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Economic Complexity and Ecological Footprint: Evidence from the Most Complex Economies in the World

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Abstract: The paper introduces economic complexity as an explanatory variable of ecological footprint change, along with income per capita and fossil fuel energy consumption. The link between the ecological footprint and economic complexity is explored within a panel of 48 complex economies over the period 1995–2014. The panel analysis is based on the annual data series of the economic complexity index (ECI), fossil fuel energy consumption, income per capita, and the ecological footprint of production. The econometrical analysis, based on second-generation unit root tests, cointegration testing, and estimation of fully modified ordinary square (FMOLS) and dynamic ordinary least square (DOLS) models in a heterogeneous panel of countries, revealed a validated positive long-run association between the ecological footprint of production as dependent variable and the economic complexity index, gross domestic product per capita, and fossil fuel energy consumption. The paper sheds light on the critical situation of environmental sustainability, taking into consideration that 75% of countries under examination are in ecological deficit.

Keywords: economic complexity; ecological footprint; panel data

1. Introduction

One of the major challenges for humanity in this century is to cope with the rising levels of environmental degradation and energy demand while keeping economic growth rates high. The relationship between economic activities, energy consumption, and environmental pollution has been thoroughly studied by different researchers (e.g., [1–22]), and an extensive and systematic review of such studies is provided by Vaheed et al. (2019) [23].

The main conclusion was that energy consumption, income, and CO_2 or GHG emissions are evolving into a cointegrating relationship. Additionally, a significant part of the aforementioned studies was focused on providing evidence to support the environmental Kuznets curve (EKC) hypothesis (the inverted U-shaped relationship between air pollutant emissions and income). A great limitation of these studies was their focus on a singular or small group of air pollutants (mainly carbon dioxide, which is responsible for more than 76% greenhouse effect) as a proxy of environmental degradation [24]. The impact of economic activities on the environment has several dimensions that cannot be embedded within one measure of environmental degradation.

In the last few years, new literature that considers the ecological footprint (EF) as a comprehensive and globally comparable indicator of environmental degradation caused by human activities has emerged. It is viewed as a more accurate expression of environmental depreciation compared to carbon dioxide or GHG emissions, given that it tracks human demand for natural resources and ecosystem services (e.g., [25–31]). As a concise indicator of environmental pressure, the ecological footprint (EF) expresses the total quantity of natural resources that a population consumes [32] and measures the area of productive

land and water necessary to support human activities and sequester the waste they generate [33]. In the methodology of the Global Footprint Network [34], biocapacity indicates the biologically productive land and water available to provide the resources a population consumes and to absorb its wastes. The ecological footprint generally refers to the EF of consumption, which expresses the consumption of biocapacity by a country's population. It comprises the ecological footprint of production and the net ecological footprint of trade. The ecological footprint of production measures the consumption of biocapacity resulting from production processes within a given area, and its carbon component indicates the amount of carbon emissions generated by the production process. The ecological footprint of imports and exports indicates the use of biocapacity within international trade [34].

Recent literature has revealed the impact of economic and social activities (i.e., industries, globalisation, agriculture, financial development, energy consumption, investment, trade, urbanisation, and human capital) on the ecological footprint by examining its determinants in different periods of time for groups or individual countries by using various econometric methods (e.g., [26,27,35–45]).

The economic growth of a country is sustained by a specific structure of the economy, requiring a given energy consumption structure according to specific demands from various economic sectors. Complex economies are those that can manage relevant knowledge across large networks of people to generate a diverse mix of knowledge-intensive products [46]. Economic complexity refers to a country's productive structure [46], which generates a specific economic and energy consumption structure that has a specific impact on the environment. Complex products are mainly the results of industrial manufacturing or chemical sectors, working with high levels of energy intensity. Higher complexity levels are generally associated with higher energy demand. In order to ensure the necessary energy and mitigate the environmental impact, countries must develop an appropriate energy mix from several sources (i.e., fossil fuel, nuclear, renewable), depending on their natural resources and import opportunities. Thus, it is obvious that a country's productive structure (i.e., with energy-intensive industrial and chemical sectors) will impact the environment; in other words, the complexity level of products can harm the environment by generating pollution and consuming natural resources [47,48]. It is also true that it embeds knowledge and capabilities (productive knowledge), research, and innovation, which can help to introduce environmentally friendly technologies to the production process and also plan the environmental impact of new complex products at the early design stage. The complexity of an economy is measured through the economic complexity index (ECI), calculated by the experts at the Centre of International Development at Harvard University [49]. It expresses the capability of a country to produce and export complex products and estimates the amount of productive knowledge embedded in that country. In other words, a higher level of ECI denotes a higher capability to produce and export higher value-added or more complex products [46].

