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Innovation-Natural Resource Dependency-Energy-Ecological Footprint Nexus: Insights from Selected Countries according to the Global Innovation Index[1]

İnovasyon-Doğal Kaynak Bağımlılığı-Enerji-Ekolojik Ayak İzi Bağlantısı: Küresel İnovasyon Endeksi'ne Göre Seçilmiş Ülkelerden İçgörüler

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Abstract: The goal of this article is to evaluate the connections among innovation, natural resource dependency, energy and ecological footprint of the top ten countries in the global innovation index ranking in the 2009-2021 period within the framework of panel data methodology. Global innovation index, globalization and foreign direct investment parameters representing innovation are included in the model. It is seen that the literature on macroeconomic determinants of innovation capacity mostly focuses on the use of parameters such as financial development, infrastructure, eco-innovations, number of patents, research & development, foreign direct investments and human capital. However, it is noteworthy that these parameters, which are considered as innovation proxies, are evaluated separately in the studies. Therefore, in this study, the global innovation index is considered as a whole, thus expanding the scope of innovation. The situation in question is the article's contribution to the literature. The main findings from the Driscoll-Kraay robust estimator prove that, under statistical significance, an increase in the global innovation index reduces the ecological footprint, while natural resources and primary energy increase it. Causality findings point to one-way causality with no feedback effect from the global innovation index and foreign direct investments to the ecological footprint. In this context, policy implications indicate focusing on innovation as a way to reduce the ecological footprint, supporting natural resource dependency with renewable energies, and reducing non-renewable energy consumption in primary energy.

Keywords: Ecological Footprint, Global Innovation Index, Resource Dependency, Primary Energy, Environmental Sustainability, Panel Data Analysis.

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Öz: Bu makalenin amacı, küresel inovasyon endeksi sıralamasında yer alan ilk on ülkenin 2009-2021 dönemindeki inovasyon, doğal kaynak bağımlılığı, enerji ve ekolojik ayak izi arasındaki bağlantılarının panel veri metodolojisi çerçevesinde değerlendirilmesidir. İnovasyonu temsilen küresel inovasyon endeksi, küreselleşme ve doğrudan yabancı yatırım parametreleri model içerisine dâhil edilmektedir. İnovasyon kapasitesinin makroekonomik belirleyicileri konusunda literatürün çoğunlukla finansal gelişmişlik, altyapı, eko-inovasyon, patent sayıları, araştırma & geliştirme, doğrudan yabancı yatırımlar ve beşeri sermaye gibi parametrelerin kullanımında yoğunlaştığı görülmektedir. Ancak inovasyon vekili olarak ele alınan bu parametrelerin yapılan çalışmalarda ayrı ayrı değerlendirildiği dikkati çekmektedir. Dolayısıyla bu çalışmada küresel inovasyon endeksi, bir bütün olarak ele alınmakta, dolayısıyla inovasyonun kapsamı genişletilmektedir. Söz konusu durum makalenin literatüre katkısıdır. Driscoll-Kraay dirençli tahminciden ulaşılan temel bulgular, istatistiksel olarak anlamlılık altında, küresel inovasyon endeksindeki artışın ekolojik ayak izini azalttığı, doğal kaynaklar ve birincil enerjinin ise artırdığını kanıtlamaktadır. Nedensellik bulguları ise küresel inovasyon endeksi ve doğrudan yabancı yatırımlardan ekolojik ayak izine doğru geri besleme etkisi olmayan tek yönlü nedenselliğe işaret etmektedir. Bu bağlamda politika çıkarımları, ekolojik ayak izini azaltmanın bir yolu olarak yeniliklere odaklanmayı, doğal kaynak bağımlılığının yenilenebilir enerjilerle desteklenmesini ve birincil enerji içerisindeki yenilenemeyen enerji tüketiminin azaltılmasını belirtmektedir.

Anahtar Kelimeler: Ekolojik Ayak İzi, Küresel İnovasyon Endeksi, Kaynak Bağımlılığı, Birincil Enerji, Çevresel Sürdürülebilirlik, Panel Veri Analizi.

