Environmental Science and Pollution Research (2021) 28:53379–53393
https://doi.org/10.1007/s11356-021-14300-y

RESEARCH ARTICLE

The impact of globalization on the ecological footprint: do convergence clubs matter?

Şükrü Apaydin[1] · Uğur Ursavaş[2] · Ümit Koç[3]

Received: 16 February 2021 / Accepted: 3 May 2021 / Published online: 24 May 2021

Abstract

In this paper, we examine the impact of globalization on ecological footprint within the framework of the environmental convergence hypothesis for 130 countries over 1980–2016. To do so, we follow a two-stage empirical procedure. First, we test the overall convergence in ecological footprint across countries and identify possible convergence clubs using the nonlinear time-varying factor model developed by Phillips and Sul (2007). Then, we perform panel unit-root and panel cointegration tests used under the presence of cross-sectional dependence to analyze the impact of globalization and economic growth on the ecological footprint both for the full panel sample and convergence clubs. Finally, we estimate long-run coefficients using the Common Correlated Effects Mean Group (CCE-MG) and Augmented Mean Group (AMG) techniques. The club clustering algorithm identifies five convergence clubs, each converging to a different ecological footprint level. The results show cointegration between variables for the full panel sample and two of the five convergence clubs. Furthermore, there is no significant relationship between ecological footprint and globalization, whereas economic growth is significantly and positively related to the ecological footprint for full panel sample and one of the five convergence clubs. In other words, the impact of globalization and economic growth on ecological footprint differs across full panel sample and convergence clubs.

Keywords Globalisation · Growth · Ecological footprint · CCE-MG · AMG

Introduction

Globalization is one of the most controversial areas since the last quarter of the twentieth century. It can be defined as an increasing pattern and intensification of international interactions that promote the cultural, ecological, political, technological, and social integration and enable transnational structures at global, supranational, national, regional, and local levels (Rennen and Martens 2003: p. 143). In the globalization process where international interdependencies and relations have gradually increased (Jones 2010), in addition to the globalization of trade and finance, innovations in information and communication technologies and developments in transportation led to the globalization of production, consumption, and markets. Through economic globalization, companies have sold their products in markets that are profitable, and these goods have been commercialized globally. The globalization of financial capital has made it possible to produce different parts of a product in different regions of the world, assembled in different countries, and sold in different markets. Thus, significant changes happened in the location and structure of both production and companies. In other words, globalization has contributed to the expansion of world production (scale effect), shifting the location and composition of production and consumption (structural effect). More specifically, it enables improving technological developments (technological

Responsible Editor: Ilhan Ozturk

✉ Şükrü Apaydin
sukruapaydin@nevsehir.edu.tr

Uğur Ursavaş
ugur.ursavas@beun.edu.tr

Ümit Koç
umitev@gmail.com

[1] Department of International Trade and Logistics, Faculty of Economics and Administrative Sciences, Nevşehir Hacı Bektaş Veli University, 50300 Nevşehir, Turkey

[2] Department of Economics, Faculty of Economics and Administrative Sciences, Zonguldak Bülent Ecevit University, 67100 İncivez, Zonguldak, Turkey

[3] Central Bank of the Republic of Turkey, Hacı Bayram Mahallesi İstiklal Caddesi No. 10 06050 Ulus, Altındağ, Ankara, Turkey

effect) and allows the production and consumption of different product combinations (product effect) (Organization for Economic Cooperation and Development [OECD] 1997).

Globalization which links international markets through commercial and financial activities, as well as increasing industrialization and urbanization, advances in information and communication technologies, and rapid population growth, led to an increase in economic activities and total demand on a global scale, which causes more energy consumption[1] and carbon emissions (OECD, 1997; Panayotou 2000; Shahbaz et al. 2018). However, the environmental impacts caused by the globalization process are not limited to problems such as carbon emission and global warming. In this process, increasing production and consumption activities have led to a decrease in arable land, forests, grazing land, built-up land, clean and potable water, and seafood production. In other words, ecological pressures related to globalization have caused environmental problems such as a decrease in arable land, loss of biodiversity, increase in waste, and pollution. Increasing global competition has extended the environmental issues beyond borders and reached an international dimension by directly affecting nature as a whole. At this point, humankind is experiencing an ecological deficit or "overshoot" where the demands exceed the biocapacity of the world (OECD, 1997: 23; Panayotou 2000: 30; Ewing et al. 2010, pp. 8–9) (Fig. 1).

Figure 1 shows the ecological deficit over 1961–2016. We observe that the total ecological reserves were at a sufficient level, and there was no ecological deficit during 1961–1970. After the 1970s, there is a consistently increasing trend in ecological deficit. However, the main point is that the ecological deficit has significantly increased y from the 1990s onwards with the momentum of globalization.

In the globalization process, where environmental issues reached international dimensions, whether countries converge in terms of environmental values has attracted the researcher's attention, and the subject has been investigated within the framework of the environmental convergence hypothesis. According to this hypothesis, the environmental values of countries will converge to each other. In other words, countries will eventually have same environmental quality or degradation levels (Herrerias 2013: 1142; Ulucak 2018: 30; Bilgili and Ulucak 2018). It is clear that the environmental convergence hypothesis has become more important in the globalization process where integration of world's economies has occurred, and international relations have gained momentum. In this context, two main interrelated questions arise: The first question is whether countries converge in terms of environmental values, which has been investigated by many studies by testing overall convergence and/or identifying convergence clubs. The second, possibly more important, is whether the impact of economic growth and globalization on ecological footprint are conditional on convergence clubs identified within the framework of the environmental convergence hypothesis.

In this context, this study aims to analyze the impact of globalization and economic growth on the ecological footprint for convergence clubs. In other words, we investigate whether the impact of globalization and economic growth on ecological footprint differs across convergence clubs. For this purpose, we follow a two-stage empirical procedure. First, we test the overall convergence in ecological footprint across countries and identify possible convergence clubs using the nonlinear time-varying factor model developed by Phillips and Sul (2007). Next, we perform panel unit-root and panel cointegration tests used under the presence of cross-sectional dependence to investigate the impact of globalization and economic growth on the ecological footprint both for the full panel sample and each convergence club. Finally, we estimate long-run coefficients using the Common Correlated Effects Mean Group (CCE-MG) and Augmented Mean Group (AMG) techniques.

In the current literature, the studies either test convergence in ecological footprint or analyze the factors affecting the ecological footprint for a group of countries or a single country. However, this study contributes to the current literature by investigating the impact of globalization and economic growth on the ecological footprint for convergence clubs identified within the environmental convergence hypothesis.

