Nathaniel and Khan 2020; Zafar et al. 2020; Ahmed et al. 2020b; Destek and Sinha 2020; Danish 2019; Alola et al. 2019; Ozcan et al. 2019; Li and Sun 2018; Ulucak and Lin 2017).

Conclusions and policy implications

This study examined the role of energy consumption structure in reducing ecological footprint in a panel of 64 middle- and upper-middle-income countries from 1990 to 2017. For this purpose, three methods of Shannon–Wiener index, club convergence, and MM-QR econometric technique have been applied. First, the energy consumption structure of the countries is calculated using the Shannon–Wiener index. Then, in the second step, using the club convergence method, countries with similar behavior in the ecological footprint were selected. Finally, using the MM-QR econometric technique, the heterogeneous effects of ECS on the ecological footprint in two categories of countries (club I: 23 countries) and (club II: 29 countries) with similar ecological footprint have been estimated. This study uses a set of variables that were expected to have theoretical and empirical explanatory power on the ecological footprint. These independent variables are GDP, foreign direct investment, industrialization, trade openness, population, and energy consumption, which have also been used as control variables.

Considering that the club convergence model showed the two main categories of converging countries (club I: 23 countries) and (club II: 29 countries) in the ecological footprint, two models were estimated to analyze the effects of each club. In both clubs, heterogeneous effects of explanatory variables on the ecological footprint were observed. The results of both clubs show that economic growth, energy consumption, and population increase the ecological footprint. However, trade openness reduces environmental degradation. The results of energy consumption structure (LECS) indicates that, in the lower quantiles, it has positive effects on the ecological footprint (LEFP), while, in the high quantiles, it reduces the ecological footprint. According to the coefficients, it can be said that the effects of LECS in club I on the ecological footprint are greater than club II, and that LECS in club I has positive effects in quantiles (10th, 25th, and 50th), and it has negative and significant effects in 75th and 90th. However, the effects of LECS in club II have positive effects in quantiles 10th and 25th, and it has only negative and significant effects in 75th. These results well confirm that changing the structure of energy consumption from highly polluted fossil fuels to less-polluted energies (such as natural gas) or renewable energies improves the environmental quality. The main differences between the two clubs is that, in club I, industrialization (LIND) has negative and significant effects on the ecological footprint in quantiles 50th and less, while, in club II, industrialization (LIND) in quantile 10th has a negative effect and, in 75th and 90th, has positive and significant effects on ecological footprint. Also, in club I, foreign direct investment (LFDI) has positive and significant effects on the ecological footprint only in the upper quantities (75th and 90th), while, in club II, foreign direct investment (LFDI) in 25th and 50th quantiles has negative and significant effects.

Policy implications

Given that economic growth and energy consumption increase the ecological footprint, therefore, on the one hand, in order to improve the quality of the environment, countries must take actions to increase energy efficiency by strengthening environmental regulations and increasing government and private sector investment. The middle-income countries, e.g., lower-middle-income and upper-middle-income countries, should also considerably encourage private–public partnership investments to achieve their long-term benefits. These necessary steps may significantly control or reduce the ecological footprint and facilitate environmental sustainability. On the other hand, expanding trade and attracting foreign investment provide the conditions for technology transfer and upgrading of infrastructure and clean energy technologies. The middle-income countries need to focus equally on the generation of new and renewable energy sources, including solar, wind, hydro, and thermal energy. In this respect, governments should use foreign investment to develop clean energy and reduce the cost of installing renewable energy. It is also suggested that the future new and renewable energy consumption for the middle-income countries should meet the upward trend. To this end, the middle-income countries require to develop technological innovations by increasing the investments, which can improve the energy efficiency. It is also needed to increase the prices of conventional energy sources, which may lead to non-carbon-based fuel portfolio. Increasing the use of renewable energy will both diversify the structure of energy consumption and improve energy security, as well as help improve the quality of the environment. In addition, governments must enforce stricter environmental laws to prevent the transfer of polluting industries to the country. In the industrialization process, governments should support low-pollution and environmentally friendly industries by using incentive policies and support packages, and impose environmental taxes on high-pollution industries, which develop environmental quality and create the demand for new and renewable energy sources.

Limitations and future recommendation

This research significantly focuses on the 64 middle-income countries, e.g., lower middle-income and upper middle-income countries, from 1990 to 2017 by exploring the energy consumption structure on ecological footprints. The policy issues and recommendations can considerably promote the capability of these countries in preparing their energy demands for the current and future activities. The findings of this study indicate some applicable recommendations for later research directions. These future studies would arouse curiosity to explore the relationship between energy consumption structure, controlling variables, and environmental quality by applying time-varying regime-switching models for individual countries and, also, for other panel frameworks.

Author contribution Emad Kazemzadeh: writing—original draft—editing, validation, data curation, formal analysis, and visualisation; Mohammad Reza Lotfalipour: investigation, supervision, project administration, conceptualization; Masoud Shirazi: introduction and literature review; Ali Sargolzaie: methodology and data collection. All authors have read and agreed to the published version of the manuscript.

Funding The research was supported by the Ferdowsi University of Mashhad (FUM), Economics Department (Faculty of Economics and Administrative Sciences).

Data availability Corresponding authors can provide the data used in the study on appropriate request.

Declarations

Ethical approval The authors attested that this paper has not been published elsewhere, the work has not been submitted simultaneously for publication elsewhere, and the results presented in this work are true and not manipulated.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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