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ORIGINAL RESEARCH ARTICLE

How green finance, digitalization, and transport technologies affect the load capacity factor in Organization for Economic Cooperation and Development countries

Azad Erdem[1,2,3], Nazli Demirtas[4], Ayse Nur Cirak[5], Abdulkadir Barut[6,7]*, and Azadeh Amoozegar[3]

[1]Department of Public Finance, Faculty of Economics and Administrative Sciences, Gaziantep University, Gaziantep, Turkiye
[2]Department of Economics and Business, Western Caspian University, Baku, Azerbaijan
[3]Faculty of Education and Liberal Arts, INTI International University, Nilai, Negeri Sembilan, Malaysia
[4]Department of Public Finance, Faculty of Economics and Administrative Sciences, Sakarya University, Serdivan, Sakarya, Turkiye
[5]Department of Banking and Insurance, Faculty of Business, Istanbul Medipol University, Istanbul, Turkiye
[6]Department of Accounting and Taxation, Siverek Vocational School, Harran University, Sanliurfa, Turkiye
[7]Department of Finance and Banking, Fındıklı Faculty of Applied Sciences, Recep Tayyip Erdogan University, Rize, Turkiye
***Corresponding author:** Abdulkadir Barut (kadirbarut@harran.edu.tr)

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Abstract: With environmental pollution on the rise, the Organization for Economic Cooperation and Development (OECD) member countries have recognized the need to invest heavily in environmentally sound technologies and digitalization. These economies have enacted a series of agreements to ensure environmental sustainability on a global scale. This study aims to achieve Sustainable Development Goals 7 and 11, which focus on a clean environment, and to assess the impact of transport technologies, digitalization, and green finance on the load capacity factor. To the best of our knowledge, this study is the first to examine the impact of transportation technologies, digitalization, and green finance on environmental quality in OECD economies. In addition, the study assesses the implications of achieving carbon neutrality by 2030, which was highlighted at the United Nations Conference of the Parties on Climate Change. In this context, the study analyzes data from 1995 to 2020, and OECD member countries were selected for inclusion. The findings reveal that no mutual causal relationship was found between load capacity and green finance. However, there is a reciprocal causal relationship between transportation technologies and freight capacity, as well as a unidirectional causal relationship between digitalization and freight capacity. In addition, this study provides policy recommendations to support the Sustainable Development Goals.

Keywords: Green finance; Digitalization; Transport technologies; Load capacity factor; Organization for Economic Cooperation and Development countries

1. Introduction

Countries' economies have grown significantly; however, this economic growth has led to several environmental challenges, including increased pollution and degradation of environmental quality. In response, countries are cooperating to reduce pollution and improve environmental quality.[1,2] The European Union (EU) aims to achieve carbon neutrality by 2050. In contrast, the United Nations (UN), announced and endorsed at the 29th Conference of the Parties (COP-29) on Climate Change in Glasgow, set the goal of attaining carbon neutrality by 2030. At the summit, all participating nations made a significant pledge to to limit global warming to below 2°C and, where possible, to 1.5°C. Achieving this objective requires reducing coal consumption, advancing energy technologies, and increasing investments in renewable energy sources.[3,4] Moreover, a number of Sustainable Development Goals (SDGs) have been established by the UN.[5,6] These targets aim to achieve the goals in SDG-7 and SDG-11 (Figure 1).

One of the world's most important infrastructures is the transportation industry. Supporting regional cohesion and economic growth requires a robust transportation infrastructure. Nonetheless, this sector is among the highest energy-consuming and polluting industries. Petroleum and other liquid fuels are consumed in large quantities by the transportation industry, contributing to environmental pollutant emissions. According to the latest report of the European Environment Agency,[7] the transportation sector is one of the largest polluters and producers of carbon dioxide (CO_2). Transforming this sector from traditional practices which have the most negative environmental impact to green development requires coordinated EU efforts.

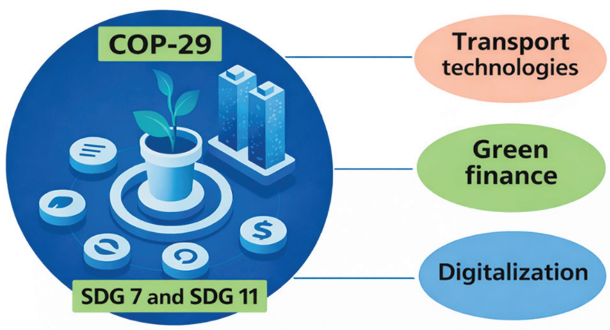

Figure 1. Relationship among variables in the context of the 29th Conference of the Parties (COP-29) on Climate Change and Sustainable Developmental Goals (SDG)

However, compared to other sectors, the International Energy Agency estimates that the transportation sector is responsible for around 25% of global carbon emissions, and this level is projected to increase. The growing number of motor vehicles on the road is one of the main causes of this growth in emissions. Approximately 1.2 billion automobiles are thought to be in use worldwide, burning 13.5 billion barrels of oil per year and releasing 6.1 billion tons of CO_2 into the environment. Due to this rising energy consumption and increased vehicle travel, global CO_2 emissions are predicted to increase by approximately 50% by 2030 and 80% by 2050.[8,9] As a result, the transportation industry is one of the top sectors to target for CO_2 emission reductions. A number of policy measures have been proposed globally to reduce pollution from the transport sector, including reducing fossil fuel consumption, transitioning to renewable energy in transportation, and improving road safety by 2030, as established in SDG-11 of the COP-29, thereby ensuring that everyone has access to safe, affordable, accessible, and sustainable transport systems, including enhanced public transport.

