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The effect of economic complexity, fertility rate, and information and communication technology on ecological footprint in the emerging economies: a two-step stirpat model and panel quantile regression

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Abstract
The importance of environmental performance in today's world is not hidden from anyone. On the other hand, the remarkable growth of Information and Communication Technology (ICT) has affected various aspects of life, including the environment. The effect of economic complexity, fertility rate, and ICT on the ecological footprint of emerging countries using the STIRPAT model and quantile panel regression from 2000 to 2016 were examined. The quantiles of 10th, 25th, 50th, 75th, and 90th have been used to consider the explanatory variables' effects on the ecological footprint. The results show that economic complexity, for all quantile levels except the 10th quantile, has a negative and statistically significant effect on the ecological footprint. This effect is greater in 75th and 90th quantiles. The fertility rate has a positive and statistically significant impact on the ecological footprint in all quantiles. This effect is higher in the middle quantile. ICT in all quantiles has a statistically significant negative effect on the ecological footprint. ICT has a lower effect on ecological footprint, among other variables. The panel fixed effect model results show that ICT has no significant effect on the ecological footprint. In contrast, economic complexity and fertility rate have significant positive and negative effects on environmental footprint. Are proposed a set of policy measures to mitigate/reduce the ecological footprint.

Keywords Internet ICTs · Economic complexity · Ecological footprint · Environmental degradation · Panel quantile regression

1 Introduction

Today, due to increasing industrialization, population growth, the rapid growth of information and communication technology (ICT), and increasing economic growth, environmental threats are increasing day by day. Over the past century, the world's population has multiplied, leading to increased human activity and increased demand for resources, affecting the environment (Mikati et al. 2018; Xu and Lin 2018). On the other hand, the World

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Health Organization predicts that natural resource extraction will grow more than 50% by 2030, which will increase the demand for environmental resources (Galli et al. 2015). In addition, the use of ICT has recently been considered a valuable tool in development programs around the world (Majeed and Ayub 2018). Therefore, several studies have examined appropriate solutions to solve environmental problems.

In most studies on environmental quality, CO_2 emissions have been considered a proxy for environmental degradation (Shahbaz et al. 2016). However, considering that economic activities affect different dimensions of the environment, such as water, air, and land, studying CO_2 emissions as a measure of environmental quality would not be a suitable choice (Neagu 2020). Over the past few years, a new comprehensive index called the Ecological Footprint (EF) had been proposed as a proxy of Degradation and Environmental Quality. The Ecological Footprint Index measures the biological capacity required to produce goods and services consumed by individuals in each country, as well as the capacity required to absorb the pollutants created by them (Nijkamp et al. 2004). The EF index correctly interprets the depreciation of the environment caused by human activities. This index is more comprehensive and complete than CO_2 emissions (Destek et al., 2018; Ahmad et al. 2020; Gomezand Rodríguez 2020). In recent years, some researchers have studied the impact of factors (including, for example, financial development, renewable energy consumption, and non-renewable energy consumption) on the ecological footprint in a panel from different countries (Chen et al. 2019; Destek and Sarkodie 2019; Danish et al. 2019; Dogan et al. 2020). Despite researchers' attention to the EF index as an environmental proxy, few studies have examined the impact of the economic complexity, fertility rate, and ICT on the ecological footprint (Alola et al. 2019; Yilanci and Pata 2020).

Technology and knowledge have advanced markedly over the past decades. With the advancement of science and technology, the structure of production, the quality of manufactured goods, and the lifestyle of households have also changed, contributing to economic growth while preserving the environment (Dogan et al. 2020). With the advancement of knowledge and technology, the production structure of countries has shifted towards the production of knowledge-based goods. As a result, it has introduced a new indicator called economic complexity to societies. Economic complexity is an indicator that shows the ability to produce complex and high-tech products of a country. With increasing economic complexity, the production structure of countries changes from inefficient and straightforward products to complex products with environmentally friendly technology and clean technologies that help improve the environment (Gozgor and Can 2017; Dogan et al. 2019).

On the other hand, countries with advanced technologies and complex economic structures have high-quality products, which gives them an international competitive advantage. Competitive advantage in producing knowledge-based and complex goods creates income and high profits for these countries. Thus, countries with higher economic complexity improved production processes with low-carbon economic goals (Hausmann et al. 2014). On the other hand, complex economic structures have demanded more energy. Higher energy demand also produces more harmful pollutants. Therefore, some studies have considered increasing economic complexity as a cause of environmental degradation (Can and Gozgor 2017; Neagu 2019). These contradictions raise concerns and reveal the environmental challenges facing researchers and policymakers. However, it is indisputable that using resources requires advanced and environmentally friendly technologies.

ICT is essential for the growth of industrialization and the increase of complex production. Therefore, with the increase of ICT, economic growth and the environment are affected (Danish and Baloch 2018). ICT plays a significant role in economic growth by improving human interactions. However, it also has undesired consequences for the environment and economic growth. Therefore, understanding the environmental consequences of using the internet, cell phones, and complex goods is vital in the digital age.

ICT can change the pattern of consumption and production by considering the economic, social, cultural, and health conditions to help reduce greenhouse gas emissions and reduce the harmful effects of human activities. In addition, ICT can increase public awareness of environmental degradation issues because it can influence decision-makers and the general public (Pouri and Hilty 2018; Bieser and Hilty 2018). ICT programs help predict and manage environmental hazards through computer simulation tools. Simulation programs (learning and simulation) facilitate decision-making and reduce the severe consequences of trial and error (Lu 2018; Majeed and Khan 2019). From one perspective, ICT can be considered a tool to achieve growth and development and environmental protection because using ICT can increase energy efficiency. Therefore, improving the production process and using environmentally friendly technologies enhance the quality of the environment (Ozcan and Apergis 2018; Lu 2018).

On the other hand, ICT has many detrimental effects on the environment. Increased ICT leads to increased industrial production, energy demand, and electronic waste, which leads to environmental degradation (Asongu 2018). Some studies did not find a significant relationship between ICT and the environment (Amri et al. 2019). Some other studies also argue that the impact of ICT on the environment depends on the level of development of countries (Danish et al. 2019). As can be seen, a few studies have examined the impact of ICT on the environment, and most of them used CO_2 as an environmental proxy. However, they did not reach the same results. These results are due to differences in the countries studied, econometric methods, and period studied.

Understanding the environmental consequences of increasing and decreasing fertility rates and subsequent lifestyle changes has become very important in moving towards sustainable development. Nowadays, despite the growth of the world's population, some issues, such as incompatibility between work and family life, have reduced the fertility rate in advanced societies. As a result, most European Union (EU) member states constantly see declining fertility rates (Alola et al. 2019). Until the 1980s, low fertility rates were only seen in highly developed countries. However, recently, the fertility rate decline has spread to the rest of the World (Sobotka et al. 2021). In this study, the countries' fertility rates also had a decreasing trend during the studied period. The average total fertility rate of these countries in 2000 was 2.5% and decreased to 2% in 2016 (World Bank Data 2020). Reducing fertility rates reduces the pressure on resources and energy, helping to preserve the environment.