The relationship between economic complexity and ecological footprint has not been analysed to date excepting in very few studies (i.e., [50–53]). The aim of the paper is to analyse the impact of economic complexity, per capita income, and energy consumption on the ecological footprint within a panel of 48 of the most complex economies in the world. From the global ranking of economic complexity index (ECI) [49], including 142 countries with ECI values in the range of −2.5 to 2.5, the first positions with ECI average value higher than 0 for 1995–2014 were extracted. It is resulted a sample of 48 complex economies, with complete data series for all considered variables. The study uses the most complex economies for several reasons. First, 75% of them are in ecological deficit (their ecological footprint exceeds the biocapacity area). The environmental quality concern raises the problem of identifying all the determinants of ecological degradation, and economic complexity could be included among them. The complexity level of products depends on the consumption of resources, which is related to ecological footprint. Second, these countries have some common features: similar economic structure (with large industrial sectors: machinery, chemical); a diversified energy mix, including renewable and nuclear energy; large public budgets for energy technology development and R&D activities. Complex economies have extended industrial

sectors that are energy, pollutant and knowledge-intensive. The Economic Complexity Index (ECI) captures information regarding institutions and governance, productive knowledge, human capital and economic competitiveness [46]. Economic complexity contributes to the environmental pressure but also, provides the required resources (i.e. institutions, knowledge, and competitiveness resources) to address the ecological deficit (i.e. the gap between biological capacity and ecological footprint). A high value of economic complexity index (ECI) indicates a high level of knowledge (embedded in people and technologies) and capabilities of an economy. These can also include its capacity to develop specific R&D activities meant to reduce environmental degradation. Economic complexity is positively associated with higher per capita income [46] suggesting the availability of funding resources for such R&D activities, investment in clean and energy-efficient technologies, development of alternative energy sources (i.e., renewable, nuclear) as well as for policy measures stimulating the transition to a low-carbon economy. Third, the quality of governance and institutions together with the competitive environment in complex economies would activate other factors (i.e., knowledge networks) meant to ensure an efficient use of resources (i.e., human, financial, knowledge, technologies).Therefore, the present analysis could serve as a case study for further research on environmental sustainability in developed countries and guidelines for other countries with similar pattern of economic structure.

There are several contributions of this study to the existing literature. First, it introduces the ecological footprint (EF) as a variable of environmental quality in the analysis of the impact of economic complexity on the environment, along with other traditional factors (GDP per capita and energy consumption). Second, it analyses the impact of energy consumption on the ecological footprint of production. In this way, it addresses a critical aspect of the sustainable development of the most complex economies in the world and contributes to the literature of energy and environmental economics by taking as examples their energy policies and strategies. Third, the paper adds to the recent literature focused on the impact of economic complexity on the ecological footprint, with the aim of enriching it, given the very few studies in this field. It is different from existing studies through the extension of analysis from individual countries to a panel of countries, with similar levels of economic complexity, energy mix and policies, as well as efforts towards energy efficiency, decarbonisation, and investment in energy technology and innovation. This could outline a pattern of sustainability in the presence of high economic complexity that could be given as a basis for further research directions. Moreover, guidelines for countries with sophisticated products could be suggested. Fourth, to the best of the author's knowledge, this is the first attempt to test the impact of economic complexity on the ecological footprint in a panel of countries with the highest complex products. The countries included in the panel are in the top positions in the world for economic complexity. It is important to know how these countries use their energy mix to obtain a higher economic complexity and sustain their environmental quality. Some of them are leaders by example in decarbonisation and energy efficiency policies, as well as public budgets dedicated to R&D activities and investments in clean energy technology. Fifth, the present study is different from similar studies (i.e., [48]) by using new econometrical methods for panel data (i.e., second-generation unit root and cointegration tests in the presence of cross-sectional dependence among the panel members) in order to demonstrate the cointegration between the considered variables (economic complexity index, GDP per capita, fossil fuel energy consumption).

The rest of the paper is organised as follows: Section 2 consists of a short review of the relevant literature, Section 3 presents the materials and methods used in the study, Section 4 exposes the empirical results, Section 5 provides a discussion of results and Section 6 contains the conclusions.

2. Brief Literature Review

Energy consumption has been identified as an augmenting factor for the ecological footprint, which threatens environmental sustainability [29,30,54–59]. Various forms of energy (fossil fuel, renewable, nuclear) have different impacts on the ecological footprint. Renewable energy has a positive contribution to environmental quality by decreasing the ecological footprint [60] while nonrenewable

energy leads to an increase in the ecological footprint in the long- and short-run [37,61]. Similar results were revealed by Destek and Sinha (2020) [62] for OECD countries. It has also been demonstrated that hydroelectricity consumption can help to reduce the carbon footprint, water footprint and ecological footprint [63].

Energy consumption and economic growth are considered traditional determinants of the ecological footprint. Economic growth contributes to environmental degradation by leading to the extension of the ecological footprint [40,64–68]. Destek and Okumus (2019) [68] found that increased energy consumption and economic growth lead to an increase in the ecological footprint in newly industrialised countries for the period from 1982 to 2013. Similar results were obtained by Zafar et al. (2019) [69] for the US economy and by Usman et al. (2020) [70] for 33 upper- to middle-income countries from Asia, Africa, Europe and America.