The global economic structure, competitive landscape, innovation, and overall influence have all undergone substantial changes due to developments in the digital economy. By disseminating information and encouraging the servitization of industries, the digital economy accelerates industrial change and supports the growth of low-carbon economies. The digital economy may enhance the development of environmentally friendly products and services, increase businesses' carbon and production efficiency, and facilitate the shift to a low-carbon economy.[10] Furthermore, by encouraging innovation and promoting the transition from conventional to environmentally friendly green technologies, the digitalization of production models required by the SDGs enables businesses and industries to achieve effective and efficient production.[11] The COP-29's SDG-7 aims to align with the accomplishment of these contributions. Given these advantages of the digital economy in building a sustainable environment, it is anticipated that the broad integration of digital technology into the economy will help reduce global emissions by 15%.[11]

Green finance refers to a sustainable financial system that considers environmental, social, and governance aspects. It represents an approach to financing that emphasizes the long-term impacts of investments on individuals and the environment. The primary aim of green finance is to facilitate the transition to a low-carbon, climate-resilient economy through the establishment of a supportive financial infrastructure.[12,13] This involves directing national cash flows toward initiatives that are both ecologically sustainable and socially beneficial.[14] Green finance encompasses not only a set of financial instruments aimed at reducing greenhouse gas emissions and addressing the impacts of climate change but also includes all financial products and services that promote environmental sustainability.[15] Moreover, green finance plays a pivotal role in accelerating the transition to sustainability.[16]

The Environmental Kuznets Curve has been used in most prior research to analyze the link between economic growth and environmental contamination. According to this curve, environmental contamination is expected to rise during the initial phase of economic expansion. As economic expansion reaches a saturation point, it is anticipated that environmental pollution will decline as national income rises. Thus, the link between economic expansion and environmental pollution is represented by an inverted U-shaped curve.[17,18] However, the Environmental Kuznets Curve hypothesis is not used in the present study to evaluate the link between economic growth and environmental pollution; instead, the "load capacity curve (LCC)" hypothesis is applied. According to this theory, the link between environmental quality and economic growth is U-shaped. Early economic growth is characterized by a negative correlation between income and environmental quality, as well as a decline in the load capacity factor (LCF) value. After a certain point, economic development continues to rise, which improves environmental quality. This is due to the fact that countries tend to adopt cleaner manufacturing techniques and reduce environmental pollution after they reach a particular degree of economic growth.[19,20] The present study tests the LCC hypothesis in this context.

Considering existing literature, this study makes several unique contributions to the existing body of knowledge. This study analyzes data from 1995 to 2020. By selecting the OECD member countries (e.g., Austria, Australia, Belgium, Czechia, Germany, France, Italy, Luxembourg, Luxembourg, Spain, Hungary, Finland, Switzerland, Sweden, Norway, and Mexico), the study examines the impact of transport technologies (Trtec), green finance (GF), and digitalization (DG) on the LCF. The following points are expected to contribute to the literature:

(i) To the best of our knowledge, this is the first study to examine the impact of Trtec, GF, and DG on LCF for selected OECD countries
(ii) There are no studies in the literature to measure the impact of DG and Trtec on environmental pollution. Rather, the existing literature mostly focuses on the impact of renewable energy, environmental technologies, transportation, transportation-related energy consumption, and green technological innovation on environmental pollution
(iii) The choice of these variables in the study is determined by both COP-29 and SDG-7 and SDG-11
(iv) The panel data method used in the study provides both robust results and country-specific insights due to its innovative nature
(v) This study highlights the relationship between Trtec, GF, and DG on LCF, and provides efficient policy recommendations for selected OECD countries.

This paper is organized as follows: Section 2 presents the literature review, Section 3 describes the data, model, and methodology, and Section 4 presents empirical results and policy implications.

2. Literature review

From 1995 to 2020, the influence of GF, Trtec, and DG on LCF was investigated across selected OECD countries. Based on the literature review, we found that no research has assessed the influence of Trtec on environmental pollutants. Rather, research in the available literature has focused on the impacts of environmental technology, transportation, and transportation-related energy consumption on environmental pollution.[21] For example, Mustapa and Bekhet[22] evaluated how effective linear programming and sensitivity analysis methodologies were in reducing CO_2 emissions in Malaysia. The findings indicate that transportation-related energy consumption accounts for 28% of total CO_2 emissions. Saidi and Hammami[23] examined the interaction between transportation and Economic Growth (ECG) on environmental pollutants across 75 countries from 2000 to 2014. They found a unidirectional causal relationship between transportation and environmental deterioration in high-income nations. In middle- and low-income nations, environmental contamination is driven by economic expansion and freight traffic.

Neves *et al*.[24] examined the association between energy consumption in the transportation sector by source and CO_2 emissions in OECD countries from 1995 to 2014. Their findings reveal that the use of fossil fuels in transportation has a significant impact on the economic development of OECD countries while also increasing CO_2 emissions. Huang *et al*.[25] investigated the influence of transportation, urbanization, and ECG on greenhouse gas emissions in Association of Southeast Asian Nations (ASEAN) countries from 1995 to 2018. They determined that transportation, urbanization, and ECG increase greenhouse gas emissions. They also provide crucial measures such as ecologically friendly transportation services and environmental control levies to help ASEAN countries reduce their greenhouse gas emissions. Hussain and Dogan[26] conducted a study on the BRICS countries from 1992 to 2016, recommending investments in environmental technologies to mitigate ecological impact.