Nevertheless, as fertility declines, so does the active young population. Alola et al. (2019) studied fertility rates on the ecological footprint in 16 EU countries. They found that the fertility rate positively affects the ecological footprint in the short run. However, in the long run, the fertility rate has a negative effect on ecological footprint. The United Nations Population Fund approved their findings. In addition, the long-run challenge of low fertility in the EU has led to an ongoing review of fertility rates. Therefore, most EU member states face an aging population due to low fertility rates and effectively reducing environmental degradation (Hoff 2011). The critical question is whether reducing fertility rates due to reduced human activities improves the environment. The reducing fertility rates and increasing the elderly population put challenging questions to society. For example, is the use of advanced technologies to replace the young workforce causing environmental degradation due to more industrial and electronic waste? Therefore, it is crucial examining the less obvious policy consequences of the fertility rate on the environment.

As can be seen, environmental studies with factors such as economic complexity (ECI) and fertility rate have not been widely considered. Furthermore, studies on the effects of internet and telephone use are also different and contradictory. In addition, the selection of ecological footprint, as a proxy for environmental degradation, provides more comprehensive results from various aspects of environmental degradation. Therefore, this study aims to enrich the literature related to these topics.

As far as we know, no study has examined the impact of ECI, fertility rates, and ICT in the emerging economies' ecological footprint. Indeed, essential policy implications have arisen due to the increasing use of the internet and mobile phones, the increase in complex production, and the duality of policies to reduce or increase the fertility rate. Therefore, we seek to answer the following questions: Will increasing complex and knowledge-based production in emerging economies improve the environment? On the other hand, is increasing the use of ICT harmful to the environment? Which one improves the environmental quality, increasing fertility rate or decreasing fertility rate?

The primary purpose of this study is to investigate the effect of economic complexity, fertility rate, and ICT on the ecological footprint. Nineteen emerging economies are studied using the STIRPAT model and quantile panel regression. The experimental findings of this study contribute significantly to the literature related to ECI, ICT, and environmental quality.

The rest of this research is as follows: Sect. 2 reviews the literature. Section 3 presents model specifications and data used. Section 4 includes the experimental results and discussion. Finally, Sect. 5 contains policy implications, and Sect. 7 shows the conclusion of this study.

2 Literature review

This section provides an overview of previous studies on the effects of economic complexity, fertility rates, and ICT on the environment. Recently, some studies have reported a relationship between economic complexity index and environmental quality, which did not reach a single conclusion. Some studies argue that increasing economic complexity helps improve the environment's quality (Can and Gozgor 2017; Kazemzadeh et al. 2021; Lapatinas et al. 2019; Pata 2020; Doğan et al. 2021). A group of studies also found a positive relationship between environmental degradation and the increasing complexity of economic structures (Neagu 2019; Yilanci and Pata 2020).

Can and Gozgor (2017) analyzed the relationship between ECI and CO_2 emissions in France from 1964 to 2014, using the DOLS (dynamic least squares) approach. Their results showed that per capita income and energy consumption cause environmental degradation and increase CO_2 emissions. However, increasing the ECI reduces CO_2 emissions. Kazemzadeh et al. (2021) examined the effect of economic complexity on ecological footprint. The results showed that economic complexity at low quantiles negatively affects ecological footprint, but 75th and 90th quantiles have no significant effect. Lapatinas et al. (2019) examined the relationship between economic complexity and environmental performance in 88 developing and developed countries with the ARDL approach from 2000 to 2012. They found that as the economic complexity increased, so did the environmental quality. Pata (2020) studied the relationship between ECI and CO_2 emissions in the context of the Kuznets curve for the United States from 1980 to 2016. These results showed that economic complexity is negatively related to environmental degradation. Doğan et al. (2021) examined the effect of economic complexity, economic progress, renewable energy consumption, and population growth on CO_2 emissions in 28 OECD selected countries from 1990 to 2014. Their results showed that increasing ECI helps to improve the environment.

Some other studies have also found a positive relationship between ECI and CO_2 emissions and environmental degradation. Neagu (2019), in a study of 25 selected EU countries, analyzed the relationship between ECI and CO_2 emissions during 1995–2017. He argued a long-run relationship between ECI, energy intensity, and carbon emissions. Yilanci and Pata (2020), the relationship between ECI and ecological footprint in the framework of Kuznets hypothesis for China during 1965–2016, with ARDL model and time-varying causality test. Their results showed that increasing economic complexity raises the ecological footprint in the short and long run.

After reviewing previous studies on the relationship between economic complexity and the environment, we have reviewed previous studies on the effect of fertility rate and population growth on environmental quality. Charfeddine and Mrabet (2017), in a study of 15 MENA countries from 1975 to 2007, showed that the fertility rate increases environmental degradation. Alola et al. (2019), in a study for European countries using the model (PMG-ARDL) during 1997–2014, showed that the fertility rate has a positive effect in the short run but a negative effect on the quality of the environment in the long run. In a study for the United States, Khan et al. (2021) examined the impact of natural resources, energy consumption, and population growth on environmental quality using the General Momentum (GMM) method from 1971 to 2016. They found that population growth increased the ecological footprint and CO_2 emissions. In a study of the top 50 economies during 1990–2015, de Souza Mendonça et al. (2020) found that population causes an increase in CO_2 emissions. In a study of 128 countries from 1990 to 2014, Dong et al. (2018) found that population positively affects CO_2 emissions. Toth and Szigeti (2016) stated that population is not the cause of environmental degradation, but the population consumption pattern causes environmental degradation.

There are two perspectives on the environmental impact of ICT. The first states that ICT leads to increased environmental quality through (i) improved technology, (ii) increased productivity, and (iii) the creation of smart cities (Houghton 2010). The second view states that the expansion of ICT negatively impacts the environment through increased industrial production, energy consumption, and globalization (Avom et al. 2020). Some authors, such as Chai et al. (2016), Gergel et al. (2017), and Ozturk et al. (2016), point out that the potential consequences of environmental degradation are so severe that large investments have to be made to reduce it. Barratt (2006) states that education can improve energy management and reduce environmental crises by improving the distance learning infrastructure and internet tools. The ICT's positive impact on the environment through the construction, operation, and improvement of network equipment has been reported by Williams (2011). Danish (2019) stated that ICT reduces CO_2 emissions in countries worldwide. Besides, a moderating effect of ICT was found through the capacity of foreign direct investment to reduce CO_2 emissions and strengthen the interaction between ICT and international trade. Khan et al. (2018), in a study for emerging economies using panel mean group (MG) and augmented mean group (AMG) models from 1990 to 2015, stated that ICT reduces CO_2 emissions.

Nevertheless, some other researchers, such as Cho et al. (2007), Hilty and Ruddy (2010), Chiabai et al. (2010), and Ishida (2015), have raised doubts about the significant reduction in energy consumption following the ICT development. Hilty and Ruddy (2010) stated that ICT development stimulates and increases the demand for energy through globalization, and the distribution of production forms results in the growth of telecommunications networks. A study of 27 EU countries, developed by Díaz-Roldán and Ramos-Herrera (2021), found that advances in ICT reduced CO_2 emissions. In a study of 21 Sub-Saharan African countries, Avom et al. (2020) stated that ICT positively affects CO_2 emissions. In a study of 44 sub-Saharan African countries during 2012–2002, Asongu (2018) stated that ICT would increase CO_2 emissions. Amri et al. (2019), in a study for Tunisia using the ARDL model from 1975 to 2014, found that ICT has no significant effect on CO_2 emissions.