A consistent part of the literature examining the determinants of the ecological footprint discusses the validity of the environmental Kuznets curve (EKC) hypothesis. Aşici and Acar (2016) [45] confirmed the inverted U-shaped relationship between income and the ecological footprint of production for a panel of 116 countries from 2004 to 2008. Uddin et al. (2017) [44] illustrated a positive effect of real income on the ecological footprint in the 27 highest-emitting countries. In Wang and Dong's study (2019) [71], similar results were obtained for a panel of 14 sub-Saharian African countries. Destek and Sarkodie (2019) [39] confirmed the validity of the EKC hypothesis on 11 newly industrialised countries. The EKC hypothesis is also confirmed for 17 countries in Africa by Sarkodie (2018) [72]. Uddin et al. (2019) [73] provided evidence in support of the EKC hypothesis in some Asian countries, with Destek et al. (2018) [26] doing the same for the EU countries.

As an expression of a country's knowledge level and skills needed in the production of the exported goods, economic complexity has been included by several authors as a factor in pollution (i.e., [47,48,74–76]). More recently, some studies have explored the role of economic complexity for environmental quality, expressed through the ecological footprint. An example is the study of Swart and Brinkman (2020) [50], who found that economic complexity is associated with decreasing environmental degradation in Brazil. Yilanci and Pata (2020) [51] analysed the short- and long-term relationship between economic growth, economic complexity, energy consumption and ecological footprint in China over the period 1965–2016. Their results illustrated that economic complexity, energy consumption and economic growth have led to the extension of the ecological footprint in China. Pata (2020) [52] found that an inverted U-shaped EKC relationship between economic complexity and the ecological footprint is valid in the USA for the period 1980–2016. The US economy was also investigated by Shahzad et al. (2021) [53], who confirmed that economic complexity and fossil fuel energy consumption raised the ecological footprint.

3. Materials and Methods

3.1. Model and Data

The study uses the following econometrical model:

$$\mathrm{EF} = \mathrm{f}\,(GDPpc, FFC, ECI) \tag{1}$$

where *EF* denotes the ecological footprint, *GDPpc* is Gross Domestic Product per capita, *FFC* represents the share of fossil fuel in the total energy consumption and *ECI* is the economic complexity index.

Ecological footprint (*EF*) represents a method of ecological economics expressing the consumption of natural resources and waste generation. According to the methodology developed by the Global Footprint Network [34], it is measured in global hectares (biologically productive hectares with world average biological productivity for a given year).

The economic complexity index (*ECI*) reflects a country's productive structure through a combination of diversity (number of exported products) and ubiquity (the number of countries that export that product [77].

For the purpose of the study, a panel of 48 countries with a positive average value of economic complexity index (*ECI*) for 1995–2014 and with complete data series for all other variables under examination were selected: Japan, Switzerland, Germany, South Korea, Singapore, Czech Republic, Sweden, Austria, USA, Hungary, Finland, Slovenia, United Kingdom, Italy, France, Slovenia, Slovakia, Mexico, Ireland, Denmark, The Netherlands, Israel, Spain, Poland, Brazil, Portugal, Norway, New Zealand, Canada, Estonia, Latvia, Lithuania, Croatia, Bulgaria, Romania, Belarus, Russia, Australia, Malaysia, Thailand, Greece, India, Turkey, South Africa, Saudi Arabia, Uruguay and Colombia (please see Appendix A). The *ECI* data series were retrieved from the Atlas of Economic Complexity [49].

The data set for the ecological footprint of production (in global hectares per capita) was extracted from the Global Footprint Network [34], whereas data for fossil fuel energy consumption (as % of total final consumption), as well as gross domestic product (*GDP*) per capita (PPP; constant 2017 international dollars), come from the World Development database [78].

We translate the econometrical model (1) in the following regression equation, namely, Equation (2):

$$\ln EFP_{it} = \alpha_i + \beta_{1it} \cdot ECI + \beta_{2it} \cdot FFC + \beta_{3it} \cdot RE + \beta_{4it} \cdot \ln GDPpc_{it} + \mu_{it} \quad (2)$$

where i denotes the country, respectively; t denotes the time; *EFP* is the ecological footprint of production per capita; *GDPpc* means the gross domestic product per capita; *FFC* is the share of fossil fuel in the total energy consumption; *ECI* is the economic complexity index; β_1, β_2, β_3, β_4 are regression coefficients; α is the intercept (a scalar); μ_{it} is the error term.

3.2. Econometric Approach

Within the paper's methodology, the following steps are taken: (i) checking the cross-sectional dependence among variables; (ii) testing the variables' stationarity (the presence of unit root); (iii) if the data series at a level have a unit root and the stationarity is found for the I(1) level series, their cointegration relationship is checked; (iv) if the cointegration relationship between variables is identified, coefficients of the fully modified ordinary square (FMOLS) and dynamic ordinary least square (DOLS) regression models are estimated.