In another analysis, five African nations with the highest carbon emissions between 1990 and 2019 were selected. This study evaluated the effects of environmental technologies, renewable energy, and natural resource dependency on CO_2 emissions. They found that investing in environmental technologies lowers CO_2 emissions.[27] Zhou *et al*.[28] investigated the effects of environmental technology, economic policy uncertainty, and renewable energy on carbon emissions in the top five polluting economies from 1992 to 2020. The findings indicate that environmental technologies enhance environmental quality. Pata *et al*.[29] employed LCF as an indicator of environmental pollution rather than CO_2 emissions or ecological footprint factors. They examined the influence of clean energy technology on LCF in the United States. The autoregressive distributed lag model was utilized in the study, which included data from 1974 to 2018. The findings of the empirical investigation indicate that clean energy technologies had no effect on LCF. In another study, Aydin *et al*.[30] evaluated the influence of environmental technologies, institutional quality, and globalization on LCF in EU member nations between 1990 and 2019. The findings suggest that in Austria, the adoption of environmental technology improves environmental quality.

In addition to Trtec, several studies address GF. For example, Wang *et al*.[31] investigated the influence of GF, foreign direct investment, ECG, trade openness, and renewable energy on carbon emissions in BRICS nations between 2000 and 2018. The results reveal that GF has a negative impact on carbon emissions. In this context, the analysis shows that GF is the most effective financial approach for reducing CO_2 emissions. Nawaz *et al*.[32] examined the influence of GF, foreign direct investment, the human development index, and ECG on CO_2 emissions in the Next Eleven countries from 2000 to 2019. They found that GF decreases CO_2 emissions. Meo and Abd Karim[33] employed monthly data from November 2008 to June 2019 to examine the association between GF and carbon emissions in the top 10 nations that actively utilize GF. GF has been shown to be an effective financial solution for reducing carbon emissions.

Kirikkaleli and Adebayo[34] used data from Q1 2000 to Q4 2018 in Brazil to investigate the effects of GF, ECG, social globalization, political risk, and green innovation on LCF. GF and green innovation boost LCF, but ECG has the opposite effect. Li *et al*.[35] examined the relationship between GF, ECG, natural resource rent, energy innovation, renewable energy utilization, and environmental pollution in Mexican, Indonesian, Nigerian, and Turkish economies from 1990 to 2002. The findings suggest that GF helps reduce environmental pollution. Liu *et al*.[36] investigated the influence of GF, green technology, and consumption-based trade openness on CO_2 emissions in the BRICS nations between 2000 and 2020. The findings indicate that GF and green technology reduce CO_2 emissions in the long run. Afshan *et al*.[37] evaluated the influence of GF, environmental regulatory stringency, and eco-innovation on China's ecological footprint from 2000 to 2017. The findings indicate that GF had a favorable impact on the ecological footprint. Another study investigated the influence of GF, ECG, renewable energy consumption, agricultural added value, information and communication technology, and natural resource rent on South Asian economies' ecological footprints between 1990 and 2017. The findings reveal that GF minimizes environmental impact.[38]

Du *et al*.[39] examined the association between DG and environmental contamination in 30 Chinese regions from 2011 to 2019. The study found that DG reduces environmental pollutants. Shi *et al*.[40] utilized data from 30 Chinese provinces spanning 2011 to 2019 and reported that DG significantly reduces environmental pollutants. Li and Guo[41] investigated the influence of DG on environmental pollution in 274 Chinese provinces from 2011 to 2018. They discovered that both DG and its sub-variables improve environmental quality. Wan *et al*.[42] studied the influence of DG and technological innovation on environmental pollution in 273 Chinese cities between 2010 and 2017. The findings reveal that DG improves environmental quality and is a significant determinant of environmental sustainability. Chen *et al*.[43] conducted research encompassing 30 Chinese provinces between 2013 and 2020 and investigated the influence of DG on CO_2 emissions. Evidence suggests that DG significantly reduces carbon emissions. Zhang and Qian[44] observed similar outcomes for 30 Chinese provinces between 2011 and 2019. A different study examined yearly data from 97 countries from 2003 to 2019, investigating the effects of DG, anti-corruption regulations, and natural resource rent on CO_2 emissions. When considered as a whole, DG increases carbon emissions, with an inverted U-shaped relationship between them.[10] Karlilar *et al*.[45] examined the influence of DG, renewable energy, green innovation, and financial growth on the ecological footprint in 36 OECD nations from 2000 to 2018. All variables were found to reduce environmental pollution. Ali *et al*.[46] evaluated the influence of DG, electricity consumption, renewable energy, industrial added value, foreign direct investment inflows, and global value chain involvement on the environment in 112 developing countries from 1990 to 2018. The findings indicate that DG is a significant strategy for lowering carbon emissions.

In summary, GF, Trtec, and DG showed a generally favorable influence on environmental outcomes. However, no study has examined the relationship between GF, Trtec, DG, and LCF. Therefore, this study aims to address this gap in the literature.