Yang et al. (2020) examined the effect of energy consumption and globalization on CO_2 emissions in 97 countries. The results show that energy consumption increases CO_2 emissions, while globalization reduces it. Jahanger et al. (2021b), in a study of 74 countries, stated that globalization and energy consumption increase CO_2 emissions. In another study of 93 countries, Usman and Jahanger (2021) stated that financial development, energy consumption, and trade openness significantly increase the ecological footprint. In contrast, foreign direct investment improves environmental sustainability. Yang et al. (2021a), in a study for BICS countries, stated that financial development significantly increases the ecological footprint, while technological innovations reduce the ecological footprint. Jahanger et al. (2021a), in a study for China, stated that economic growth is moving towards sustainable development with low carbon emissions. In another study for GCC countries, Yang et al. (2021b) stated that globalization, financial development, and energy use significantly degrade environmental quality.

In a study for Arctic countries, Usman et al. (2021) stated that financial development and renewable energy consumption significantly reduce environmental degradation, while globalization, economic growth, and non-renewable energy play a role in increasing environmental degradation. Usman et al. (2022), in a study for countries rich in natural resources, stated that financial development, natural resources, and non-renewable energy have a positive effect on ecological footprint, while globalization and renewable energy reduce the ecological footprint. Jahanger (2021b) evaluated the role of globalization on CO_2 emissions in 78 developing countries. The results showed that globalization generally reduces environmental quality. Qiang et al. (2021), in a study of 30 Chinese provinces, stated that in the short run, environmental regulation hurts export trade while it has a positive effect in the long run.

This study fills the gap in the previous literature (i) the lack of extensive studies on the impact of economic complexity and fertility rate on the environment, and (ii) the scarcity of literature concerning the link between ICT and the environment. For this purpose, this study analyzes the impact of economic complexity, fertility rate, and ICT on the ecological footprint in a panel of emerging economies from 2000 to 2016, using the STIRPAT model and quantile panel regression. This study is innovative for several reasons and contributes to the literature. In most previous studies, CO_2 emissions were considered an indicator of environmental degradation. Nevertheless, in this study, we consider the ecological footprint, a more comprehensive indicator than CO_2, as an indicator of environmental degradation.

First, given that few studies have explored the ecological footprint, this research could open a new line of research in the subject literature. Second, the research uses quantile panel regression instead of using OLS regression. On the one hand, OLS regression can only explain the effect of influencing factors on the dependent variable and does not show the heterogeneous effect of different values. On the other hand, quantile panel regression is rarely used in the literature and does not have OLS regression problems. Third, according to the existing literature, the effect of economic complexity, fertility rate, and ICT on the ecological footprint in emerging economies has not been studied.

3 Materials and methods

3.1 Emerging countries

The sample of this study includes 19 countries of the MSCI Emerging Markets Classification. These countries were classified based on financial market criteria (access, liquidity, and market size). So, revenue is not the only feature of an emerging market. However, most of them are economies with solid growth and stable stability that can produce higher value-added goods and are more like advanced economies in revenue, global trade participation, and financial market integration. This condition shows the similarity of the structure of the studied countries. In addition, previous studies have not examined the effect of economic complexity, fertility rate, and ecological footprint in emerging economies. Therefore, this study presents important policy implications for environmental protection (MSCI). These 19 countries selected from the Emerging Market Classification are Bangladesh, Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Romania, South Africa, South Korea, Thailand, and Turkey. The latitude, longitude, and climatic conditions of emerging countries are revealed in Table 1.

3.2 Panel quantile regression

Panel quantile regression model was introduced by Koenker and Bassett Jr (1978) and became a comprehensive method for statistical analysis of linear and non-linear models

Table 1 Introduction of emerging countries

Country	Latitude and longitude	Climate
Bangladesh	24° 00’ N and 90° 00’ E	Subtropical climate
Brazil	14° 23′ S and 51°92′ W	Warm and tropical climate
Chile	30° 00’ S and 71° 00’ W	Mediterranean climate
China	35° 00’ N and 105° 00’ E	Subtropical with very hot summers and mild winters
Colombia	04° 00 N, 72 ° 00 W	Tropical climate
Egypt	30° 06’ N and 31° 25’ E	Semi-desert climate
Hungary	47º 00’ N and 20º 00’ E	Continental climate
India	21°76 N and 76°87E	Hot and humid climate
Indonesia	2° 5′ S and 11°8′ E	Tropical climate
Malaysia	2° 30’ N and 112° 30’ E	Tropical climate
Mexico	23°00′ N and 102°00′W	Hot and dry climate
Morocco	32° 00 N and 05° 00 W	Mediterranean climate
Peru	10° 00’ S and 76° 00’ W	Dry and mild climate
Philippines	3° 00 N and 122° 00 E	Tropical and maritime climate
Romania	46° 00’ N and 25° 00’ E	Temperate-continental climate
South Africa	1°13′N and 1°06′S	Mild climate
South Korea	35°90′ N and 127°76′E	Hot and cold climate
Thailand	15° 00’ N and 100° 00’ E	Tropical climate
Turkey	38°96′ and 35°24′	Mediterranean climate

in various fields like climate (Paltasingh and Goyari 2018), agriculture (Balducci et al. 2018), soil resource improvement (Steers et al. 2011), economics (Zhu et al. 2016), and the environment (Xu et al. 2017). Moreover, this model provides a robust and efficient coefficient estimation compared to OLS (Marasinghe 2014; Xu and Lin 2018). Therefore, this research applies the quantile panel regression method to evaluate the effect of economic complexity, fertility rate, and ICT on the ecological footprint of emerging countries.

The mathematical formula of the quantile regression model is as follows in Eq. 1.

$$y_i = x_i b_{\theta i} + \mu_{\theta i}.\ 0 < \theta < 1$$
$$Quant_{i\theta}\left(y_i/x_i\right) = x_i \beta_\theta \tag{1}$$

where X and y represent the vector of independent variables and dependent variable, respectively; μ is a random error, whose conditional quantile distribution is zero; $Quant_{i\theta}\left(y_i/x_i\right)$ is the θth quantile of the explanatory variable; the β_θ estimate shows the quantile regression θth and solves the Eq. 2:

$$min \sum_{yi \geq x_i' \beta} \theta \left| y_t - x_i' \beta \right| + \sum_{yi < x_i' \beta} (1 - \theta) \left| y_t - x_i' \beta \right| \tag{2}$$

As θ is equal to different values, different parameter estimations are obtained. The mean regression is a particular case of quantile regression under θ = 0.5 (Xu and Lin, 2018).

3.3 Model specification

The STIRPAT model is a classical model for determining environmental pollution factors (Ge et al. 2018). The equation can be represented as follows in Eq. 3.

$$I_t = aP_t^b A_t^c T_t^d e_t, \tag{3}$$

where I, P, A, and T indicate pollution, population size, economic ability, and technical factors, respectively. The research goal of this article is to assess the impact of a set of variables on ecological footprint. The pressure on the ecological footprint is not only through the population, economic development, and technology. Many other factors influence it. For example, the following factors are closely related to ecological footprint. Information and communication technology (**ICT**)**:** Sustainable development requires inclusive development, so ICT development is essential.

On the one hand, the development of ICT, by helping to pay bills, bank transactions, and online purchases, reduces unnecessary transportation costs, and on the other hand, reduces transportation pollution (Asongu et al. 2017). Fossil energy consumption (FOSSIL): Achieving sustainable development requires economic growth. Increasing economic growth leads to more energy consumption. The consumption of nonrenewable energy causes more pollution of the environment, so paying attention to clean energy is essential to improve the quality of the environment and reduce environmental degradation. TO: Trade openness, through two channels, can have a positive or negative effect. On the one hand, trade openness can lead to economic activities and economic growth, increasing energy consumption and environmental pollution.