In the next part of the study, we give a summary of the related empirical literature. The "Data and econometric methodology" section presents the data set and econometric methods. The "Empirical results" section provides the empirical results. Finally, the "Conclusion" section concludes.

Literature review

The debate on the effects of globalization on the environment mainly relies on the two opposite poles, whether globalization will improve environmental quality or damage the natural environment. Globalization may have positive and/or negative effects, depending on the other external factors, and its impact can be analyzed with theoretical and empirical evidence. For example, it is argued that the increase in international trade will lead to an increase in economic activity that will cause an increase in carbon dioxide emissions, which will result in a negative impact on the environment. On the other hand, it is mentioned that globalization enables the spread of energy-efficient technologies, which will decrease carbon emissions (Panayotou 2000; Sharif et al. 2019).[2]

[1] Fluctuations of energy consumption are also significantly related to economic conditions and policies. For detailed information, see Yilanci and Tunali (2014).

[2] On the environmental impact of globalization, the studies of Grossman and Kruger (1991), Antweiler et al. (2001), Copeland and Taylor (2004), Copeland (2005), and Dasgupta et al. (2006) can also be referred.

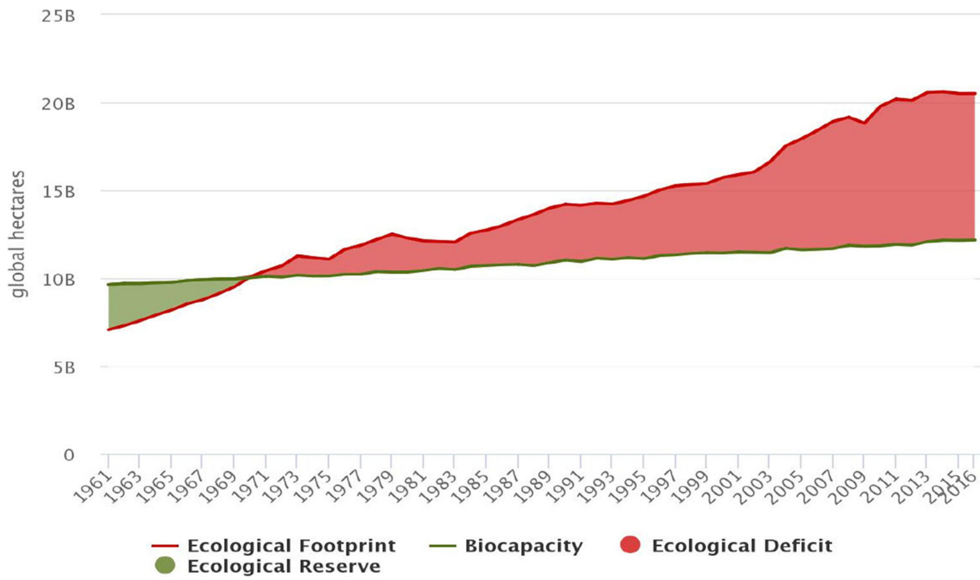

Fig. 1 Global ecological footprint, biocapacity, and ecological deficit. Source: http://data.footprintnetwork.org

In this context, it is observed that the studies in the literature follow two main lines. The first group of studies focuses on the impact of globalization on environmental indicators. The second group of studies investigates the convergence in ecological indicators within the framework of the environmental convergence hypothesis. Therefore, the literature section includes both literature on the relationship between globalization and ecological footprint and the convergence in environmental indicators.

Globalization, previously just thought as trade openness, later has been taken into account with its financial, social, and political dimensions and also its effects on the environment. These effects are measured via the globalization indices which are covering the economic, political, social aspects, of globalization. With these indices, the impact of globalization on ecological indicators such as carbon dioxide, sulfur dioxide, forest area, and oxygen consumption are investigated. For example, Dreher et al. (2008) use the KOF globalization index with the panel regression analysis. The results show that the general globalization index reduces sulfur dioxide levels with a higher level of oxygen consumption but there are no clear results on carbon emission and forest regions. On the other hand, the study concludes that economic globalization has a small effect on the forest regions, political globalization reduces water pollution, and the increase in social globalization increases carbon emissions. Farhani and Ozturk (2015) find short-run unidirectional causal relationships from CO2 emissions per capita to trade openness. Shahbaz et al. (2015) reach a different result in their study for India. According to the findings of the authors, the relationship between globalization (economic globalization, social globalization, and political globalization) and CO2 emissions is independent. The study also shows that while economic globalization attempts to self-control over carbon emissions, social and political globalization still contributes to carbon emissions. Ahmed et al. (2019) conclude that trade openness increases environmental degradation for five selected economies of South Asia. Furthermore, the results show that there is bidirectional causality between energy consumption and trade openness and uni-directional causality running from trade openness to CO2 emission.

Ecological footprint, which can be considered as an indicator of sustainability or sustainable development, is widely used in recent studies analyzing the environmental impacts of globalization. Using different samples and econometric methods, the studies generally find a positive relationship between globalization and ecological footprint. However, the studies find mixed results between sub-indices of globalization and ecological footprint.

Rudolph and Figge (2017), one of the pioneer studies, argue that the general globalization index is positively related to ecological footprint. However, the social globalization index is negatively related to ecological footprint of production and consumption, whereas it is positively related to the ecological footprint of export and import. The results also show that there is no significant relationship between ecological footprint and political globalization index. Using Maastrich Globalization Index (MGI), Figge et al. (2017) find similar results. The estimation results show that the general globalization index of MGI has an increasing effect on the ecological footprint of consumption, export, and import but has no impact on the ecological footprint of production. On the other hand, while economic globalization only increases the ecological footprint of consumption and imports, it does not affect production and exports. Socio-cultural globalization only affects the ecological footprint of foreign trade, similar to the effect of technological globalization on the ecological footprint of imports. Finally, political globalization does not affect any ecological footprint. Sabir and Gorus (2019) test the impact of economic globalization and technological changes on the environmental degradation of the South Asian countries over 1975–2017. The authors find that globalization positively affects environmental degradation through unsustainable economic development. Sharif et al. (2019) find that while globalization positively affects ecological footprint in some countries (Belgium, Netherlands, Sweden, Switzerland, Denmark, Norway, Canada, and Portugal), there is a negative relationship between ecological footprint and globalization for some countries (France, Germany, UK, and Hungary). Yilanci and Gorus (2020) find one-way causality running from ecological footprint to economic globalization and trade globalization. Furthermore, the authors conclude that there is a two-way causality between ecological footprint and financial globalization in MENA countries.