3. Data and methodological background

In this study, causality analysis was employed to analyze the relationship between GF, Trtec, DG, and LCF in selected countries from 1995 to 2020. The countries included Austria, Australia, Belgium, the Czech Republic, Germany, France, Italy, Luxembourg, Spain, Hungary, Finland, Switzerland, Sweden, Norway, and Mexico. The model for the study was constructed using Equation (1):[47]

$$\text{LCF } i_{it} = a_0 + \beta_1 gf_{it} + \beta_2 trtec_{it} + \beta_3 dg_{it} + \varepsilon_{it} \quad (1)$$

where LCF is the load capacity factor (biocapacity/ecological footprint ratio), gf is green finance, trtec is transportation technologies, and dg is the percentage of the population using the internet. a_0 is the constant term, which indicates how much the LCF will change even if all variables are fixed, and εit is the error term in the equation. β_1, β_2, and β_3 are the coefficients that show how much GF, Trtec, and internet usage rates affect the LCF, respectively. Table 1 provides the description of the variables.

Summary statistics of the variables (Table 2) show that they exhibit geometric growth. Therefore, it can be inferred that all series should be included in the model logarithmically. After taking the logarithm of

Table 1. Details of the variables

Variables	Specifications	Origin
LCF	Load capacity factor=Biocapacity/ecological footprint (GHa per person)	Global Footprint Network
GF	Green finance=Environmental protection products by residents (%)	OECD
Trtec	Transportation technologies (index)	OECD
DG	Individuals using the internet (% of population)	World Bank

Abbreviations: DG: Digitalization; GF: Green finance; LCF: Load capacity factor; OECD: Organization for Economic Cooperation and Development; Trtec: Transportation technology.

the variables, the scale differences across countries and among variables were reduced. For the 15 countries and 26 years (1995–2020) included in the analysis, the average of the LCF variable was approximately 0.70%, while the average of the GF (lngf) was about 2.14%; the average of Trtec (lntrtec) was approximately 0.88%, and the average of internet users as a percentage of the population (lndg) was about 3.65%.

According to Table 3, Finland has the highest average LCF (0.70), followed by Australia (0.62) and Sweden (0.4), whereas Luxembourg has the lowest average LCF. The countries with the highest average GF are Luxembourg, Norway, Finland, and Spain, whereas the country with the lowest average GF is Italy. In terms of Trtec, the countries with the highest average Trtec are Australia, France, and Mexico, while the lowest average values are observed in Finland, Hungary, and the Czech Republic. The countries with the highest internet usage rates are Norway, Sweden, and Finland, whereas the country with the lowest internet usage rate is Hungary.

In panel data analyses, the first step is to test whether the model contains cross-sectional dependence or not. Cross-section dependence indicates whether there is interaction between units. If the model contains cross-section dependence, first-generation panel unit root tests are used, and if it does not, second-generation panel unit root tests are used. In this study, due to data limitations, the analysis was conducted with the data of 15 OECD countries from 1995 to 2020. Here, the number of countries is N = 15 and the year interval is T = 25. Therefore, given that the time dimension is larger than the cross-sectional dimension, the Lagrange multiplier (LM) test developed by Breusch and Pagan[48] was used in this study. As this constraint of the LM test caused dimension distortion when $N>T$, it was used only when $T>N$.[49]

Table 2. Descriptive statistics of the variables

Variable	Observations	Mean	Standard deviation	Min	Max
LCF	390	0.72	0.64	0.10	2.44
gf	390	10.04	3.67	0.17	19.90
trtec	390	1.05×10^{8}	6.55×10^{8}	0.15	5.57×10^{9}
dg	390	56.70	31.16	0.10	98.82
lnLCF	390	−0.70	0.87	−2.30	0.89
lngf	390	2.14	0.83	−1.74	2.99072
lntrtec	390	0.88	3.52	−1.89	22.44
lndg	390	3.65	1.21	−2.28	4.59

Abbreviations: dg: Digitalization; gf: Green finance; LCF: Load capacity factor; trtec: Transportation technology.

Table 3. Descriptive statistics by country

Countries	lnLCF			Lngf			lntrtec			lndg		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Australia	0.62	0.47	0.89	2.30	2.06	2.58	8.47	−3.28	22.43	3.92	1.01	4.56
The Czech Republic	−0.863	−1.00	−0.69	2.44	2.11	2.73	0.31	−1.25	1.55	3.38	0.37	4.39
Belgium	−1.74	−1.87	−1.71	2.14	1.64	2.50	−0.08	−1.15	0.74	3.67	−0.008	4.51
Germany	−1.16	−1.27	−0.98	2.46	2.15	2.76	1.09	0.20	1.75	3.78	0.60	4.49
France	−0.69	−0.79	−0.53	2.30	1.82	2.73	1.01	−0.11	1.82	3.54	0.49	4.43
Italy	−1.61	−1.76	−1.37	−0.28	−1.74	2.06	0.26	−0.42	1.10	3.26	−0.64	4.30
Luxembourg	−2.16	−2.30	−2	2.53	2	2.99	0.77	−0.55	1.66	3.84	0.46	4.59
Spain	−1.12	−1.45	−0.79	2.26	1.56	2.80	0.07	−0.88	0.67	3.37	−0.96	4.53
Hungary	−0.50	−0.68	−0.36	2.19	1.19	2.58	−0.14	−1.88	1.33	3.24	−0.38	4.43
Austria	−0.65	−0.73	−0.49	2.49	2.17	2.76	0.89	0.15	1.51	3.80	0.63	4.47
Finland	0.70	0.50	0.85	2.30	1.66	2.80	−0.24	−1.70	0.78	4.09	2.63	4.52
Switzerland	−1.37	−1.49	−1.18	1.97	1.58	2.35	−0.04	−0.73	0.72	3.98	1.26	4.54
Sweden	0.48	0.21	0.66	2.26	1.72	2.70	0.71	−0.08	1.45	4.12	1.62	4.55
Norway	0.25	0.08	0.43	2.38	1.93	2.82	0.004	−1.008	1.16	4.16	1.85	4.58
Mexico	−0.71	−0.96	−0.45	2.30	1.43	2.72	0.16	−1.62	2.27	2.53	−2.27	4.26

Abbreviations: dg: Digitalization; gf: Green finance; LCF: Load capacity factor; trtec: Transportation technology.