On the other hand, trade openness leads to the transfer of new technologies with high energy efficiency and thus helps to improve the environmental quality (Copeland and Taylor 2013). Gross Domestic Product (GDP): The relationship between increasing economic growth and the environment can be expressed using the Kuznets curve that increasing economic growth can initially lead to more pollution, but then with the advancement of technology, efficiency increases and reduces the increasing trend of environmental degradation (Alvarado and Toledo 2017). Economic complexity (ECI): The advancement of technology increases the efficiency of energy goods and reduces energy consumption, thereby affecting the quality of the environment. Fertility rate (FR): Increasing the fertility rate leads to population growth and increases the demand for energy and natural resources, and reduces the amount of physical capital per person ("Solow effect") and natural capital per person ("Malthus effect"), this, in turn, causes environmental degradation (Casey and Galor 2016; Sarkodie 2018). Urbanization (URB): Urbanization is a socio-economic process of large-scale. Labor flow from an agricultural-based economy to an urban-based industrial economy causes an expansion of the urban lifestyle. This rapid urbanization leads to increased energy consumption and environmental impacts (Azam and Khan 2016; Wang et al. 2018b). Therefore, many researchers have used the extended STIRPAT model (Eq. 4) to investigate their effects on the environment (Xu and Lin 2018).

$$EFPG_t = aICT_t^b GDP_t^c\ FOSSIL_t^d\ FR_t^{\alpha}\ ECI_t^{\beta}\ TO_t^{\gamma} URB_t^{Z} e_t, \tag{4}$$

where EFPG represents ecological footprint measured in global hectares; ICT is information and communication technology; GDP is Gross Domestic Product; FOSSIL denotes non-renewable energy consumption (which includes oil, gas, and coal) calculated in a million tonnes of oil equivalent; FR is fertility rate; ECI represents economic complexity and is used as a proxy for technology; TO is trade openness that measures the sum of exports and imports in GDP; and URB is urban population (in % of the total population).

The econometric theory states that model variables must be logarithmic to eliminate possible heterogeneity phenomena. Therefore, Eq. 4 is logarithmized and originates Eq. 5, as follows.

$$LEFPG_{it} = La + \beta_1 LICT_{it} + \beta_2 LGDP_{it} + \beta_3 LFOSSIL_{it} + \beta_4 LFR_{IT} + \beta_5 LECI_{it} + \beta_6 LTO_{it} + \beta_7 LURB_{it} + \delta_{it.} \tag{5}$$

This research applied panel quantile regression to measure the ecological footprint in emerging countries. After that, Eq. 5 is converted into Eq. 6:

$$\begin{aligned} Q_\tau\left(LEFP_{it}\right) = (La)_\tau + \beta_{1\tau} LICT_{i\tau} + \beta_{2\tau} LGDP_{i\tau} + \beta_{3\tau} LFOSSIL_{i\tau} + \beta_{4\tau} FR_{i\tau} + \beta_{5\tau} ECI_{i\tau} \\ + \beta_{6\tau} LTO_{i\tau} + \beta_{7\tau} LURB_{i\tau} + \delta_{i\tau}. \end{aligned} \tag{6}$$

where Q_r denotes the estimation of the quantile regression τth in the ecological footprint, and $(la)_r$ is a constant component. The coefficients of $\beta_{1\tau}, \beta_{2\tau}, \beta_{3\tau}, \beta_{4\tau}, \beta_{5\tau}, \beta_{6\tau}, and \beta_{7\tau}$ indicate the quantile regression parameters and show the influential factors.

3.4 Data source and variable description

A panel data for the period from 2000 to 2016, and for the 19 emerging countries (Bangladesh, Brazil, Chile, China, Colombia, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Romania, South Africa, South Korea, Thailand, and Turkey), was used. There was significant progress in ICT, economic complexity growth, and data availability for all variables during this period. Table 2 provides definitions of all variables.

Table 3 also shows the descriptive characteristics of the used indicators, namely mean, standard deviation, maximum, and minimum. The number of observations is 327. The

Table 2 Variables, definition, and sources

Variable	Definition	Sources
EFPG	Ecological footprint (global hectares)	Global Footprint Network (GFN) (2020)
ECI	Economic complexity	Observatory of Economic Complexity (OEC) (2020)
ICT	Information and communication technology (percentage of the population using the internet)	World Bank Data (WBD) (2020)
GDP	GDP per capita (constant 2010 US$)	WBD (2020)
FOSSIL	Non-renewable energy consumption in million tonnes oil equivalent	WBD (2020)
FR	Fertility rate, total (births per woman)	WBD (2020)
TO	Total openness = (import + export)/GDP	WBD (2020)
URB	Urban population = % of total population	WBD (2020)

All of the data are annual from 2000 to 2016; given the economic complexity data comprises values from −2.5 to 2.5, it was added 3 to all observations to allow the use of logarithms

Table 3 Summary of descriptive statistics

Variable	Mean	Std. dev	Min	Max	Obs
EFPG	4.88e+08	9.85e+08	2.89e+07	5.17e+09	323
FR	2.220816	0.6174167	1.076	3.811	323
ICT	30.84856	23.82979	0.527532	92.84303	323
FOSSIL	2.26e+08	4.89e+08	9,901,212	2.65e+09	323
GDP	8.98e+11	1.40e+12	5.75e+10	9.49e+12	323
ECI	3.309023	0.6034272	2.12205	4.90646	323
TO	72.80446	42.16373	22.10598	220.4068	323
URB	61.56343	17.24498	27.667	87.422	323

Obs. denotes the number of observations in the model; Std.-dev denotes the Standard Deviation; Min and Max denote Minimum and Maximum, respectively

mean ecological footprint is 4.88e+08 global hectares. The mean percentage of ICT is 30.85%, and the mean fertility rate is 2.2208 births per woman. The minimum fertility rate is 1.076, and the maximum is 3.811.

Figure 1 reveals the emerging countries' per capita ecological footprint (EFPG). South Korea, Hungary, and Malaysia have the highest per capita ecological footprint. The trend of ecological footprint global hectares per capita in China has increased since 2001. Other countries have had relatively stable trends. The lowest per capita ecological footprint is in Bangladesh, India, and the Philippines.

4 Results

The best econometric practices require pre-estimation procedures to ensure estimation results' reliability. Pre-estimation starts with testing the data normality. The absence of normally distributed data is a precondition for quantile regression. Two approaches are used to appraise the data normality, the graphical and the numerical. The pre-estimation procedures pursue the assessment of multicollinearity among independent variables. The variance inflation factor (VIF) was used to assess the extent of multicollinearity. Two phenomena that can compromise an accurate interpretation result are cross-sectional dependence and spurious regression. Cross-sectional dependence compromises the significance

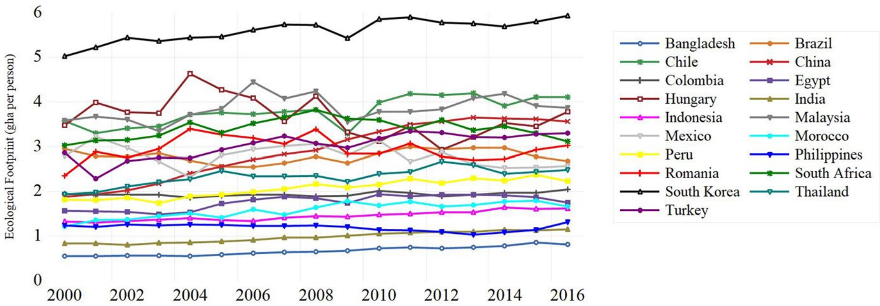


Fig. 1 Ecological footprint (global hectares per person) for emerging countries

of estimated parameters. The spurious regression occurs when nonstationary variables are non-cointegrated among them. The cross-sectional independence of variables and the presence of unit roots were tested to assess the severity of these potential problems. The pre-estimation procedure end with testing for cointegration.