The studies testing the relationship between globalization and ecological footprint for a single country also reach mixed results. Ahmed et al. (2019) find that while globalization increases the ecological footprint, it is not significant determinant of the ecological footprint in Malaysia. However, Apaydın (2020) and Kirikkaleli vd. (2021) conclude that globalization is positively and significantly related to the ecological footprint in Turkey. Apaydın (2020) finds that globalization increases the ecological footprint of consumption, production, and import, whereas it decreases the ecological footprint of export. Kirikkaleli et al. (2021) show that globalization positively affects ecological footprint both in the short and long run. Usman et al. (2020) show that financial development and globalization positively affect the ecological footprint both in the short and long run.

The literature on the convergence of environmental degradation indicators may be divided into two parts. The first group of studies on the convergence in environmental indicators has mainly focused on the convergence of CO2 emissions. Most of the studies (Strazicich and List, 2003; Lanne and Liski 2004; Westerlund and Basher 2008; Panopoulou and Pantelidis 2009; Yavuz and Yilanci 2013; Burnett 2016; Acaravci and Erdogan 2016; Acar and Lindmark 2017; Apergis et al. 2017; Karakaya et al. 2019; Emir et al. 2019; Payne and Apergis 2020) test the convergence in CO2 across states, regions, or countries, whereas some of the studies (Moutinho et al. 2014; Wang and Zhang 2014; Brännlund et al. 2015; Apergis and Payne 2017) analyze the C02 convergence hypothesis at the sector level. However, these studies find mixed results. Some of these studies find convergence in CO2 (Strazicich and List 2003; Westerlund and Basher 2008; Lee et al. 2008; Jobert et al. 2010; Li and Lin 2013; Yavuz and Yilanci 2013; Acaravci and Erdogan 2016; Li et al. 2017; Presno et al. 2018; Payne and Apergis 2020; Erdogan and Solarin 2021), whereas some papers (Lanne and Liski 2004; Aldy 2007; Lee and Chang 2008; Herrerias 2013; Ahmed et al. 2017a, 2017b; Kounetas 2018) find the opposite.

In recent years, the second group of studies (Ulucak 2018; Ulucak and Apergis 2018; Bilgili and Ulucak 2018; Bilgili et al. 2019; Solarin 2019; Haider and Akram 2019; Erdogan and Okumus 2021) analyzes the convergence in ecological footprint as an environmental indicator. Using the convergence methodology developed by Phillips and Sul, Ulucak and Apergis (2018) test the club convergence in ecological footprint across EU countries over 1961–2013 and identify convergence clubs. Bilgili and Ulucak (2018) test the stochastic, deterministic, and club convergence in ecological footprint in G20 countries over 1961–2014. The results support the stochastic and deterministic convergence, and the club convergence analysis identifies convergence clubs. Solarin (2019) analyze the convergence in CO2 emissions, carbon footprint, and ecological footprint across OECD countries over the period 1961–2013. According to the results of RALS-LM and LM unit root tests, conditional convergence exists in 12, 15, and 13 countries for CO2 emissions per capita, carbon footprint per capita, and ecological footprint per capita, respectively. Yilanci and Pata (2020) test the convergence in ecological footprint among the ASEAN-5 countries over 1961–2016 using a two-regime threshold autoregressive (TAR) panel unit root test. The authors find that the ecological footprint of ASEAN-5 countries is nonlinear, and the authors identified Vietnam as the transition country. According to the results, absolute convergence exists in the first regime, whereas divergence exists in the second regime. Ulucak et al. (2020) analyze the convergence in ecological footprint and its sub-components for twenty-three countries in Sub-Saharan Africa over 1961–2014. The authors identify for each sub-component except forest-land and built-up-land footprints.

As one can see, the impact of globalization and economic growth on ecological footprint has not been studied in terms of convergence clubs. In this context, this study may contribute to the literature by analyzing the relationship between globalization, economic growth, and ecological footprint within the environmental convergence hypothesis.

Data and econometric methodology

Data

In this study, we use three variables: the real GDP as a proxy for economic growth, ecological footprint, and globalization index. Our sample consists of 130 countries, and the dataset covers the period 1980–2016 period. The main reason for choosing this time interval is that neoliberal globalization generally covers the post-1980 period. As an indicator of globalization, KOF Swiss Economic Institute General Globalization Index, developed by Dreher (2006) and Dreher et al. (2008), is used, and we obtain the data from the KOF Globalization

Index database. For the ecological footprint indicator, we follow Wackernagel and Rees (1996) and we obtain the data from the Global Footprint Network database. As a proxy variable for economic growth, the source of the real GDP data is the World Bank. All variables are used in logarithmic forms.

Table 7 in Appendix shows the descriptive statistics for the full panel sample and convergence clubs identified by Phillips and Sul (2007) methodology.

Econometric methodology

The panel data model in which the ecological footprint is the dependent variable is defined as follows:

$$logEFCONS_{i,t} = \alpha_0 + \alpha_1 logKOF_{i,t} + \alpha_2 logGDP_{i,t} + u_{i,t} \quad (1)$$

In Eq. (1), $logEFCONS_{i,t}$, $logKOF_{i,t}$, and $logGDP_{i,t}$ represent ecological footprint, globalization level, and real GDP in the country. i, for period t, respectively, and $u_{i,t}$ is the error term.

In the study, we analyze the impact of globalization on the ecological footprint both for the full panel sample and convergence clubs. To do so, we apply the following steps:

- In the first step, we analyze the full panel convergence and identify possible convergence clubs using the club convergence methodology developed by Phillips and Sul (2007).
- In the second step, we test for cross-section dependence for each panel.
- If the results show evidence for cross-sectional dependence, in the third step, we apply the panel CADF test proposed by Pesaran (2007).
- If the panel is determined to be *I(1)*, we apply the cointegration test proposed by Westerlund (2007) as the fourth step.
- Finally, if the panel is cointegrated, we estimate the cointegration coefficient using Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) methods.