As mentioned in the analysis section, cross-section dependence was detected in the model, and the Augmented Dickey–Fuller test (ADF) Fisher test and the cross-sectionally expanded Im, Pesaran, and Shin (CIPS) tests developed by Pesaran[50] both first-generation unit root tests were applied to assess unit roots. However, before applying unit root tests, an appropriate lag length should be determined according to the Modified Akaike Information Criterion (MAIC), Modified Bayesian Information Criterion (MBIC), and Modified Hannan–Quinn Information Criterion (MQIC). In the continuation of the analysis, when the variables are stationary at the level or at the first difference, causality analysis can be started. However, before proceeding to causality analysis, it should be determined whether the variables are heterogeneous or homogeneous with the slope homogeneity test. As the variables are heterogeneous in this study, the Dumitrescu and Hurlin panel Granger causality test was applied. An overview of the analysis procedure is provided in Figure 2.

4. Methodology and empirical results

When analyzing panel data, especially when the time period is long, the stationarity of the series should be examined, and panel unit root tests are typically used. Panel unit root tests are divided into first- and second-generation tests according to the presence of

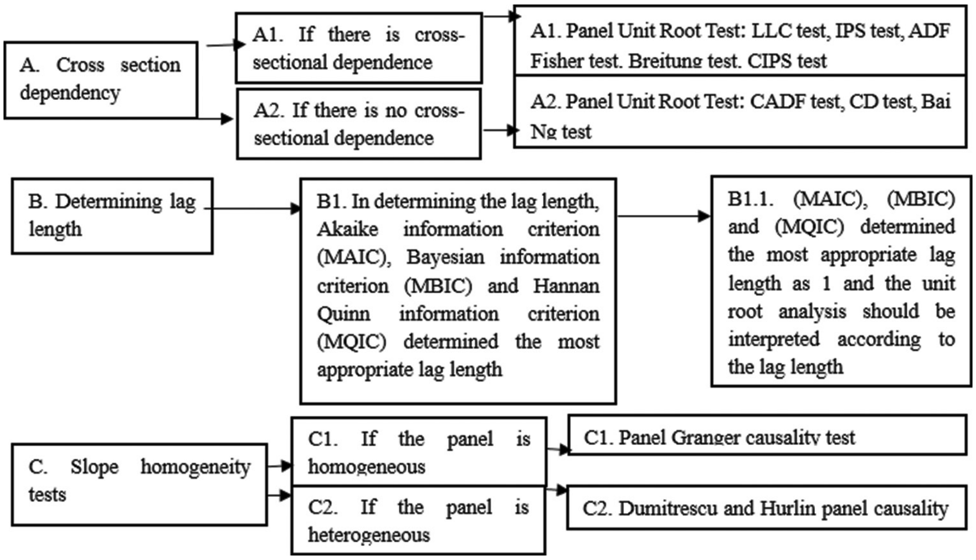

Figure 2. Schematic diagram of the analysis workflow

Abbreviations: ADF: Augmented Dickey–Fuller test; CADF: Cross-section Augmented Dickey-Fuller; CD: Cross-section dependence; CIPS: Cross-Sectionally Augmented Panel Unit Root Test; IPS: Im, Pesaran, and Shin unit root test; LLC: Levin, Lin, and Chu unit root test; MAIC: Modified Akaike information criterion; MBIC: Modified Bayesian information criterion; MQIC: Modified Hannan–Quinn information criterion.

cross-section dependence. Cross-section dependence can be tested using different methods depending on the number of cross-sections (*N*) and the size of the time dimension (*T*). For example, in cases where *T*>*N*, the LM test proposed by Breusch and Pagan[48] is used, while in cases where *T*<*N*, the cross-section dependence test (CD) developed by Pesaran[51] is employed.[52] As the time dimension in this study is *T*=26 (1995–2020) and the number of countries is *N*=15, the CD test developed by Pesaran[51] was used in this study. The main hypothesis of this test is expressed as follows:[53]

$$H_0=E\,[u_{it,}\,u_{jt}]=0 \tag{2}$$

$$CD_{NT}=\sqrt{\frac{2T}{N(n-1)}}\sum_{i-1}^{N-1}\sum_{j=i+1}^{n}\rho ij \tag{3}$$

$$\acute{P}_{ij}=\ T^{-1}\sum_{t=1}^{T}PiTPiJ \tag{4}$$

For the CDNT test, the above statistics are asymptotically normally distributed as CD→d N(0, 1), N→∞ and are applicable to a wide range of panel data models, including heterogeneous dynamic models with multiple breaks in slope coefficients and error variances. $\acute{P}_{it}$ refers to the scaled residuals[47] and is calculated as:

$$\acute{P}_{it}=\frac{eit}{\left(T-1ej.ej\right)1/2} \tag{5}$$

where *eit* is the pooled least squares residuals, and *ei* is the least squares estimated residuals for each unit. The CDNT test is based on unit-specific least squares residuals that are robust to heterogeneity in slope parameters and error variance.[54]

After determining the existence of inter-unit correlation, second-generation unit root tests were employed. For the data used in this study, cross-sectional dependence was assessed. The findings indicate that cross-sectional dependence exists. Therefore, it was considered appropriate to use one of the second-generation unit root tests. Specifically, the CIPS test was employed. The CIPS panel unit root test, developed by Pesaran,[50] models inter-unit correlation through a common factor. Pesaran[50] argues that this method eliminates cross-sectional dependence using time-averaged cross-sectional averages of the series as an unobservable instrumental variable in the model. In this context, the ADF regression is extended with cross-sectional averages and lagged values of the series, and the first-order difference of this regression is taken.