3.2.1. Cross-Sectional Dependence

In order to check the cross-sectional dependence among variables, we use the Pesaran (2004) [79] CD test. The null hypothesis of no cross-sectional dependence, the correlation of disturbances between different cross-sections, is zero: H_0:$\rho_{ij} = corr(u_{it}, u_{jt}) = 0$, for $i \neq j$, while the alternative hypothesis states that it exists, namely, $i \neq j$, making $\rho_{ij} = corr(u_{it}, u_{jt}) \neq 0$ The test statistic is given by Formula (3):

$$CD = \sqrt{\frac{2}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij} \rightarrow N(0,1)\right) \quad (3)$$

where $\hat{\rho}_{ij}$ denotes the correlation coefficients obtained from the residuals; N and T denote the countries and the years of observation, respectively.

The null hypothesis of no cross-sectional dependence is rejected when the values of Prob. are under 0.05.

3.2.2. Stationarity of Variables

As Phillips and Sul (2003) [80] have indicated, the efficiency of the estimated results may decrease when cross-serial correlation across sections in the panel is identified. In order to ensure accurate and reliable results, given the presence of cross-sectional dependence, we apply two types of second-generation unit root tests proposed by Pesaran (2007) [81]: the cross-sectional ADF

(PES-CADF) and the cross-sectional augmented IPS (CIPS). These tests take into account the existence of cross-sectional dependence generated by unknown common factors affecting the panel sections.

Pesaran (2007) [81] introduced the cross-sectionally augmented Dickey–Fuller (CADF) test, consisting of standard Dickey–Fuller (DF) regressions augmented with cross-sectional averages of lagged levels and the first difference series of the i-th cross-section in the panel:

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} + \delta_i y_{t-1} + \sum_{j=0}^{k} \delta_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{k} \Delta y_{i,t-j} + \varepsilon_{it} \quad (4)$$

where $y_{t-1} = \frac{1}{N}\sum_{i=1}^{N} y_{i,t-1}$; $\Delta y_t = \frac{1}{N}\sum_{i=1}^{N} y_{it}$; α_i is constant; k is the lag specification; $t_i(N,T)$ is the t-statistic of the estimated ρ_i in the above equation, computed in individual ADF statistics.

CIPS is the average of individual CADF statistic values for individual cross-sections:

$$CIPS = \frac{1}{N}\sum_{i=1}^{N} t_i(N,T) \quad (5)$$

where $t_i(N,T)$ is the CADF statistic for the i-th cross-section unit given by ρ_i in the CADF regression.

In both tests, under the null hypothesis of homogeneous unit root, all sections in the panel are nonstationary, while the alternative states that at least one individual section in the panel is stationary.

Application of these second-generation unit root tests is common in several studies that focus on the link between pollution, economic growth and energy consumption. For example, Eggoh et al. (2011) [82] used them in support of evidence regarding the relationship between energy consumption and economic growth for 21 African countries. Dogan and Seker (2016) [83] employed them with respect to carbon emissions, real growth, and energy consumption; Asafu-Adjaye et al. (2016) [84] and Dogan and Aslan (2017) [85] applied them with regard to carbon emissions, energy use and economic growth in the EU and other candidate countries. Jardon et al. (2017) [86] employed such tests for Latin America and Caribbean countries to analyse the link between carbon emissions and economic growth, while Mensah et al. (2019) [87] used them in a panel of 22 African countries for the relationship between carbon emissions, economic growth, fossil fuel energy consumption and oil price. Destek and Sinha (2020) [62] also used these tests in their study examining the validity of the environmental Kuznets curve hypothesis in 24 OECD countries.

3.2.3. Panel Cointegration Tests

According to Engle and Granger (1987) [88], a combination of two or more nonstationary series may be stationary, meaning that they are cointegrated. This linear combination reflects the long-run relationship between variables. In the Engle–Granger cointegration test, the residuals of a regression performed using I(1) variables are examined. When the variables are cointegrated, then the residuals should be I(0). In our case, if the considered variables are not stationary at their level value, but integrated in their first order (I(1)), we check the cointegration relationship between them through the Pedroni test (1999, 2004) [89,90]. This test is based on Engle–Granger two-step (residual-based) cointegration tests for heterogeneous panel data. It allows for heterogeneous intercepts and trend coefficients of the cointegration equation across cross-sections and assumes the cross-sectional dependence. It involves the computation of seven statistics (ingroup and intergroup statistics). If at least four values of Prob. corresponding to these statistics are under the selected significance level (1% or 5%), the null hypothesis of no cointegration for all i is rejected, indicating a long-term relationship between the considered variables.

In addition, to ensure the robustness and accuracy of results in the presence of cross-sectional dependence, the Westerlund (2005) [91] cointegration test will be also applied. The test is computed using the alternative hypothesis that some of the panels are cointegrated, based on the group-mean

variance-ratio (VR) statistic, testing for no cointegration by testing the presence of a unit root in the residuals. The test uses two assumptions: cointegration of variables is present in *some of the panels* or *in all the panels*. Under the first assumption, the AR parameter is panel-specific, and the alternative hypothesis is that the series in some panels are cointegrated. Under the second option (*all panels are cointegrated*), the AR parameter is the same over the panels. The *p*-value of the VR statistic indicates the rejection/acceptance of the null hypothesis of no cointegration. When this value is less than the chosen significance level, the null hypothesis of no cointegration is rejected in favour of the alternative that at least some panels or all panels are cointegrated.