Empirical results

Club convergence analysis

In this study, in the first step of the analysis, we apply the club convergence procedure[3] (termed log-*t* regression test) developed by Phillips and Sul (2007) to analyze convergence in ecological footprint across countries. Compared to the alternative convergence methods, log-*t* regression test has some advantages. First, the log-*t* regression test does not require any particular assumptions concerning trend stationarity or stochastic nonstationarity, therefore being robust to the stationarity property of the series. Second, the log-*t* regression test solves the problem of biased and inconsistent estimation induced by endogeneity and omitted variables in the augmented Solow regression model (Du 2017). The new algorithm developed by Phillips and Sul (2007) allows analyzing overall convergence and identify possible convergence clubs.

Phillips and Sul (2007) show that the null of convergence can be statistically tested using the log-*t* regression below:

$$\log\left(\frac{H_1}{H_t}\right) - 2logL(t) = \widehat{\alpha} + \widehat{b}logt + \varepsilon_t \quad (2)$$

where $H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it}-1)^{\ 2}$ indicates the calculation of the cross-sectional variance ratio $\frac{H_1}{}H_t$; and $h_{it} = \frac{X_{it}}{\frac{1}{N}\sum_{i=1}^{N}X_{it}}$ represents the relative transition parameter. The null hypothesis of convergence is rejected at the 5% level of significance when $t_{\widehat{b}} < -1.65$ (Sun et al. 2020). This study uses Stata codes developed by Du (2017) to estimate convergence clubs.

Table 1 shows the results of the log(t) tests for ecological footprint. The results indicate that the null hypothesis of full panel convergence in ecological footprint is rejected at a 5% level of significance. The results state that ecological footprint values have not converged to the same equilibria over the period 1980–2016.

Even if the null hypothesis of convergence in the full panel is rejected, convergence clubs that converge to different equilibrium may exist. The club clustering algorithm can be employed to identify convergence clubs within the panel. Therefore, we use the club-clustering procedure to identify possible convergence clubs. After the clustering algorithm, we identify 11 initial convergence clubs and one divergent group.[4] The club clustering algorithm tends to overestimate the actual number of clubs. Therefore, the club merging tests can be applied to examine whether clusters can be merged into larger clubs following Phillips and Sul (2009). After applying club merging analysis[5], we end up with five convergence clubs and one divergent club. The final classification is reported in Table 2. Each convergence club consists of countries that converge to each other. Besides, each convergence club converges to a different constant. For instance, the club which converges to a higher ecological footprint level is club 1. As shown in Table 7, club 1 has the highest mean value of ecological footprint.

[3] We shortly introduced the club convergence methodology developed by Phillips and Sul (2007). For more detailed information, see Phillips and Sul (2007, 2009).

[4] Initial club classification is presented in appendix Table 8.

[5] Club merging test results are presented in appendix Table 9.

Table 1 Log (*t*) test results (130 countries)

Variable	Coefficient	Standard error	T-statistic
Ecological footprint	−0.526	0.015	−36.226

Truncation parameter (Phillips and Sul (2007) suggest using $r = 0.20$ for data series with $T \geq 100$, and $r = 0.30$ for data series with $T < 50$) $r = 0.3$, *t*-statistic at 5% significance level −1.65

Figure 2 shows the relative transition paths (calculated as the cross-sectional mean of the relative transition paths of the members of each club) of five convergence clubs. A transition path below the unity indicates that the level of the club is below the panel average. In contrast, a transition path above the unity indicates that the level of the club is above the panel average (Panopoulou and Pantelidis 2009:58; Panopoulou and Pantelidis 2012, p.3913). It is observed that while club 1 is above the panel average, club 2, club 3, club 4, and club 5 are below the panel average.

Cross-section dependence test

In the globalization process where relationships and interactions between countries have been increasing, it is also possible to observe the dependency between the cross-sections of each panel. In other words, in an increasing globalization process, the interactions and the effects of the countries on each other are the stylized facts. Therefore, for determining the appropriate panel unit root and cointegration tests, we first apply the cross-section dependence test for both the full panel sample and convergence clubs.

Table 2 Final club classification

Clubs	Countries	Coefficient	T-statistic
Club 1 [49]	| Afghanistan | Algeria | Angola | Argentina | Australia | | Bangladesh | Bolivia | Brazil | Cameroon | Canada | Chile | | Colombia | Egypt | Equatorial Guinea | France | Germany | | Ghana | Guatemala | India | Indonesia | Israel | Italy | Japan | | Jordan | Malaysia | Mali | Mexico | Morocco | Myanmar | | Netherlands | Niger | Nigeria | Pakistan | Peru | Philippines | | Poland | Qatar | Russian Federation | Singapore | | South Africa | Spain | Thailand | Trinidad and Tobago | | Turkey | United Arab Emirates | United Kingdom | | United States of America | Vietnam | Yemen |	−0.058	−1.375
Club 2 [58]	| Albania | Austria | Bahrain | Belgium | Benin | Botswana | | Bulgaria | Burkina Faso | Cambodia | Chad | Congo | Costa Rica | | Cote d'Ivoire | Cuba | Denmark | Dominican Republic | Ecuador | | El Salvador | Finland | Gabon | Greece | Guinea | Haiti | | Honduras | Hungary | Ireland | Kenya | | Lao People's Democratic Republic | Lebanon | Liberia | | Luxembourg | Madagascar | Malawi | Mauritania | Mauritius | | Mongolia | Mozambique | Nepal | New Zealand | Nicaragua | | Norway | Panama | Papua New Guinea | Paraguay | Portugal | | Romania | Rwanda | Senegal | Sierra Leone | Sri Lanka | Sudan | | Sweden | Switzerland | Togo | Tunisia | Uganda | Zambia | | Zimbabwe |	−0.038	−0.996
Club 3 [11]	| Bhutan | Burundi | Central African Republic | Cyprus | Fiji | | Gambia | Guinea-Bissau | Guyana | Jamaica | Lesotho | Uruguay |	0.238	4.935
Club 4 [8]	| Bahamas | Barbados | Comoros | Malta | Samoa | | Sao Tome and Principe | Timor-Leste | Tonga |	0.003	0.076
Club 5 [2]	| Bermuda | Saint Lucia |	2.091	1.187
Not convergent group 6 [2]	| China | Dominica |	−0.731	−937.713

Truncation parameter $r = 0.3$, t-statistic at 5% significance level −1.65. The number of club members is reported in brackets