The CIPS statistics, which is the average of the cross-sectionally ADF statistic obtained from the ADFs, is defined as follows:

$$CIPS\ \left(N,\ T\right)\ =N^{-1}\sum_{t=1}^{N}ti(N,T) \tag{6}$$

The discrete type of this statistic is calculated as follows:

$$CIPS^* \left(N,\ T\right) = N^{-1}\sum_{t=1}^{N} t * i(N,T) \tag{7}$$

The most notable aspect of this test is its favorable small-sample properties. In addition to the CIPS test, which is a second-generation unit root test accounting for cross-section dependence, a first-generation panel unit root test—which assumes no cross-sectional dependence—is also included in the study. For this, the ADF test developed by Maddala and Wu[55] was applied. The equation of the test is given as follows:[56]

$$\Delta Y_{i,t} = a_i + \delta Y_{i,t-1} + \sum_{j=1}^{p} Y_{i,j}\Delta Y_{i,t-j} + v_{it} \tag{8}$$

$$\Delta Y_{i,t} = a_i + \mu_i t + \delta Y_{i,t-1} + \sum_{j=1}^{p} Y_{i,j}\Delta Y_{i,t-j} + v_{it} \tag{9}$$

In Equations (8) and (9), Y_t represents the mean of all N observations at time t. The presence of lagged cross-sectional means and first differences accounts for cross-sectional dependence through a factor structure. In cases of autocorrelation in the residuals or factors, the lagged first differences of Y_{it} and Y_t must be included, as given in Equation (9).[54] In the estimation process, the appropriate lag length should be determined for each cross-sectional unit according to the information criteria in the ADF test statistics.

The hypotheses of the Fisher ADF test statistics are as follows:

(i) H_0: δ_i=0

(ii) H_1: δ_i<0

The test statistic is calculated as follows:

$$\Pi = -2\sum_{i=1}^{N} lnpi \tag{10}$$

The probability value of the unit root test for cross-section i (pi) is calculated. Here, ln represents the logarithm.

The delta test developed by Pesaran and Yamagata[57] was employed to test heterogeneity among variables. The regression coefficients of each variable were averaged, and their variance was analyzed. If the variance is close to zero, the variables are homogenous; if it is far from zero, there is heterogeneity. The equations of the test are given as follows:

$$W_{NT}^{\ HNC} = N^{-1}\sum_{i=1}^{N}\left(Wi,T\right) \tag{11}$$

$$\Delta_{\text{adj}} = \sqrt{N}\ \mathrm{N}^{-1}\mathrm{S} - \mathrm{k} / \sqrt{var(t.k)} \tag{12}$$

where Δ denotes the test statistic for small samples, Δadj denotes the test statistic for large samples, N represents the number of observations, and *var (t, k)* denotes the variance.

$$yi,t=ai\quad+\quad\sum\delta i(k)yi,kKkt-k=1+\sum\theta i(k)xi,t\text{-}kKk=1+\varepsilon it \tag{13}$$

where i represents cross-sections and t denotes time. ai represents fixed individual effects. $\delta i(k)$ and $\theta i(k)$ are autoregressive parameters and regression coefficients, respectively.

The Dumitrescu–Hurlin[58] causality examines the null hypothesis of no causality. Test statistics are defined as follows:

$$W_{NT}^{\ HNC} = N^{-1}\sum_{i=1}^{N}\left(Wi,T\right) \tag{14}$$

$$W_{NT}^{\ HNC} = \sqrt{N/2M}\left(W_{NT}^{\ HNC} - M\right) \to N(0,1) \tag{15}$$

where Wi,T denotes individual Wald statistical values. W_{NT}^{HNC} and Z_{NT}^{HNC} represent the average and standardized test statistics, respectively. N denotes the number of cross-sections, and M is the appropriate lag length.

Cross-section dependence can be tested using different methods depending on the number of cross-sections (N) and the length of the time dimension (T). In this study, as the number of cross-sections (countries) is 15 and the time dimension (years) is 26 (T>N), the LM CD test, developed by Pesaran,[51] was applied. However, the LM CD test developed by Pesaran,[51] which can be used for both T>N and N>T cases, was also applied to

Table 4. Results of cross-section dependence and slope homogeneity tests

Cross-section dependency/ slope homogeneity test	Test	Statistic	*p*-value
Cross-section dependency	LM	422.2	0.0000***
	LM adj*	51.3	0.0000***
	LM CD*	16.27	0.0000***
Slope homogeneity	Δ	9.830	0.000***
	Δadj.	11.208	0.000***

Note: ****p*<0.01.
Abbreviations: adj: Adjusted; LM: Lagrange multiplier; LM CD: Lagrange multiplier cross-section dependence.

check for cross-section dependence. The hypotheses of the test are as follows:
(i) H_0 = There is no cross-section dependence
(ii) H_1 = There is cross-sectional dependence.