3.2.4. Estimation of Long-Run Relationship Through FMOLS and DOLS Models

We estimate the regression equations (2) and (3) by using the panel fully modified ordinary square (FMOLS) and the panel dynamic ordinary least square (DOLS) models developed by Pedroni [92,93].

The panel FMOLS equation is specified below as Equation (6).

$$y_{it} = \alpha_{it} + \delta_{it}t + \beta x_{it} + \mu_{it} \tag{6}$$

$$x_{it} = x_{it-1} + e_i \tag{7}$$

where y_{it} is the dependent variable; x_{it} is the independent variable; α_{it} denotes the constant effects; β is the estimated long-term cointegration coefficient/vector.

The panel FMOLS estimator for the *i*-th section in the panel is computed according to Formula (8) below:

$$\hat{\beta}^*_{FM} = n^{-1}\sum_{i=1}^{n} \hat{\beta}^*_{FM,i} \tag{8}$$

The cointegration coefficient for the overall panel is computed by using the mean value of FMOLS coefficients in the cross-sections.

The *t*-statistic for the panel cointegration coefficient ($t^*_{\hat{\beta}^*_{FM}}$) is computed through Formula (9) below:

$$t^*_{\hat{\beta}^*_{FM}} = n^{-1}\sum_{i=1}^{n} t_{\hat{\beta}^*_{FM,i}} \tag{9}$$

Within the panel DOLS method, the following Equation (10) is used:

$$y_{it} = \alpha_i + \beta_i x_{it} + \sum_{k=-K_i}^{K_i} \gamma_{it}\Delta x_{it-K} + \varepsilon_{it} \tag{10}$$

The estimation of Equation (10) is first made for each cross-section of the panel, and then the overall panel cointegration coefficient is computed as the average value of the DOLS coefficients in the cross-sections.

The panel DOLS estimator is calculated with Formula (11) below:

$$\hat{\beta}^*_{D} = n^{-1}\sum_{i=1}^{n} \hat{\beta}^*_{D,i} \tag{11}$$

Finally, the *t*-statistic for the panel cointegration coefficient is given by Formula (12):

$$t^*_{\hat{\beta}^*_{D}} = n^{-1}\sum_{i=1}^{n} t_{\hat{\beta}^*_{D,i}} \tag{12}$$

4. Results

4.1. Descriptive Statistics of Variables

The descriptive statistics of the variables under examination are displayed in Table 1.

Table 1. Descriptive statistics of variables.

Variable	Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
Ecological Footprint of production (ln*EFP*)	1.524169	1.464386	2.669424	−0.240926	0.532601	−0.097331	3.900412
Economic Complexity Index (*ECI*)	0.910613	0.831334	2.463821	−0.398851	0.614959	0.373760	2.204241
Fossil fuel Consumption (*lnFFC*)	4.317339	4.397530	4.605138	2.673479	0.270459	−2.101228	−0.885131
Gross Domestic Product per Capita (ln*GDPpc*)	10.15539	10.28386	11.38292	7.64995	0.629779	−0.885131	3.995018
Observations	960	960	960	960	960	960	960

Table 2 exhibits the correlation coefficients between the explanatory variables. We noticed the value of 0.6261, illustrating a strong positive correlation between gross domestic product per capita (ln*GDPpc*) and the economic complexity index (*ECI*).

Table 2. Correlation matrix of independent variables.

	Economic Complexity Index (*ECI*)	Fossil Fuel Consumption (ln*FFC*)	Gross Domestic Product per Capita (ln*GDPpc*)
Economic Complexity index *(ECI)*	1	−0.1264	0.6261
Fossil Fuel Consumption (ln*FFC*)	−0.1264	1	−0.0166
Gross Domestic Product per Capita (ln*GDPpc*)	0.6261	−0.0166	1

In order to test the multicollinearity of independent variables, we used the variance inflation factor (VIF) algorithm. The VIF values are exposed in Table 3. For all variables FIV has values less than 4, indicating the absence of multicollinearity.

Table 3. Multicollinearity test.

	Variance Inflation Factors (VIF) (Uncentered)	
Variable	**FMOLS Model**	**DOLS Model**
Economic Complexity Index (*ECI*)	1.2821	1.3026
Fossil Fuel Consumption (ln*FFC*)	1.0457	1.0487
Gross Domestic Product per Capita (ln*GDPpc*)	1.3269	1.3526

4.2. Cross-Sectional Dependence Test

Table 4 depicts the results of the cross-sectional dependence check for all variables by using the Pesaran CD test. The probability values for the CD test of all variables are significant at the 1% level, indicating the rejection of the null hypothesis of cross-sectional independence. This result is important to the next methodological step, namely, the stationarity of variables by applying second-generation panel unit root tests that account for cross-sectional dependence.

Table 4. Results of the cross-sectional dependence test.