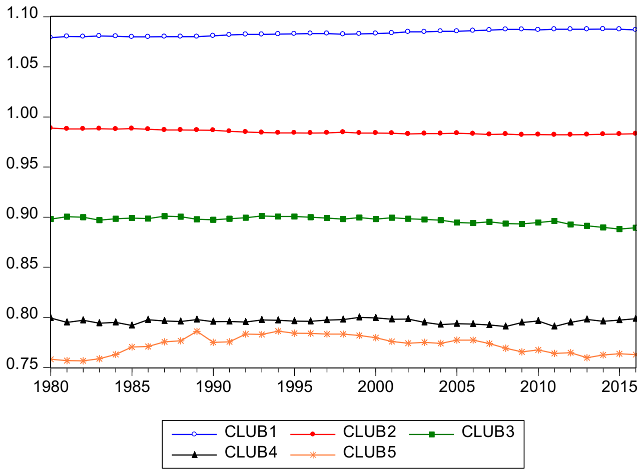

Fig. 2 Relative transition paths of clubs

In the study, we apply the Breusch and Pagan (1980) LM, the scaled LM and CD tests suggested by Pesaran (2006) and Baltagi et al. (2012) bias-corrected scaled LM tests, which are the most widely used tests in the empirical literature. Table 3 summarizes test results that the null hypothesis of "no cross-section dependence" is strongly rejected for the time series in all panels.

Panel unit root test

Since the null hypothesis that "there is no cross-section dependence" is rejected in all panels, we test the stationarity of the panels with the CIPS panel unit root test proposed by Pesaran (2007), which considers cross-section dependence. The CIPS panel unit root test is based on cross-sectional augmented ADF (CADF) test statistics. In this method, first, the CADF test statistics of each cross-section unit are calculated, and then, the CIPS test statistics are calculated as the average of individual CADF statistics as follows:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} CADF_i \tag{3}$$

In the study, we apply the CIPS test for all specifications (with and without trend). Table 4 shows the results of unit root tests. According to the output given in Table 4, the variables in all panels generally exhibit non-stationary feature at the level. However, they are stationary in their first differences at the 1% significance level. In the model with the trend, only *loggdp* series in club 4 becomes stationary at the 10% significance level. This ratio is in the generally acceptable confidence interval. Therefore, we decide on the presence of unit root in all panels and apply the cointegration test.

Panel cointegration test

We apply the error correction-based cointegration test developed by Westerlund (2007) to examine the cointegration relationship between variables in all panels. In this test, which considers the cross-section dependence and allows the bootstrap procedure, four test statistics are calculated based on the least-squares estimation of the error correction parameter (α_i), and its t value for each cross-section.

Two of these, referred as group mean statistics, are as follows:

$$G_\alpha = \frac{1}{N}\sum_{i=1}^{N}\frac{T\widehat{\alpha}_i}{\widehat{\alpha}_i(1)} \qquad G_\tau = \frac{1}{N}\sum_{i=1}^{N}\frac{\widehat{\alpha}_i}{SE\left(\widehat{\alpha}_i\right)} \tag{4}$$

The statistics for the full panel are as follows:

$$P_\alpha = T\alpha \qquad P_\tau = \frac{\widehat{\alpha}}{SE\left(\widehat{\alpha}\right)} \tag{5}$$

Group mean test statistics (G_α and G_τ) examine the alternative hypothesis that at least one unit is cointegrated while the panel tests (P_α and P_τ) have the alternative hypothesis that the panel is cointegrated as a whole.

In the study, we examined the cointegration relationship in each panel with both constant and constant and trend term specifications. Table 5 shows the results of cointegration test. The first noteworthy finding in the table is that both the mean group and panel test statistics do not reject the null hypothesis of no cointegration for club 5. In other words, there is no cointegration between variables in club 5.

In the estimates with the only constant term for full sample, club 1, club 2, and club 3, the null hypothesis of panel test statistics rejected at the 1% and 5% significance levels. Accordingly, it has been determined that the panels are cointegrated in this specification. On the other hand, while the group-mean test statistics cannot reject the null hypothesis of no cointegration for club 4, however, it shows that at least one cross-section unit cointegrated in the other clubs and the full panel sample.

However, when the trend term is added to the model, the results considerably differ for panels except club 5. Accordingly, the panel test statistics rejected the null hypothesis of no cointegration for the full panel sample, club 1 and club 4. The null hypothesis of the group-mean tests could not be rejected. In other words, in this specification, only panel test statistics indicate the cointegration for the full panel sample, club 1 and club 4.

Long-run estimations

We use two methods that consider cross-section dependence in the estimation of long-run coefficients for each cointegrated panel. The first method is the Common Correlated Effects Mean Group (CCEMG) estimator developed by Pesaran (2006); the second is the Augmented Mean Group (AMG)

Table 3 Cross-section dependence test results

		BP_{LM}	CD_{LM}	LM_{adj}	CD
Full panel	*logefcons*	182,172.8 (0.00)	1342.0 (0.00)	1340.1 (0.00)	304.0 (0.00)
	logkof	263,663.2 (0.00)	1971.2 (0.00)	1969.4 (0.00)	511.2 (0.00)
	loggdp	236,476.0 (0.00)	1761.3 (0.00)	1759.5 (0.00)	477.1 (0.00)
Club 1	*logefcons*	29,080.6 (0.00)	575.3 (0.00)	574.7 (0.00)	127.7 (0.00)
	logkof	388,807.7 (0.00)	775.9 (0.00)	775.2 (0.00)	196.7 (0.00)
	loggdp	35,368.9 (0.00)	705.0 (0.00)	704.3 (0.00)	185.9 (0.00)
Club 2	*logefcons*	34,410.8 (0.00)	569.7 (0.00)	568.9 (0.00)	121.2 (0.00)
	logkof	53,388.9 (0.00)	899.7 (0.00)	898.9 (0.00)	230.8 (0.00)
	loggdp	45,638.4 (0.00)	764.9 (0.00)	764.1 (0.00)	208. (0.00)
Club 3	*logefcons*	1125.4 (0.00)	102.0 (0.00)	101.9 (0.00)	24.6 (0.00)
	logkof	1621.7 (0.00)	149.3 (0.00)	149.2 (0.00)	40.1 (0.00)
	loggdp	1499.4 (0.00)	137.7 (0.00)	137.5 (0.00)	38.3 (0.00)
Club 4	*logefcons*	391.1 (0.00)	48.5 (0.00)	48.4 (0.00)	14.6 (0.00)
	logkof	686.8 (0.00)	88.0 (0.00)	87.9 (0.00)	25.6 (0.00)
	loggdp	611.5 (0.00)	77.9 (0.00)	77.8 (0.00)	23.5 (0.00)
Club 5	*logefcons*	16.1 (0.00)	10.6 (0.00)	10.6 (0.00)	4.0 (0.00)
	logkof	24.0 (0.00)	16.3 (0.00)	16.2 (0.00)	4.9 (0.00)
	loggdp	25.3 (0.00)	17.2 (0.00)	17.1 (0.00)	5.0 (0.00)