Table 4 presents the results of CD tests and the Pesaran and Yamagata[57] delta test. The findings indicate that the H_0 hypothesis is rejected at 1% significance level, indicating the presence of cross-section dependence in the series. Based on the Pesaran and Yamagata[57] delta test, the slope parameters of the variables are heterogeneous.

Table 5 presents data on the determination of lag lengths. To test the stationarity of the variables, a unit root test should be applied, with the appropriate lag length determined first. While determining the lag length, MAIC, MBIC, and MQIC identified the most appropriate lag length as 1, and the unit root analysis should be interpreted using this lag length.

Table 6 presents the results of level unit root tests for the variables, as well as the unit root test results for the

Table 5. Determination of the lag length

Lag	CD	J	J *P* value	MBIC	MAIC	MQIC
1	1	94.54227	0.635237	−453.5211*	−105.4572*	−245.7016*
2	1	73.24547	0.535783	−337.8025	−76.75453	−181.9378
3	0.9999999	25.32355	0.9985858	−248.7084	−74.67645	−144.7986
4	0.9999097	12.16645	0.9851763	−124.8495	−37.83355	−72.89464

Notes: *p<0.05.
Abbreviations: CD: Cross-section dependence; MAIC: Modified Akaike Information Criterion; MBIC: Modified Bayesian Information Criterion; MQIC: Modified Hannan–Quinn Information Criterion.

Table 6. Results of the panel unit root test

Specification without trend				Specification without trend			
Variable	**Lags**	**ADF-Fisher**	**CIPS-Pesaran**	**Variable**	**Lags**	**ADF-Fisher**	**CIPS–Pesaran**
lnlcf	1	39.114 (0.123)	0.260 (0.602)	d.lnlcf	1	258.0613 (0.000)***	−5.811 (−2.25, 5%)**
lngf	1	37.226 (0.171)	0.428 (0.666)	d.lngf	1	204.5137 (0.000)***	−5.188 (−2.25, 5%)**
lntrtec	1	26.046 (0.673)	−0.364 (0.358)	d.lntrtec	1	348.3391 (0.000)***	−5.602 (−2.25, 5%)**
lndg	1	561.722 (0.000)***	−7.113 (0.000)***	d.lndg	1	361.0478 (0.000)***	−4.567 (−2.25, 5%)**
Specification with trend				**Specification with trend**			
lnlcf	1	35.036 (0.241)	−2.148 (0.016)**	d.lnlcf	1	241.5584 (0.000)***	−5.906 (−2.76, 5%)**
lngf	1	44.529 (0.043)**	1.350 (0.911)	d.lngf	1	153.2828 (0.000)***	−5.036 (−2.76, 5%)**
lntrtec	1	77.384 (0.000)***	−3.637 (0.000)***	d.lntrtec	1	275.5289 (0.000)***	−5.556 (−2.76, 5%)**
lndg	1	221.514 (0.000)***	−7.327 (0.000)***	d.lndg	1	240.1156 (0.000)***	−5.026 (−2.76, 5%)**

Notes: **p<0.05 and *** P<0.01. The expression "d." indicates the first-order difference of the series.
Abbreviations: dg: Digitalization; gf: Green finance; LCF: Load capacity factor; trtec: Transportation technology.

Table 7. Dumitrescu–Hurlin Granger causality test results

Models	Lag	W-bar	Z-bar	Z-bar tilde	Decision
Lngf→lnLCF	1	1.5592	1.5314; *p*: 0.1257	1.0584; *p* value: 0.2899	lngf does not Granger-cause lnLCF
lnLCF→lngf	1	1.1025	0.2808; *p*: 0.7789	0.0058; *p*: 0.9954	lnLCF does not Granger-cause lngf
lntrtec→lnLCF	1	2.7444	4.7772; *p*: 0.0000***	3.7902; *p*: 0.0002***	lntrtec Granger-causes lnLCF
lnLCF→lntrtec	1	1.6008	1.6453; *p*: 0.0999*	1.1543; *p*: 0.2484	lnLCF Granger-causes lntrtec at 10% (Z-bar) but is not significant (Z-bar tilde)
lndg→lnLCF	1	2.1491	3.1468; *p*: 0.0017***	2.4181; *p*: 0.0156***	lndg Granger-causes lnLCF
lnLCF→lndg	1	1.4746	1.2998; *p*: 0.1937	0.8635; *p*: 0.3879	lnLCF does not Granger-cause lndg

Note: *p<0.1 and *** p<0.01.
Abbreviations: dg: Digitalization; gf: Green finance; LCF: Load capacity factor; trtec: Transportation technology.