	Ecological Footprint of Production (ln*EFP*)	Economic Complexity Index (*ECI*)	Fossil Fuel Consumption (ln*FFC*)	Gross Domestic Product per Capita (ln*GDPpc*)
CD statistic	14.059	5.771	28.509	126.734
***p*-value**	0.000	0.000	0.000	0.000

4.3. Data Stationarity

As aforementioned, we checked the presence of unit root by using the second-generation unit root tests, as suggested by Pesaran (2007) [87], PES-CADF and CIPS. Results from these panel unit tests are robust in the presence of heterogeneity and cross-sectional dependence and are reported in Table 5. Both tests show that the null hypothesis of the nonstationarity of variables at their level value cannot be rejected, but a stationary process is identified in their first difference series.

Table 5. Results of the second-generation unit root tests.

Variable	PES-CADF Test		CIPS Test	
	z (*t*-Bar)		CIPS Statistic	
	Constant	Constant and Trend	No Constant	Constant and Trend
ln*EFP*	1.879	−2.531 ***	−1.191	−2.659 **
ECI	−4.622 ***	0.855	−1.003	−2.251
ln*FFC*	−1.112	−0.760	−1.469	−2.603 *
ln*GDPpc*	−5.158 ***	−0.936	−0.185	−1.681
Δln*EFP*	−7.037 ***	−5.635 ***	−4.470 ***	−4.949 ***
Δ*ECI*	−7.140 ***	−4.242 ***	−3.791 ***	−3.774 ***
Δln*FFC*	−10.801 ***	−8.387 ***	−4.016 ***	−4.255 ***
Δln*GDPpc*	−2.985 ***	−4.595 ***	−2.617 ***	−2.960 ***

4.4. Panel Cointegration Test

When established that the variables were integrated by first order I(1), the residual Pedroni and Westerlund cointegration tests were performed. The results of Pedroni cointegration test show that in five cases out of 11, the value of Prob. is under 5% for the variables of each equation Equation (2), as shown in Table 6. This leads us to the conclusion that the cointegration relationship between ln*EFP*, *ECI*, ln*EFC* and ln*GDPpc* is identified.

Table 6. Results of the Pedroni residual cointegration test.

Variables: Ecological Footprint of Production, Economic Complexity, Fossil Fuel Consumption, Renewable Energy, Gross Domestic Product Per Capita					
Test	**Statistic**	**Prob.**	**Statistic**	**Prob.**	
Panel v-statistic	0.6844	0.2468	0.913678	0.1804	common AR coefficients (within-dimension)
Panel rho-statistic	1.753668	0.9603	1.301084	0.9034	
Panel PP-statistic	−1.496151	0.0673	−2.571833	0.0051	
Panel ADF-statistic	−3.555778	0.0002	−5.076073	0.0000	
Panel rho-statistic	4.011549	1.000			individual AR coefficients (between-dimension)
Panel PP-statistic	−2.098280	0.0179			
Panel ADF-statistic	−6.167930	0.0000			

Table 7 depicts the results of the Westerlund cointegration test. We noticed that the values of Prob. for both assumptions (*some panels are cointegrated* and *all panels are cointegrated*) are less than 0.01. This suggests the rejection of the null hypothesis of no cointegration between ln*EFP*, *ECI*, ln*FFC*, ln*GDPpc* for a significance level of 1% under both assumptions.

Table 7. Results of the Westerlund (2005) cointegration test.

Assumptions			
"Some Panels are Cointegrated"		**"All Panels are Cointegrated"**	
Statistic	***p*-Value**	**Statistic**	***p*-Value**
−2.8941	0.0019	−3.3311	0.0004

4.5. Estimation of Long-Run Parameters

Given the identified cointegration relationship through both tests (Pedroni and Westerlund), we further estimated the FMOLS and DOLS equations. We estimated their coefficients in several stages by starting with the traditional determinants of the ecological footprint and adding them one by one: GDP per capita, fossil fuel energy consumption and lastly, we added our variable of interest, economic complexity.

The estimation of the FMOLS and DOLS models shows that *ECI*, ln*FFC* and ln*GDPpc* have a positive and validated influence on the ecological footprint of production. The estimated coefficients of the FMOLS equation show that for a 1% increase of *ECI*, the ecological footprint of production (in ln of global hectares per capita) will rise by 0.0734 percentage points for 5% level of significance. When ln*FFC* increases with 1%, the ecological footprint of production will extend by 0.2292, for 5% level of significance, respectively, when the growth of ln*GDPpc* is 1%, the growth in the ecological footprint of production is of 0.1756 percentage points, for 1% significance level. The estimated coefficients of the DOLS model are validated for 1% significance level. An increase of 1% of *ECI* would lead to an increase of 0.0534 percentage points of ecological footprint of production. Respectively, if ln*FFC* rises with 1%, the augmentation of ecological footprint of production is of 0.2201 percentage points. The 1% increase of ln*GDPpc* would generate an extension of 0.2539 percentage points of ecological footprint of production (Table 8).

Table 8. Estimation of coefficients of the fully modified ordinary square (FMOLS) and dynamic ordinary least square (DOLS) models.