Values in parentheses denote *p* values. BP_{LM}, CD_{LM}, *CD*, and *LMadj* are the cross-sectional dependence tests by Breusch and Pagan (1980), Pesaran (2006) scaled LM and CD, and the Baltagi et al. (2012) bias-corrected scaled LM tests, respectively

Table 4 Panel unit root test results

		Without trend				With trend			
		Levels		First differences		Levels		First differences	
		Z[t-bar]	*p* value	Z[t-bar]	*p* value	Z[t-bar]	*p* value	Z[t-bar]	*p* value
Full panel	*logefcons*	0.279	0.610	−22.449	0.00*	1.248	0.894	−18.664	0.00*
	logkof	−6.181	0.000*	-	-	−0.208	0.418	−16.971	0.00*
	loggdp	2.919	0.998	−12.612	0.00*	6.769	1.000	−8.792	0.00*
Club 1	*logefcons*	−2.671	0.004*	-	-	1.351	0.912	−11.320	0.00*
	logkof	68.067	0.991	−13.358	0.00*	85.154	0.819	−11.262	0.00*
	loggdp	57.801	1.000	−7.181	0.00*	93.940	0.597	−4.997	0.00*
Club 2	*logefcons*	−0.481	0.315	−15.634	0.00*	3.237	0.999	−13.441	0.00*
	logkof	−7.840	0.000*	-	-	−0.110	0.456	−6.888	0.00*
	loggdp	1.401	0.919	−10.512	0.00*	2.400	0.992	−7.496	0.00*
Club 3	*logefcons*	−0.017	0.493	−6.367	0.00*	0.039	0.516	−5.555	0.00*
	logkof	0.127	0.550	−6.261	0.00*	1.885	0.970	−5.034	0.00*
	loggdp	−0.553	0.290	−6.091	0.00*	1.050	0.853	−4.330	0.00*
Club 4	*logefcons*	−0.373	0.355	−4.939	0.00*	−0.575	0.283	−4.107	0.00*
	logkof	1.127	0.870	−3.638	0.00*	−0.190	0.425	−2.206	0.01**
	loggdp	2.396	0.992	−1.813	0.03**	1.832	0.966	−1.275	0.10***
Club 5	*logefcons*	−4.102	0.000*	−3.556	0.00*	−0.618	0.268	−4.562	0.00*
	logkof	−0.041	0.483	−3.208	0.00*	1.028	0.848	−2.776	0.00*
	loggdp	−0.072	0.471	−2.147	0.01**	1.316	0.906	−1.836	0.03**

*, **, and *** show the 1%, 5%, and 10% significance levels, respectively. The maximum lag length is set to 2

Table 5 Panel cointegration test results

	Statistic	Constant				Constant and Trend			
		Value	Z-value	*p* value	Robust *p* value	Value	Z-value	*p* value	Robust *p* value
Full panel	Gt	−2.363	−4.059	0.000	0.020	−2.865	−4.560	0.000	0.005
	Ga	−9.654	−0.961	0.168	0.000	−11.517	3.290	1.000	0.353
	Pt	−25.546	−5.823	0.000	0.000	−30.034	−4.380	0.000	**0.005**
	Pa	−9.309	−7.022	0.000	0.000	−11.527	−1.754	0.040	**0.018**
Club 1	G	−2.392	−2.716	0.003	0.025	−2.904	−3.129	0.001	0.003
	Ga	−10.747	−1.810	0.035	0.000	−10.750	2.753	0.997	0.595
	Pt	−16.593	−4.456	0.000	0.008	−18.646	−2.919	0.002	**0.050**
	Pa	−10.874	−6.271	0.000	0.000	−12.464	−2.047	0.020	**0.030**
Club 2	Gt	−2.372	−2.786	0.003	0.003	−2.783	−2.307	0.011	0.018
	Ga	−8.770	0.430	0.666	0.018	−8.579	5.250	1.000	0.875
	Pt	−15.111	−1.999	0.023	0.025	−17.624	−0.224	0.411	0.165
	Pa	−6.976	−1.513	0.065	0.023	−7.168	3.740	1.000	0.758
Club 3	Gt	−2.364	−1.184	0.118	0.062	−2.884	−1.404	0.080	0.058
	Ga	−10.135	−0.534	0.297	0.033	−12.522	0.502	0.692	0.060
	Pt	−7.524	−1.784	0.037	0.043	−8.296	−0.786	0.216	0.180
	Pa	−9.162	−1.956	0.025	0.018	−11.258	−0.378	0.353	0.110
Club 4	Gt	−2.259	−0.689	0.246	0.238	−2.554	−0.085	0.466	0.310
	Ga	−10.173	−0.473	0.318	0.035	−12.976	0.253	0.600	0.180
	Pt	−7.976	−3.032	0.001	0.025	−9.022	−2.829	0.002	**0.035**
	Pa	−15.378	−4.812	0.000	0.000	−17.981	−3.136	0.001	**0.003**
Club 5	Gt	−2.118	−0.127	0.449	0.355	−2.212	0.532	0.703	0.603
	Ga	−6.950	0.490	0.688	0.395	−6.492	1.377	0.916	0.758
	Pt	−2.810	−0.375	0.354	0.372	−2.959	0.306	0.620	0.613
	Pa	−5.915	−0.013	0.495	0.423	−5.641	1.014	0.845	0.800

The optimal lag and lead length is set to 1 since some series do not contain sufficient observations. The width of the Bartlett kernel window is set to 3. The number of bootstraps to obtain the robust *p* values is set to 400. Values in bold show the existence of cointegration

estimator developed by Eberhardt and Teal (2010) as an alternative to the CCEMG method.