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1. Introduction

In the Global Risk Report (2024) published by WEF, it is stated that extreme weather events, biodiversity loss and ecosystem collapse, critical change in world systems, natural resource scarcity and pollution are the most important environmental risks facing the world in the next decade. Various practices are being developed against the mentioned risks, such as diversifying sustainable innovation processes, increasing energy efficiency, encouraging foreign direct investments that enable technology transfers that affect research & development (R&D) intensity and changes in production styles, expanding the scope of carbon neutral applications, and accelerating carbon capture, use and storage technologies. Ecological footprint (EF) calculations, which explain human demand for nature through an ecological accounting system, are used as an important parameter reflecting the measurement results of these applications. At the same time, there is a growing body of scientific evidence that anthropogenic activities are the cause of environmental problems, and this problem appears to be mainly caused by EF (Appiah et al., 2023; WEF, 2024).

Ecological footprint is one of the sustainable development indicators and considers the environmental data of a region from a broad perspective, details both the demand for human actions and natural resources (NR) and accounts the biological capacity of the region (Ullah et al., 2021). Variables thought to affect EF were examined in the literature and it was noticed that there was a gap in the independent variable basis in this study. The stated gap is the absence of the global innovation index (GII) in studies based on the independent variable that is thought to affect EF in the literature.

While Schumpeter stated that economic growth and development are driven by innovation (Croitoru, 2012), Romer (1986) argued that technological innovations can be revealed through R&D activities, human capital (HC) and technical knowledge use in the endogenous growth model. Despite the damage caused by environmental destruction to economic growth and development, technical aspects should not be neglected in achieving this goal, taking into account the growth and development goals of countries (Du et al., 2022). In endogenous growth models, the importance given to innovation and the increase in R&D expenditures are emphasized (Aghion & Howitt, 1998; Romer, 1990). It seems that innovation is an important tool in reducing environmental destruction (Ibrahim & Vo, 2021). Therefore, increasing the volume of innovation will reduce EF. According to British Petroleum (2022) statistics data, among primary energy sources worldwide, the share of fossil-based energy is approximately 80% while the share of energy consumption, especially oil and coal, is around 60% (BP, 2022). Intensive energy consumption from fossil sources causes EF to increase. Globalization is a concept that needs to be addressed comprehensively, having both economic dimensions and political, environmental, cultural and social dimensions (Keohane & Nye, 2000). When considered from this perspective, the intensification of national and transnational technological, environmental, cultural and political integrations is closely related to globalization (Rennen & Martens, 2003). Acceleration of industrial activities, population growth, increased urbanization rate and technological developments have increased economic activities on a global scale. For this reason, increasing demand has caused the consumption of NR. With globalization, decrease in the amount of arable land, loss of biodiversity, environmental pollution, etc. increases environmental problems. The environmental effects of globalization are not only regional, but have moved to an international dimension due to the effect of climate change (Panayotou, 2000). When the relationship among foreign direct investments (FDI) and EF is examined, it must first be stated that countries want to attract FDI. The main reason for this is that they see FDI as an alternative option to finance capital accumulation in order to achieve their growth and development goals. There are two different perspectives on the effect of FDI on EF. The first of these views, which is more accepted in the literature, is that FDI causes environmental degradation in the countries of origin (investments from developed countries to developing countries) and therefore increases EF. The second view is that FDI cause technological advances and R&D in the countries where they come from. Increasing environmental quality reduces EF by increasing development activities (Hoffmann et al., 2005).

Researching the variables that cause EF attracted the attention of the authors, attributing it to the gap in the literature, and they wanted to give inferences so that the necessary measures in this regard can be implemented by policy makers. The aim of this study is to seek answers to the research questions listed below:

- Do the variables of innovation, natural resource dependency, globalization, primary energy and foreign direct investments affect the ecological footprint?
- Is there a causal link among ecological footprint and innovation, natural resource dependency, primary energy, globalization and foreign direct investments?

Among the variables affecting EF, the GII variable in particular was the main source of motivation. In this direction, the goal of the research is to evaluate the relationships among the ecological footprint and innovation, natural resource dependency, globalization, foreign direct investments and primary energy in the 2009-2021 period of the top ten countries in the global innovation index ranking, namely Switzerland, Sweden, USA, United Kingdom, Singapore, Finland, Netherlands, Germany, Denmark and Korea.