Dependent Variable: Ecological Footprint of Production (ln*EFP*)						
	FMOLS			**DOLS**		
	Gross Domestic Product per Capita (ln*GDPpc*)	**Fossil Fuel Consumption (ln*FFC*)**	**Economic Complexity Index (*ECI*)**	**Gross Domestic Product per Capita (ln*GDPpc*)**	**Fossil Fuel Consumption (ln*FFC*)**	**Economic Complexity Index (*ECI*)**
Coefficients	0.1960 **			0.2018 **		
	0.2126 **	0.2322 *		0.2359 **	0.3877 **	
	0.1756 **	0.2292 *	0.0734 *	0.2539 **	0.2201 **	0.0534 **
R-squared	0.9353	0.9393	0.9304	0.9504	0.9544	0.9737
Observations	960	960	960	960	960	960
Cross-sections	48	48	48	48	48	48

** $p < 0.01$; * $p < 0.05$.

5. Discussion

The econometrical analysis performed in the present study concluded that an increase of economic complexity in the 48 most complex economies in the world leads to an extension of the ecological footprint in production, contributing in this way to the ecological deficit of these countries. As expected, energy consumption based on fossil fuel and income (GDP per capita) also has an extension effect on the ecological footprint in production. This paper's findings suggest that economic complexity

should be seen as a threat of environmental quality. It also must be mentioned that three quarters of the countries under examination are in ecological deficit, which raises the question of how to ensure environmental sustainability given their economic complexity development. More complex and sophisticated products require an increased energy demand that can be covered through an appropriate energy mix, generating less pollution.

The influence of fossil fuel energy consumption on the ecological footprint of production is still positive in these complex economies. The continued usage of fossil fuel will be detrimental to environmental quality. Therefore, to ensure sustainable development, the share of renewable sources in the energy mix should be extended along with strategies for decarbonisation and large investments in R&D for energy technology development. Based on World Bank data (2020) [78] an increasing share of renewable energy consumption is noticed in 34 of the 48 examined countries. The highest shares of renewable resources in the energy mix at the end of the examined period of time (2014) are registered in Norway (57.1%), Sweden (49.9%), Finland (43.3%), Latvia (40.2%), Austria (35.3%), Croatia (33.6%) and Denmark (33.2%), while the lowest are in Saudi Arabia (0.005%), Singapore (0.62%), Israel (2.8%), South Korea (2.8%), Ukraine (3.4%) and Russia (4.2%).

Embedding productive knowledge and a high quality human capital, complex economies posses the potential to stimulate the application of clean technologies and plan the environmental impact of a product at its design stage. This would also stimulate research that is oriented to find and discuss how more complex products (embedding more sophisticated human and technological capabilities) could contribute not only to economic prosperity (as already demonstrated in [77,94–97]), but also to increase environmental quality or, at least, maintain it.

Although the present study did not look at the situation when the variable of interest (economic complexity) is squared (the environmental Kuznets curve hypothesis), a decline in environmental deterioration can be expected when economic complexity will grow. This is based on previous studies revealing this quadratic dependency for the EU countries with high economic complexity (e.g., [47,98]). This suggests that starting from a certain level of economic complexity the environmental degradation could decrease. Recent studies are providing evidence in supporting the idea that reduction of the pressure on environment could come from economic complexity. For example, Dong et al. (2020) [99] found that more complex industrial structure is related to less coal consumption in China, suggesting that policies targeted on emission reduction can improve the performance of an industry with very high complexity. Based on a study examining 67 countries for 1976–2012, Romero and Gramkov (2020) [100] found that the production of complex good is associated with lower emission intensity. This is the result of various types of production technologies and the high value-added of complex products [100].

The examined countries have a specific energy mix that can provide the required energy resources, as volume and structure, for their sophisticated production. Their export baskets include complex products made in pollutant industrial sectors (chemical, agriculture, machinery). Machinery, vehicles parts are mainly included in the export basket of USA, France, Germany, Japan, Thailand, Turkey, Portugal and the Czech Republic; chemicals and electronics in Israel, Singapore, Ireland and Finland; chemical and agricultural products in The Netherlands and Denmark; chemical and machinery in the UK, Austria, Slovenia, France, Hungary and Italy; vehicles and electronics in Mexico; machinery and electronics in South Korea; refined and crude petroleum in Estonia, Canada, Malaysia, Saudi Arabia, Lithuania, Norway, Belarus, Latvia, Croatia, Ukraine, Bulgaria, Colombia, India and Greece; vehicles, machinery and agricultural products in Poland, Spain and Sweden; chemicals and jewellery in Switzerland; gold and diamonds in South Africa; packed medicaments in Lithuania, Latvia, Croatia, Greece and Bulgaria; food products in Brazil, New Zealand, Uruguay Argentina and India [49].

As Member States of the United Nations, these countries assumed the 2030 Sustainable Development Goals (SDGs). Therefore, we can believe that they are focusing on a coherent policy to obtain synergy between economic, social and environmental dimensions of sustainability. However, the ascending trend of the ecological footprint in countries like Austria, Singapore, Israel, Hungary,

Slovenia and Slovakia should be of great concern and placed at the core of their environmental and energy policies.