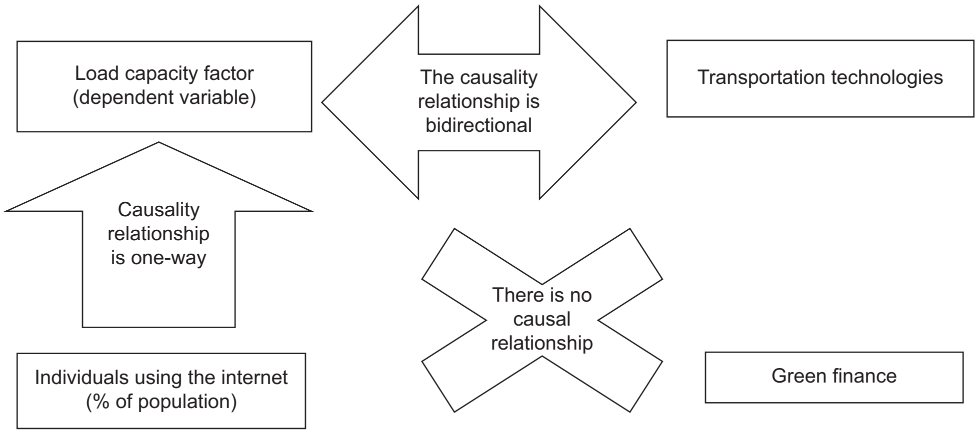

Figure 3. Causality relationships identified from the analysis

first differences of the variables. Based on the table, the *lnint* and immobile variables are stationary according to both the ADF and CIPS test results. However, according to both ADF and CIPS test statistics, *lnLCF*, *lngf*, and *lntec* variables are not stationary at the level in the fixed model. While these variables are not stationary, the remaining variables were found to be stationary. All first-differenced variables in both the ADF test statistic (a first-generation panel unit root test) and the CIPS test (a second-generation panel unit root test) are stationary at the 1% significance level in both the fixed and trend models. After determining that the parameters are heterogeneous, the Dumitrescu–Hurlin Granger causality test was applied.

According to Table 7, for the period 1995–2020 and the 15 selected countries, LCF was taken as the dependent variable, while GF (lngf), Trtec (lntrtec), and the internet usage rate (lndg) were included as independent variables. No mutual causal relationship was observed between LCF and GF. However, a mutual causal relationship was found between transportation technologies and LCF. In addition, a unidirectional causal relationship was observed from the internet user rate to LCF (Figure 3).

5. Conclusion and recommendation

The results indicate that:

(i) There is no causality between LCF and GF

(ii) There is a bidirectional causality between Trtec and LCF

(iii) There is a unidirectional causality from DG to LCF.

Environmental deterioration remains a global challenge intensified by globalization and industrialization. Therefore, it is crucial to develop novel approaches to address this challenge, highlighting the significance of environmental protection, sustainability, renewable energy sources, and environmental technologies. Addressing environmental deterioration is a complex issue that requires international collaboration and interdisciplinary solutions. It involves collaboration and coordination between scientists, decision-makers, and all societal segments. Enhanced cooperation among OECD members will support a better collective understanding. In summary, the energy sector contributes approximately 29% of total greenhouse gas emissions, followed by transportation (13%), agriculture (9%), and industrial sectors (7%).[59]

Green finance prioritizes environmental considerations, emphasizing ecosystem protection and efficient resource utilization as key criteria for assessing the performance of its activities. It seeks to align financial operations with environmental protection and ecological balance, ultimately supporting sustainable development.[60] The findings of this study show no causal relationship between LCF and GF, likely because GF operates within a broad framework of environmental protection, resource management, and ecological preservation, whereas LCF exclusively reflects environmental pollution. This distinction may limit the extent to which LCF captures the broader objectives embedded in GF. Moreover, the influence of policymakers and market dynamics across GF components may further weaken any direct link between GF and LCF.

The findings indicate a bidirectional causal relationship between Trtec and LCF. To effectively reduce emissions and mitigate climate change, transportation emission models that integrate renewable energy and environmental technologies are essential. Accelerating a shift toward a low-carbon economy requires sustained investment and commitment to energy-efficient technologies, particularly smart grids and advanced information networks. These systems support efficient resource management and environmental monitoring. Promoting the adoption of electric and hybrid vehicles also necessitates expanding charging infrastructure and strengthening government purchase incentives. In addition, transitioning public transportation systems to renewable energy sources and integrating smart transportation technologies should be supported through public–private partnerships.

In addition, the findings indicate a unidirectional causal relationship between DG and LCF. DG reflects how technological advancements influence human activities, and their effects on environmental quality vary according to the sustainability of the technologies and the regulatory frameworks in place. Managing the environmental implications of DG requires advancing technological innovation alongside environmental conservation. This includes prioritizing investment in environmentally friendly digital infrastructure and fostering collaboration in the development of digital solutions for climate change mitigation. Incentives for sustainable technology initiatives should be expanded through coordinated public–private partnerships. Furthermore, hazardous digital waste must be properly managed, and efforts to increase the use of recyclable materials in digital technology production should be strengthened.[61] These measures support the goals of SDG-7 and SDG-11. By adopting these policies, OECD countries can promote sustainable growth, reduce pollution, set a benchmark for other nations, and contribute to global climate action.

However, several limitations remain in this study. First, DG and GF are broad constructs, and available data on these metrics are limited. Future studies should expand the analysis to include the environmental sector. Second, this study focuses on OECD nations, but the effects of DG, GF, and Trtec on environmental quality may differ across other countries or regions. Subsequent research could conduct a more comprehensive assessment across diverse geographic locations. Finally, as this study used data only up to 2020, it does not account for recent events that may have significantly influenced environmental quality. Long-term trends could be better captured through extended longitudinal studies.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Azad Erdem, Nazli Demirtas
Formal analysis: Ayse Nur Cirak
Investigation: Azad Erdem
Methodology: Ayse Nur Cirak
Writing–original draft: Azad Erdem, Nazli Demirtas, Ayse Nur Cirak
Writing–review & editing: Abdulkadir Barut, Azadeh Amoozegar

Availability of data

The data that support the findings of this study are available from the corresponding author on reasonable request.

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