4.1 Normal distribution test

When sample data are not normally distributed, the estimation results from quantile regression are more robust than the OLS estimation. If the OLS method is used to estimate regression, the skewed distribution of economic variables is ignored. This will have undesirable consequences, such as increased variance and low model robustness (Koenker and Xiao 2002). Therefore, before performing a regression analysis, the normality of all variables should be tested. In the study, Shapiro–Wilk (Royston 1992) and Shapiro-France (Royston 1983) tests were applied to measure the normality of the data.

Table 4 shows that the probability values of the Shapiro–Wilk and Shapiro-France tests for all variables are significant at less than 1% level. This represents that for these variables, the null hypothesis can be rejected. In other words, the above variables have a non-normal distribution.

According to the results in Table 4, it can be seen that these variables are not distributed normally. Consequently, the quantile panel regression model for experimental analysis is more appropriate and adequate to handle the data.

4.2 Multicollinearity tests and cross-sectional independence test

After performing the normality test of the variables, we examine the preliminary tests mentioned earlier. For this purpose, the variance inflation factor (VIF) is used to examine the multicollinearity of variables (Belsley et al. 2005). The results of the multicollinearity test show that the VIP values for all variables are less than the usually accepted standard of 10. Moreover, considering that the mean VIP of the variables is 2.5 and is less than the accepted value of 6. The result shows no harmful multicollinearity problem (see Table 5, below). Before analyzing the stationary properties of the variables, this study has used the CD-test Pesaran (2004) to check the cross-sectional dependencies in each panel time-series data. Failure to pay attention to the cross-sectional dependency issue may lead to estimation errors. The results of the Pesaran CD-test for the variables analyzed are reported in

Table 4 Normal distribution test

Variables	Shapiro–Wilk test Statistic	Shapiro-Francia test Statistic	Obs
LEFPG	0.93494***	0.93706***	272
LFR	0.97071***	0.97328***	272
LICT	0.91988***	0.92184***	272
LFOSSIL	0.93580***	0.93784***	272
LGDP	0.96405***	0.96601***	272
LECI	0.9562***	0.9568***	272
LTO	0.96692***	0.96922***	272
LURB	0.92446***	0.92780***	272

***Denotes statistical significance at 1% level

Table 5 VIF and CSD test

Variables	VIF-test		Cross-sectional dependence (CSD-test)	
	VIF	Mean VIF	CD test	Corr
EFPG	n.a	2.5	46.57***	0.998
FR	2.00		44.66***	0.957
ICT	2.00		41.22***	0.884
FOSSIL	2.86		46.56***	0.998
GDP	3.25		45.71***	0.980
ECI	3.11		43.47***	0.932
TO	1.87		43.25***	0.927
URB	2.41		46.15***	0.989

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

Table 5. Since the corresponding p-values are less than 0.01, we have strong evidence to reject the null hypothesis of cross-sectional independence for all variables at the 1% significance level. In other words, the analyzed variables are cross-sectionally dependent.

4.3 Panel unit root tests

In the presence of cross-country dependencies in the panel, first-generation conventional panel unit root tests (e.g., LLC unit root tests, Fisher-ADF, Fisher-PP) should not be used because they have no dependencies on the panel. This assumption may cause estimation errors. In general, according to the confirmation of cross-sectional dependence in Table 6, in this study, the CIPS Pesaran (2007) panel unit root test is used because they have a strong cross-sectional dependence. The results of this test are reported in Table 6. The panel unit root test without trend and with the trend is used in the CIPS test. As can be seen, the only variable of urbanization (URB) with and without a trend level is stationary at the significance level of 1%, and economic complexity (ECI) is stationary at the level of significance of 1% in without trend. The rest of the variables are non-stationary at the level. The panel unit root test (CIPS) in the first-order difference shows that except LGDP that is stationary at lag zero at without and with the trend, all variables are stationary in the first-order difference. Therefore, since all variables are stationary in the first-order differences, the relationship between the ecological footprint and other variables can be determined by the cointegration test.

4.4 Panel cointegration test

The panel's unit root test results show that the variables are stationary at the first-order difference. The cointegration test can be used for long-run relationships between variables (Al-Mulali and Ozturk 2016; Wang et al. 2018a). In this research, Pedroni (1999) and Kao (1999) cointegration tests are applied to examine the long-run relationship between the variables (Azam and Raza 2016; Raza and Karim 2016; Shah 2016). The null hypothesis in both of these tests is the no-cointegration. Pedroni (1999) solves the biasness from the

Table 6 Panel unit root test (CIPS)

Variables	CIPS (Zt-bar)			Variables	CIPS (Zt-bar)		
	Lags	Without trend	With trend		Lags	Without trend	With trend
EFPG	0	1.447	−0.901	LEFPG	0	−3.876***	−3.465***
	1	1.729	0.318		1	−2.645***	−2.218***
FR	0	0.657	1.154	LFR	0	−3.265***	−2.524***
	1	1.067	1.029		1	−3.534***	−1.876**
ICT	0	0.754	1.245	LICT	0	−3.971***	−1.532*
	1	1.457	2.361		1	−2.927***	−1.757**
FOSSIL	0	1.056	1.005	LFOSSIL	0	−4.843***	−3.353***
	1	2.280	1.559		1	−3.833***	−2.462***
GDP	0	2.832	1.379	LGDP	0	−3.235***	−3.738***
	1	0.814	4.280		1	−0.503	−0.768
ECI	0	−2.665***	−1.427	LECI	0	−4.546***	−3.730***
	1	1.690	2.634		1	−3.746***	−1.948*
TO	0	0.657	1.154	LTO	0	−2.634***	−3.078***
	1	1.067	1.029		1	−3.301***	−2.142***
URB	0	−2.519***	−2.284***	LURB	0	−4.935**	−3.193***
	1	−1.505	−1.111		1	−2.408***	−0.434

*** and **Denote statistical significance at 1% and 5% levels, respectively; panel unit root test (CIPS) assumes that cross-sectional dependence is in the form of a single unobserved common factor and H_0: series is I(1)

country size bias, solves heterogeneity and biasness resulting from the country size, and allows cross-sectional interdependence with different individual effects. In contrast, Kao's (1999) test states that the cointegration vectors are homogeneous and pooled regression permitting individual fixed effects across the individual member of the panel. The results in Table 7 in both tests show the long-run equilibrium relationship between the ecological footprint (EFP) and the explanatory variables.

4.5 Quantile panel regression results

Quantile panel regression can obtain the effects of independent variables on the dependent variable in different quantiles between 0 and 1. However, it is impossible to interpret each quantile value effectively due to data fluctuations. Therefore, according to most

Table 7 Kao and Pedroni cointegration test

Kao cointegration test			Pedroni cointegration test		
Estimators	t-Statistic	Prob	Estimators	t-Statistic	Prob
ADF	−4.3272	0.0000	Modified Phillips-Perron t	6.0829	0.0000
Residual variance	0.00185		Phillips-Perron t	−10.7540	0.0000
HAC variance	0.00136		Augmented Dickey-Fuller t	−9.7635	0.0000

Table 8 Country distribution in terms of ecological footprint (gha)

Quantile	Country
The lower 10th quantile group	Hungary
The 10the25th quantile group	Morocco, Peru, Romania
The 25the50th quantile group	Chile, Colombia, Bangladesh, Malaysia, Philippines
The 50the75th quantile group	Egypt, Thailand, South Africa, Turkey, South Korea
The 75the90th quantile group	Mexico, Indonesia, Brazil,
The upper 90th quantile group	India, China

According to the level of Ecological Footprint, we divided 25 countries into six groups

researchers, quantile values of 10th, 25th, 50th, 75th, and 90th are used as representative values for experimental analysis. In this study, based on the Ecological Footprint Scale, the emerging countries are classified into six groups in Table 8.