Complex economies are prosperous and higher levels of ECI indicate a certain quality of governance, a large basis of knowledge (embedded in individuals and technologies) and high economic competitiveness [46]. Thus, the countries under examination have all resources they need and the appropriate potential to make progress toward reducing pressure on ecological capacity. This concern is not just a part of their commitment for achieving the Sustainable Development Goals (SDGs) but also, an awareness of the Intergovernmental Panel of Climate Change (IPPC) report on "climate change, desertification, land degradation, sustainable land management, food security and greenhouse gas fluxes in terrestrial ecosystems" [101].

The above considerations suggest a pattern of environmental sustainability concern derived from common features of the examined countries [102]: (i) investment in energy technology development; (ii) a diversified energy mix, including renewable and nuclear energy, taking into account safety, energy security, economic efficiency and environmental protection; (iii) increase in low-carbon sources of primary energy and electricity supply through fiscal incentives and requirements for energy efficiency and promotion of potential for innovation in critical low-carbon technologies; (iv) implementing electricity and gas market reforms; (v) fostering renewable energy deployment through consumer tariffs, advancement in new technologies and institutional arrangements to accelerate grid integration.

6. Conclusions

The paper intends to highlight the link between the ecological footprint of production and economic complexity by taking into consideration other factors influencing the environment, namely, income per capita and fossil fuel energy consumption, in 48 of the most complex economies in the world over the period 1995–2014. Second-generation unit root tests and cointegration tests, accounting for cross-sectional dependence and heterogeneity of panel data, were employed to examine the long-run relationship between the considered variables.

A stable long-run relationship is revealed between the ecological footprint of production and economic complexity, fossil fuel energy consumption and per capita income. It is found that economic complexity leads to an extension in the ecological footprint generated by production activities. This result is in line with other studies highlighting economic complexity as an additional determinant of ecological footprint extension (i.e., [50–53]). The present study extends the analysis from individual countries (i.e. the USA, China, Brazil) to a panel of countries with higher economic complexity by using a heterogeneous panel data approach with second-generation tests. The experience of complex economies in producing and exporting sophisticated goods, their specific economic structure (with large industrial and chemical sectors) and investment in clean and energy-efficient industrial technologies could serve as guidelines for other countries on how to find the balance between a high level of complexity and environmental quality.

The main conclusion of the study refers to the negative impact of economic complexity, along with other factors (fossil fuel energy consumption, income), on environmental quality, expressed by the ecological footprint. This paper uses this popular indicator of human impact on environmental resources, the ecological footprint, to emphasise that its rise due to the economic complexity of products will add to the ecological deficit in the countries under examination.

Given the revealed impact of economic complexity on environmental quality in the examined countries, national environmental policies should include, in addition to incentives for technological innovation (i.e., cleaner technologies in exports, environmentally friendly production processes, smart grids), specific goals dedicated to reducing the effect of economic complexity on the environment. Thus, the paper's findings suggest more targeted national actions, meant to place the economy on a path leading to sustainability, as policy implications.

As further directions of research, a detailed country analysis on the link between economic complexity and the ecological footprint would reveal specific factors and conditions that bring additional units to the

ecological deficit, which would be beneficial for designing energy and economic policies with realistic targets that are meant to ensure sustainability (economic, environmental and social).

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Appendix A

Table A1. Countries included in the study.

	Country	Economic Complexity Index (ECI) Average Values (1995–2014)
1	Japan	2.3289
2	Germany	1.9954
3	Switzerland	1.9851
4	Sweden	1.8588
5	United Kingdom	1.7551
6	Finland	1.7152
7	Austria	1.6579
8	USA	1.6531
9	Singapore	1.5258
10	France	1.4897
11	Czech Rep.	1.4476
12	Slovenia	1.4268
13	Ireland	1.3606
14	Italy	1.3346
15	South Korea	1.2535
16	Denmark	1.2209
17	Slovakia	1.1559
18	Netherlands	1.1274
19	Hungary	1.1016
20	Israel	1.0358
21	Spain	0.9657
22	Norway	0.9167
23	Poland	0.8265
24	Belarus	0.8091
25	Canada	0.7635
26	Mexico	0.7474
27	Brazil	0.7257
28	Croatia	0.6280
29	Ukraine	0.6325
30	Malaysia	0.5762
31	Estonia	0.5640
32	Russia	0.5914
33	Romania	0.5063
34	New Zealand	0.4731
35	Portugal	0.4648
36	Latvia	0.4409
37	Argentina	0.3802
38	Bulgaria	0.3652
39	Lithuania	0.3365
40	South Africa	0.3202
41	Australia	0.2645
42	Uruguay	0.2451
43	Greece	0.2499
44	Thailand	0.1995
45	India	0.2116
46	Turkey	0.1896
47	Saudi Arabia	0.1131
48	Colombia	0.0241

Source of data: [49].

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