In the Pesaran (2006) approach, which also considers unobserved effects, long-run parameters of independent variables are calculated by taking the arithmetic average of the coefficients of each cross-section. In this method, the panel cointegration coefficient is calculated using the following equation:

$$\widehat{\beta}_{CCEMG} = N^{-1}\sum_{i=1}^{N}\widehat{\beta}_{CCE,i} \tag{6}$$

where βi represents the slope specific to each cross-section. According to Pesaran (2006), the CCE estimator is more suitable for large panels. However, later Monte Carlo experiments by Kapetanios et al. (2011) showed that the CCE estimator is better in small samples than alternative estimators in the literature (Pesaran 2006; Kapetanios et al. 2011). The Pesaran CCEMG approach assumes that the independent variables and the unobservable common factors are stationary and exogenous. However, it gives consistent results that even the series are I(0), I(1), and/or cointegrated (Kapetanios et al. 2011: 50–51). The AMG estimator developed by Eberhardt and Teal (2010) considers both the cross-sectional dependency and the parameter differences between cross-sections. Like the CCEMG method, the AMG estimator is robust to non-stationary variables, whether cointegrated or not. The difference of this method is that it considers cross-sectional dependence by including the common dynamic process into regression (Eberhardt and Teal 2010; Eberhardt 2012). In both methods, we use a robust estimator as it puts less emphasis on outliers while computing the average coefficient (Eberhardt 2012). That is why it gives more reliable results.

Table 6 shows the results of CCEMG and AMG models for the full sample and the sub-panels. As can be seen from Table 6, we use methods with and without trend. According to the estimation results of the CCEMG and AMG methods, model 2 (CCEMG with trend) and model 4 (AMG with trend) have smaller RMSE (root mean squared error) values compared to model 1 (CCEMG) and model 3 (AMG), respectively. This result implies that it is more appropriate to evaluate the estimates of the trend-containing models in both methods.

Table 6 Long-run estimation results

	Variables	(1) CCEMG robust	(2) CCEMG (with trend) robust	(3) AMG robust	(4) AMG (with trend) robust
Full panel	*logkof*	−0.0080	0.0070	−0.0623	−0.0191
		(0.0568)	(0.0581)	(.0722)	(0.0502)
	loggdp	**0.5365***	**0.6449***	**0.4570***	**0.5314***
		(0.0398)	(0.0524)	(0.0346)	(0.0502)
	Constant	**2.8376***	1.1659	**5.6587***	**3.6965***
		(1.0399)	(1.403)	(0.8152)	(1.1573)
	Trend		−0.0010		−0.0010
			(−0.001)		(0.0023)
	Wald Chi2	**180.94***	**151.52***	**174.79***	**112.00***
	RMSE	0.0674	0.0623	0.0789	0.0700
Club 1	*logkof*	−0.1432	−0.0289	0.0480	0.1102
		(0.1113)	(0.1224)	(0.1035)	(0.0854)
	loggdp	**0.6881***	**0.8058***	**0.6059***	**0.7678***
		(0.0679)	(0.0897)	(0.0427)	(0.0792)
	Constant	**2.9551*****	**−4.5639*****	1.3445	−2.5768
		(0.093)	(2.7475)	(1.0409)	(1.9841)
	Trend		**−0.0097****		**−0.0065*****
			(0.0049)		(0.0034)
	Wald Chi2	**104.32***	**80.70***	**201.62***	**95.51***
	RMSE	0.0571	0.0529	0.0718	0.0602
Club 4	*logkof*	0.2114	−0.0480	0.5361	0.1062
		(0.4013)	(0.3614)	(0.6762)	(0.4776)
	loggdp	0.4700	0.32341	**0.6294***	0.1968
		(0.3487)	(0.3176)	(0.2260)	(0.4387)
	Constant	**6.4543***	−0.1836	0.1081	5.1662
		(2.0475)	(0.4387)	(2.5578)	(7.8574)
	Trend		0.0048		0.0159
			(0.0067)		(0.0138)
	Wald Chi2	2.09	1.05	**8.38****	0.25
	RMSE	0.0881	0.0823	0.1053	0.1000

Values in parentheses indicate standard errors in all models. * 1%, ** 5%, and *** 10% significance levels. Values in bold show the existence of cointegration

CCEMG common correlated effect mean group estimator, *AMG* augmented mean group estimator, *RMSE* root mean square error

The first noteworthy finding in Table 6 is that the long-run coefficients of economic growth estimated in both model 2 and model 4 are statistically significant for the full sample and the club 1 sub-panel, while it is insignificant for club 4. Accordingly, although the variables in club 4 are cointegrated, there is no statistically significant relationship. While the globalization variable is not statistically significant in the full sample and club 1 sub-panel estimations, only economic growth is statistically significant in both panels.

According to the estimation results of model 2 and model 4, the impact of economic growth on ecological footprint is positive. However, the economic growth coefficient in the club 1 is higher in both model 2 and model 4 compared to the full panel sample. In model 2, coefficient of economic growth is 0.6449 for the full sample and 0.8058 for the club 1 sub-panel. In model 4, where the dynamic common process is considered, the coefficients of economic growth are 0.5314 and 0.7678 for the full panel sample and club 1, respectively.

In summary, similar to cointegration analysis, long-run coefficients also differ in the case of convergence clubs. Indeed, according to the results of model 2 and model 4, the coefficient of economic growth for club 1 is significantly higher than full sample.

Conclusion

This paper analyzes the impact of globalization and economic growth on the ecological footprint within the framework of the environmental convergence hypothesis. In other words, we analyze whether the impact of globalization and economic growth differs across full panel sample and ecological footprint convergence clubs. The sample consists of 130 countries, and the data set covers the period 1980–2016. To do so, we follow a two-stage empirical procedure. First of all, we test the overall convergence in ecological footprint across countries and identify possible convergence clubs using a novel convergence methodology developed by Phillips and Sul (2007). After analyzing overall convergence within the panel and identifying convergence clubs, we apply panel unit-root and panel cointegration tests used under the presence of cross-sectional dependence to analyze the impact of globalization and economic growth on the ecological footprint both for the full panel sample and convergence clubs. Finally, we estimate long-run coefficients using the Common Correlated Effects Mean Group (CCE-MG) and Augmented Mean Group (AMG) techniques.

According to log-t test results, ecological footprint values of countries have not converged to the same equilibria. However, we identify five convergence clubs and one non-convergent group. The relative transition paths of clubs show that club 1 is above the panel average, whereas club 2, club 3, club 4, and club 5 are below the unity. Then, we apply panel unit-root and panel cointegration tests used under the presence of cross-sectional dependence to assess the impact of globalization and economic growth on the ecological footprint both for the full panel sample and convergence clubs. According to the Westerlund (2007) panel cointegration test results, the cointegration exists between variables for the full panel sample, club 1, and club 4.