Here, OLS has been used to estimate the effects of the panel fixed effects, which can only estimate the average effect of explanatory variables on the dependent variable. Moreover, the results of quantile panel regression are shown graphically in Fig. 2.

Shaded areas represent a 95% level of confidence band for the quantile regression estimates. The vertical axis indicates the elasticities of the explanatory variables. The red horizontal lines depict the conventional 95% confidence intervals for the OLS coefficient.

Different quantiles (10th, 25th, 50th, 75th, and 90th) have been used to estimate this research. The results of these estimates are reported in Table 9 and Fig. 2. For comparative analysis, we represent the results of the OLS estimation in Table 8. We need to analyze these different effects, which can support countries in formulating policies to reduce the ecological footprint.

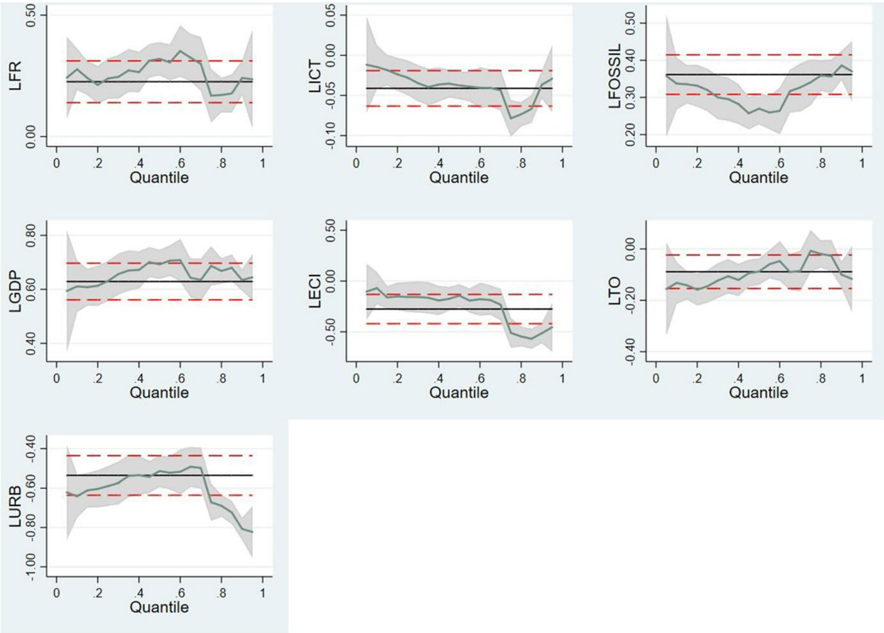
Next, the Methods of Moment's quantile (MM-QR) model is used to evaluate the robustness of the quantile panel regression. The results of MM-QR estimation are given in Table 10.

As can be seen (Table 10), the MM-QR estimation results in most quantiles confirm the quantile panel model results. In addition, the result shows that LFR, LFOSSIL, and LGDP increase the ecological footprint, while LICT, LECI, LTO, and LURB decrease the ecological footprint.

5 Discussion

5.1 The effects of fertility rate on ecological footprint

As shown in Table 9, the effect of the fertility rate on ecological footprint is positive and significant in all quantiles. The fertility rate coefficient reveals that this effect has a more severe effect on 50th quantiles' ecological footprint. So, a 1% increase in the fertility rate of the 50th quantile causes an increase of 0.3201% in the ecological footprint. Harris (2009) found that macroeconomic indicators and ecological reserves predict life expectancy at birth. So, it improves life expectancy at the biosphere's expense, which is not fair to future generations. Alola et al. (2019) also stated that the effects of fertility rate on ecology, in the long run, will lead to divergence of fertility rates in EU member states. Mondal and



Shaded areas represent a 95% level of confidence band for the quantile regression estimates. The vertical axis indicates the elasticities of the explanatory variables. The red horizontal lines depict the conventional 95% confidence intervals for the OLS coefficient.

Fig. 2 Quantile estimate

Sanaul (2019) say that Bangladesh's population almost doubled between 1980 and 2015. It accounts for about 2.2% (in 2013) of the world's population and only 0.19% of global CO_2 emissions.

Table 9 Estimation results from panel quantile regression model and panel fixed effects

Variables	Quantiles					OLS
	10th	25th	50th	75th	90th	Fixed Effects
LFR	0.2769***	0.2393***	0.3201***	0.1684*	0.2413***	0.2786***
LICT	−0.015	−0.028***	−0.038***	−0.0786***	−0.0366**	−0.0304***
LFOSSIL	0.3373***	0.3197***	0.2698***	0.3407***	0.3860***	0.3346***
LGDP	0.611***	0.6311***	0.6927***	0.6869***	0.6343***	0.6732***
LECI	−0.070	−0.157***	−0.143*	−0.5102***	−0.5136***	−0.3557***
LTO	−0.132***	−0.145***	−0.088**	−0.008	−0.1000**	−0.0929***
LURB	−0.641***	−0.589***	−0.514***	−0.6714***	−0.8071***	−0.6454**
Constant	−0.533	−0.686	−1.945***	−1.9401	−0.5271***	−1.9412***
Pseudo R^2	0.8805	0.8788	0.8746	0.8760	0.9079	0.9762

***, **, *Denote statistically significant at the 1, 5, and 10% levels, respectively; "L" denotes variables in natural logarithms

Table 10 Estimation results from Methods of Moments quantile (MM-QR) regression model

Variables	Quantiles				
	10th	25th	50th	75th	90th
LFR	0.4073***	0.3564***	0.3104***	0.2648***	0.2335**
LICT	−0.0087	−0.021**	−0.036***	−0.0594***	−0.0214
LFOSSIL	0.6182***	0.6053***	0.5936***	0.5820***	0.5741***
LGDP	0..1676	0.1829**	0.1968***	0.2105***	0.2199**
LECI	−0.1892*	−0.1630**	−0.1396***	−0.1163**	−0.1003
LTO	−0.0146	−0.1703**	−0.1121***	−0.0914***	−0.1221**
LURB	−0.223	−0.2285**	−0.2339**	−0.2391**	−0.2427

***, **, *Denote statistically significant at the 1, 5, and 10% level, respectively; "L" denotes variables in natural logarithms

5.2 The effects of ICT on ecological footprint

The effect of ICT on ecological footprint has a negative and statistically significant effect on all quantiles except for quantile 10th. Therefore, increasing ICT reduces ecological degradation in these countries. The coefficient of this variable shows that with increasing ICT progress in higher quantiles, the ecological footprint decreases, and then the ICT effect decreases in the 90th quantile. In this regard, the study "SMARTer 2030" by the Global Sustainability Initiative (GeSI) and the Industry Association for Sustainability show that ICT programs can indirectly reduce up to 20% of annual greenhouse gas emissions by 2030 (Bieser and Hilty 2018). Majeed (2018) reported that ICT plays a crucial role in the world's ecological future. So that its favorable results are seen in developed countries, and its harmful effects are seen in developing countries. Besides, this study's findings show that new ICT measures, such as online services, telecommunications infrastructure, and e-government, have mitigated the environment's harmful effects. Lashkarizadeh and Salatin (2012) reported that investing in ICT can reduce CO_2 emissions. Zhang and Liu (2015) reported the positive effects of ICT on reducing CO_2 emissions in China. Ozcan and Apergis (2018) point out that ICT has reduced pollution in emerging countries.

5.3 The effects of fossil fuel consumption on ecological footprint

As shown in Table 9, fossil fuel consumption in all quantiles increases the ecological footprint. This study shows that the greatest effect of fossil energy consumption on ecological footprint is in quantile 90th. As shown by a 1% increase in fossil energy consumption causes a 0.3860% increase in ecological footprint. These results are supported by many studies (Sharma 2011; Dogan and Turkekul 2016; Gozgor and Can 2017; Dogan et al. 2020). Fossil fuels consumption is essential for economic growth. However, it has many environmental consequences. Given that 80% of the energy consumed in the world is from non-renewable energy, reducing environmental consequences, increasing the efficiency of fossil fuels, and replacing renewable energy are necessary (Simeonovski et al. 2021).

5.4 The effects of economic growth on ecological footprint

The GDP effect on the ecological footprint in all countries' quantiles is positive and significant. From quantiles 10th to 50th, the effect of GDP on the ecological footprint increases and then decreases, which confirms the Kuznets hypothesis. This result can be compared with Alam et al. (2016), Kais and Sami (2016), Shahbaz et al. (2016), Rahman et al. (2017), and Danish and Baloch (2018) results. They stated that the effects of economic growth on the ecological footprint are positive and lead to environmental degradation, pollution, and harm to human health. Dismukes et al. (2001) reported that advances in the stock market allow companies to use their budgets and increase their production, increasing CO_2 emissions and, consequently, environmental degradation. Salahuddin et al. (2019) examined the effect of economic growth on Kuwait's CO_2 emissions using time series from 1980 to 2013 and the ARDL method. Their findings imply that economic growth has stimulated the ecological footprint in Kuwait. Khobai and Le Roux (2017) stated a long-run two-way relationship between energy consumption and GDP.

5.5 The effects of economic complexity on ecological footprint

Except for the 10th quantile, economic complexity has a negative effect on the ecological footprint in all other quantiles. As can be seen, these effects have increased dramatically in the 75th and 90th quantiles. Increasing levels of economic complexity led to the production of goods with more sophisticated technology, which increases energy efficiency. The results of several studies support these findings (Can and Gozgor 2017; Lapatinas et al. 2019; Pata 2020; Doğan et al. 2021; Kazemzadeh et al., 2021). Economic complexity is created by changing knowledge-based production and economic structures. With increased production based on high knowledge and technology, the infrastructure improves. The type of products of countries changes from producing simple goods to knowledge-based and high-productivity goods that greatly help improve the environment. However, some studies consider the increase in ECI in environmental degradation (Neagu 2019; Pata 2020).

5.6 The effects of trade openness on ecological footprint

The results show that the effect of trade openness on the ecological footprint in the 10th, 25th, 50th, and 90th quantiles are negative and significant. This effect is greater in the lower quantiles (see Table 9). According to the results, it can be said that the trade openness in these countries leads to the import of advanced technologies and provides a cleaner production process. In this way, trade openness is effective in improving environmental quality. This section's results are consistent with the findings of Destek et al. (2018) for EU countries, who stated that trade openness leads to technology transfer between countries, more accessible access to cleaner technologies, and improved environmental quality. Dogan and Seker (2016) also stated that trade openness reduces emissions for developed countries with higher levels of renewable energy consumption. In a study for EU countries, Alola et al. (2019) confirmed the findings of this study. They stated that free trade reduces environmental degradation.

On the other hand, in less developed countries, the most crucial concern of policymakers in any nation is to achieve growth, even at the cost of the environment. Therefore, cheap and polluting technologies are imported to boost production in these countries, which leads to environmental degradation. The findings from a study by Al-Mulali and Ozturk (2015), for the MENA countries, during 2012–2016 show that trade openness leads to environmental degradation.

5.7 The effects of urbanization on ecological footprint

Urbanization has a negative and significant effect on ecological footprint at all quantiles levels. It means that increasing urbanization decreases the ecological footprint. This effect is more substantial in the 90th quantile than in other levels. For example, a 1% increase in the urbanization rate in the 90th quantile causes a decrease of 0.8071% in the ecological footprint. In a study of 69 countries, Sharma (2011) stated that urbanization reduces CO_2 emissions. In another study, Saidi and Mbarek (2016) confirm Sharma's (2011) findings on the impact of urbanization on CO_2 emissions reduction. At the same time, some other studies show that urbanization increase environmental degradation. These results can be compared to Nathaniel and Khan (2020), which state that urbanization in Indonesia causes environmental degradation and worsens it in the long run. Ahmed et al. (2020) point out that G-7 countries face many challenges regarding urbanization. They support that urbanization increases the ecological footprint, while human capital reduces it. Yasin et al. (2021) also stated in a study for 59 less developed countries that urbanization increases environmental degradation.

6 Policy implications

Now we will take an overview of the policy implications of our research. First, it is helpful to remind us of what we are talking about when we refer to the ecological footprint. On the one hand, the ecological footprint is, putting in simple words, the volume of natural resources (environment) we must sacrifice to produce the goods and services. Consequently, lifestyles play a significant role in ecological footprint. However, on the other hand, the ecological footprint is related to sustainability. Therefore, people should be aware of the use of resources throughout the economy and measure the sustainability of their lifestyles and the mix of goods and services they consume.

For the convenience of exposition and from a policy point of view, we can classify the variables under analysis in three cases: (i) (macro)economic variables where it is necessary to change your composition to mitigate/reduce their impact; (ii) variables that change your contribution or turn themselves irrelevant to the issue under analysis depending on the quantiles analyzed, and (iii) variables that contribute to reducing the impact, and policy interventions can be implemented to intensify their capacity to reduce the ecological footprint.

In the first group, we have economic growth and non-renewable energy consumption. Economic growth is by large the most contributor to increasing the ecological footprint. Policymakers should mitigate this undesired effect by intervening on their economies' supply and demand sides. Before the intervention, authorities must identify the goods and services impact on the ecological footprint. After this identification, the intervention on the supply side ought to materialize, altering, for example, the taxation of goods and services to promote the substitution for goods and services with less impact on ecological footprint. On the demand side, the policy intervention can force the revealing of the ecological footprint of goods and promote consumers' recognition of the impact of their behavior on the ecological footprint. The deep and the maturity of ICT can enhance the policy intervention on the demand side. Policies to widen recycling can also mitigate the ecological footprint and attenuate the negative effect of economic growth that results from attempts to reduce the ecological footprint.

The positive effect of non-renewable energy consumption on the ecological footprint is high (only economic growth has a more substantial effect). The energy transition from fossils to renewables is urgent to revert the undesired effect of energy consumption on the ecological footprint. However, energy transition requires time to be completed. That means that policies to turn effective the transition from fossil sources of energy to renewable sources are not enough to reduce the impact of energy consumption on the ecological footprint for several years ahead. Therefore, efforts to reduce de consumption of energy are necessary to circumvent the ecological footprint damage. Policymakers must beware that the deployment of renewables (solar, wind, and the like) also impacts the ecological systems, and that impact varies by the kind of renewables deployed. Therefore, policy authorities should promote renewables' deployment with minor impacts and facilitate deployment in places already used by populations, such as in cities. This influence on the location of renewables deployment can be done, for example, recurring feed-in tariffs, the priority of access to grids, or tax rebates. An enthusiastic attitude by people can also enforce the mitigation/reduction of the footprint. Indeed, people's voluntarism is especially valuable in the initial phase of processes that require massive transformations, as is the energy transition from fossil to renewables. Indeed, incentivizing the people's voluntarism can limit the damage to the ecological footprint. Particularly the damage for the upcoming generations. The development of ICT infrastructure can play a significant role here.