Finally, we analyze the impact of globalization and economic growth on the ecological footprint in the long run using Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG) methods. The empirical findings show that while economic growth is significantly and positively related to the ecological footprint for full panel sample and club 1, there is no significant relationship between globalization and ecological footprint for full panel samples and subpanels. These results show the necessity and importance of investigating the relationship between globalization and ecological footprint considering convergence clubs. If the analysis is applied for full panel sample instead of convergence subpanels, many countries where there is no cointegration relationship between variables are included in the analysis. As a result, the magnitude and significance of coefficients differ. For instance, the impact of economic growth on the ecological footprint in club 1 is higher than the full panel sample.

In the current literature, while many studies (for example, Rudolph and Figge (2017), Figge et al. (2017), Sabir and Gorus (2019), Sharif et al. (2019), Yilanci and Gorus (2020)) find a significant relationship between globalization and ecological footprint, our findings indicate that there is no statistically significant relationship between of them. In other words, the findings of our study differ significantly from the findings of previous studies. The most likely cause of this difference is the methodological procedure that we adopted in this study.

Considering the results of this study, the most important suggestion of the paper is to classify or group countries according to the research subject while examining an economic, social, or environmental issue. In other words, it should be analyzed "similar" or "convergent" countries in terms of research topic. Otherwise, as this study reveals, it may not be possible to consistently and effectively determine the relationships between variables.

Appendix

Table 7 Descriptive statistics

	Variable	Observations	Mean	Std. Dev.	Min.	Max.
Full panel	*logefcons*	4810	16.70063	1.922839	11.34562	22.3834
	logkof	4778	3.904523	0.346734	2.829896	4.514297
	loggdp	4613	24.14984	2.331579	18.62122	30.46261
Club 1	*logefcons*	1813	18.09731	1.563244	12.59869	21.84077
	logkof	1803	3.985577	0.326686	3.021636	4.514297
	loggdp	1738	25.78923	2.007338	18.92136	30.46261
Club 2	*logefcons*	2146	16.44522	.9078561	14.02249	18.55379
	logkof	2146	3.890978	.3568143	2.870298	4.512063
	loggdp	2071	23.73887	1.555338	20.92937	27.19246
Club 3	*logefcons*	407	14.98019	.6722524	13.35433	16.67452

Table 7 (continued)

	Variable	Observations	Mean	Std. Dev.	Min.	Max.
	logkof	407	3.74138	.3482739	2.829896	4.419449
	loggdp	407	21.67174	1.288908	18.88257	24.602
Club 4	*logefcons*	296	13.29213	.8650725	11.34562	15.42902
	logkof	274	3.755317	.3009413	2.948687	4.369998
	loggdp	252	21.0432	1.360445	18.62122	23.21922
Club 5	*logefcons*	74	12.89951	.2894187	12.00556	13.21559
	logkof	74	3.834358	.1041477	3.622172	4.073873
	loggdp	72	21.4198	.8120459	19.87185	22.54695

Table 8 Initial convergence club classification

Clubs	Countries	Coefficient	T-statistic
Club 1 [4]	| India | Qatar | United States of America | Vietnam |	0.172	3.274
Club 2 [26]	| Algeria | Angola | Australia | Bangladesh | Brazil | Canada | | Egypt | Equatorial Guinea | France | Germany | Ghana | Indonesia | Italy | Japan | Malaysia | Mexico | Myanmar | Nigeria | Pakistan | | Russian Federation | South Africa | Spain | Thailand | Turkey | | United Arab Emirates | United Kingdom |	0.133	2.566
Club 3 [19]	| Afghanistan | Argentina | Bolivia | Cameroon | Chile | Colombia | | Guatemala | Israel | Jordan | Mali | Morocco | Netherlands | | Niger | Peru | Philippines | Poland | Singapore | | Trinidad and Tobago | Yemen |	0.090	1.686
Club 4 [38]	| Austria | Bahrain | Belgium | Benin | Burkina Faso | Cambodia | | Chad | Cote d'Ivoire | Denmark | Dominican Republic | Ecuador | | El Salvador | Finland | Gabon | Greece | Guinea | Honduras | | Kenya | Lao People's Democratic Republic | Lebanon | | Madagascar | Malawi | Mauritania | Mongolia | Mozambique | Nepal | New Zealand | Papua New Guinea | Portugal | Romania | Senegal | Sri Lanka | Sudan | Sweden | Switzerland | Tunisia | Uganda | Zambia |	0.180	3.800
Club 5 [13]	| Botswana | Congo | Costa Rica | Haiti | Hungary | Ireland | | Liberia | Norway | Panama | Paraguay | Rwanda | Sierra Leone | | Togo |	0.146	3.368
Club 6 [7]	| Albania | Bulgaria | Cuba | Luxembourg | Mauritius | Nicaragua | | Zimbabwe |	0.046	2.383
Club 7 [11]	| Bhutan | Burundi | Central African Republic | Cyprus | Fiji | | Gambia | Guinea-Bissau | Guyana | Jamaica | Lesotho | Uruguay |	0.238	4.935
Club 8 [3]	| Bahamas | Malta | Sao Tome and Principe |	0.153	2.731
Club 9 [2]	| Barbados | Comoros |	0.087	0.370
Club 10 [3]	| Samoa | Timor-Leste | Tonga |	0.041	1.331
Club 11 [2]	| Bermuda | Saint Lucia |	2.091	1.187
Not convergent Group 12 [2]	| China | Dominica |	−0.731	−937.713

Truncation parameter $r = 0.3$, t-statistic at 5% significance level −1.65. The number of club members is reported in brackets

Table 9 Club merging test results

Clubs	Coefficient	T-statistic
Club 1+2	0.089	1.693
Club 2 +3	−0.020	−0.470
Club 3 + 4	−0.005	−0.105
Club 4 + 5	0.025	0.607
Club 5 + 6	0.126	3.537
Club 6 + 7	−0.090	−4.725
Club 7 + 8	−0.072	−2.051
Club 8 + 9	0.141	2.747
Club 9 + 10	−0.144	−2.263
Club 10 + 11	0.245	3.284
Club 11 + Group 12	−0.797	−148.419

t-statistic at 5% significance level −1.65

Author contribution Data collection and material preparation were performed by Ümit Koç. Şükrü Apaydın and Uğur Ursavaş constructed the methodology section and empirical analysis. The first draft was written by Şükrü Apaydın. Uğur Ursavaş and Ümit Koç contributed to the interpretation of the findings and the editing of the manuscript.

All authors read and approved the final manuscript.

Data availability The data analyzed in our study can be found from KOF Swiss Economic Institute, Global Footprint Network, and World Bank.

Declarations

Ethical approval and consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

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