ICT, economic complexity, and trade openness reduce the ecological footprint in different quantiles. ICT and economic are statistically significant in all quantiles except 10th, and trade openness only faille statistical significance in 75th quantile. Policymakers can explore these characteristics by investing in ICT and economic complexity when the ecological footprint is low and promoting trade openness in the cases where the ecological footprint is concerning. In the case of ICT, policymakers should develop and extend access to ICT to all regions. Particular attention should be put on avoiding formations of monopolies, given that economies of scale tend to be huge. Our research has detected a connection with the ecological footprint beyond the literature that establishes that ICT can influence the environment. ICT can change people's consumption and production patterns if policymakers act on socio-economic, cultural, and health conditions. ICT could also raise people's awareness of environmental degradation issues, facilitating the intervention of policymakers. Indeed, the ICT allows the development of people's consciousness and works as a powerful tool to improve perceptions and behavior. Furthermore, ICT contributes to adopting environmentally friendly technologies.

Economic complexity is intimately related to the level of knowledge present in a place (e.g., city, region, or country) and is revealed to be a driver of economic development. The group of developing countries under analysis here revealed to be a mighty contributor to reducing environmental degradation, especially in the high quantiles. In accordance, policymakers ought to bet on stimulating the diversity and sophistication of their countries' exports. In other words, they must stimulate the emergence of productive capabilities in new sectors, preferably in activities with relatively low ubiquity. In parallel, policymakers should promote the increasing sophistication of their exports.

Trade openness effect over ecological footprint reflects two major situations. First, rich countries have high ecological footprints and, in general, populations that are much more concerned with environmental degradation. In this case, trade openness reflects the transfer of damage on the ecological footprint from rich to less-rich countries. Second, trade openness can also mirror different productivity levels, producing goods that demand few global hectares.

Energy efficiency has a decisive contribution to reducing the ecological footprint. However, efficiency is primarily a technological issue. In accordance, policymakers should stimulate I&D and create conditions that accelerate the adoption of more efficient technologies. That can be done, for example, by penalizing inefficiency turning energy expensive, subsidizing the change to more efficient practices, or both.

Fertility rates damage the ecological footprint in all quantiles. The fertility rate tends to be low in rich countries with aging populations. In this context, the population is not growing at all. There is no additional pressure on the environment in this way. Therefore, policymakers should try to stabilize the population more than keeping an eye on fertility. However, fertility and birth rates link with the ecological footprint beyond the population itself. Fertility and birth rates decline as countries become rich. In general, a massive investment in human capital was not compatible with numerous proles, and human capital is necessary to support economic growth. Consequently, public policies have to control the population growth more often than not to allow a takeoff on economic growth. Again, we have a contradiction (tradeoff) in the necessary policies to reduce the ecological footprint.

Urbanization outcomes typically from the population migrating from rural areas to cities. Consequently, urbanization provokes massive transformations in the economic geography of countries. This situation is because the consumption structure of urban areas tends to be less demanding in global hectares than that of rural ones. Indeed, developing countries tend to be plagued by poor farming and grazing, overuse of soil, and erosion. That situation alleviates with the migration of population to cities.

Nevertheless, urbanization is also a situation with a limit (100% of the population), restricting the contribution of this variable as time elapses. However, policymakers of developing countries should take advantage of the contribution of this variable in the course of the urbanization process. This phenomenon explains, in part, that in high quantiles, its effect on reducing the ecological footprint be more intense.

7 Conclusion and policy implications

This study investigates the effect of economic complexity, fertility rate, and ICT on the ecological footprint in 19 emerging countries using the STIRPAT model and quantile panel regression during 2000–2016. This study shows that ICT, economic growth, economic complexity, fertility rate, trade openness, and urbanization affect the ecological footprint. Moreover, the study categorized the emerging countries in terms of ecological footprint (global hectares). A country like Hungary is in lower quantiles (less than 10th), Morocco, Peru, and Romania in the 10th to 25th, and Chile, Colombia, Bangladesh, and the Philippines are in the 25th to 50th, Egypt, Thailand, South Africa, Turkey, and South Korea in the 50th to 75th. Countries like Mexico, Indonesia, and Brazil are 75th and 90th, and India and China are upper than 90th quantiles.

In summary, the effect of the fertility rate on the ecological footprint in all quantiles is positive and significant. Alola et al.'s (2019) results for European countries confirm that improving fertility rates in the short run will increase the ecological footprint. The impact of ICT in quantiles 25th, 50th, 75th, and 90th on the ecological footprint is negative and significant. Several studies have confirmed these results (Haseeb et al. 2019; Lu 2018; Wang et al. 2015). Ozcan and Apergis (2018) found that using the Internet reduces carbon dioxide emissions and improves the environment in their study of emerging countries. Like most previous studies (Dogan and Turkekul 2016; Gozgor and Can 2017; Dogan et al. 2020), fossil energy consumption positively affects the ecological footprint. The results also show that economic growth increases the ecological footprint. Increased economic growth leads to more energy consumption, leading to more pollution. Sharif et al. (2020) and Ahmed et al. (2020) emphasize that economic growth causes environmental degradation. Trade openness can help improve environmental quality by transferring new and advanced technologies. Zhang et al. (2017) confirm that trade openness reduces pollution. Urbanization also has a significant negative relationship with environmental degradation in all quantities. As urbanization increases, so do public transportation systems and environmentally friendly infrastructure, contributing to the environmental quality (Sharma 2011; Sadorsky 2014; Zhu et al. 2016; Dogan et al. 2020).

This paper shows that the most effective way for emerging economies to reduce environmental degradation is to reduce fossil energy consumption, replace renewable energy, and reduce fertility rates. However, emerging economies are pursuing economic development goals with high energy demand. On the other hand, with the increase in development in these countries and using environmentally friendly technologies, there is hope to reduce environmental risks due to their rapid growth. Furthermore, strategies such as taxing polluting products and financial incentives for low-carbon products can help improve the environment.

As seen in the section policy implications, the mitigation reduction of ecological footprint requires an extensive set of policy measures. We highlight that those authorities must identify the impact of consumption of goods and services on the ecological footprint. This intervention should consider both the demand and supply sides of economics. The development of ICT infrastructure can enhance the power of policies and have a significant role in developing peoples' ecological consciousness. Policies favoring energy efficiency and the energy transition to renewable sources help mitigate the ecological footprint. Finally, attention to the fertility rate is advised. Population growth exerts pressure on the ecological footprint.

The heterogeneity of the countries under analysis imposes some limitations on our research. The next step should be to advance research by exploring econometric techniques that allow the decomposition of short-run and long-run effects and explore the differences between developing and developed countries. Another research limitation is the unavailability of ecological footprint data for recent years. For this purpose, the study was conducted until 2016. It is also suggested that the effects of ECT on $PM_{2.5}$ emissions be investigated for future research.

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Declarations

Conflict of interest The authors declare that they have no Conflict of interests.

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