2. Literature Selection

It is seen that CO_2 emissions are utilized as a representative of environmental degradation in the majority of literature studies (Ullah & Li, 2024). Akram et al. (2023) found in their study that financial development (FD) and NR increase emissions; it shows that renewable energy and eco-innovations (EI) reduce it. Similarly, the study by Wei and Lihua (2023) highlights the favorable impact of EI on environmental quality. However, unlike EF, CO_2 emissions explain only a small part of environmental degradation and do not take into account the total impact of anthropogenic activities on the environment (Georgescu & Kinnunen, 2024; Saqib et al., 2023; Yasmeen et al., 2022). For this reason, EF, which constitutes a smaller part of the literature, is examined in this study.

2.1. Innovation and Ecological Footprint Nexus

GII consists of approximately 81 indicators grouped into input and output sub-indexes. In calculating the index, firstly the innovation input sub-index is measured by taking the mean of the five variables that make up the input sub-index, and the innovation output sub-index score is measured by taking the mean of the two variables that make up the output sub-index. GII score and input sub-index, output sub-index score and innovation efficiency values are calculated by taking the average of these two indices. Innovation efficiency rate is obtained by dividing the output sub-index to the input sub-index. It is seen that the literature on the macroeconomic determinants of innovation capacity generally focuses on infrastructure, patent numbers, R&D activities, EI, FD, FDI, HC, supportive business environment and innovation-supporting policy practices (Baykul, 2022). However, it is noteworthy that these parameters, which are considered as innovation proxies, are evaluated separately in the studies. Therefore, in this study, GII is considered as a whole. The stated situation appears as an innovation that the study provides to the literature.

It is seen that countries with high GII values have a favorable impact on environmental quality by reducing ecological costs and resource use (Qing et al., 2024). In this context, evidence is presented that the numerical indicators in the GII, such as R&D, eco-innovation and/or human capital, have a unfavorable impact on EF. The hypothesis in question is confirmed in the studies conducted by Ahmad and Wu (2022), Ahmad et al. (2024), Alfalih and Hadj (2024), Ali et al. (2022, Appiah et al. (2023), Aytun et al. (2024), Bashir et al. (2023), Dai et al. (2023), Dao et al. (2024), Gupta et al. (2022), Jahanger et al. (2022), Li and Xu (2023), Luo and Mabrouk (2022), Ma et al. (2024), Nketiah et al. (2024), Qing et al. (2024), Saqib et al. (2023), Satrovic et al. (2024), Wei et al. (2023), Xia and Liu (2024), Xu et al. (2022b), Yasmeen et al. (2022), Zafar et al. (2019), Zhang and Chen (2023). However, Özarslan Doğan (2023), Usman and Radulescu (2022), Wang et al. (2024), Zhang et al. (2022) empirically prove in their studies that EI increases EF. The effect of FD on environmental quality appears to be generally asymmetrical. For the favorable effect of FD on ecological dimensions, Aytun et al. (2024) and Nathaniel et al. (2024) are examples of literature. Ahmad and Wu (2022), Ali et al. (2022), Jahanger et al. (2022), Özarslan Doğan (2023), Saqib et al. (2023), Usman and Makhdum (2021) show the contribution of FD to environmental degradation in their studies.

Globalization, as an important economic factor for countries, explains the critical level of innovation, innovation management and efficiency. It affects the carbon footprints of individuals and countries by causing changes in consumption patterns, environmental policies and lifestyles of countries. Perspectives on the effectiveness of innovations are considered as key success factors in achieving economic well-being and competing in markets. In this context, GII helps economies keep up with changing and developing technologies while revealing countries' perspectives on innovation (Aytekin et al., 2022; Karimli et al., 2024). It is said that the effects of globalization on EF are not certain because the relationship among variables is complex and dynamic. The level of globalization depends on various factors, for example the use of clean energy resources, the composition and structure of the economy, and the environmental consciousness of society (Karimli et al., 2024). Ahmad et al. (2024), Jahanger et al. (2022), Luo and Mabrouk (2022), Qing et al. (2024) states that globalization reduces environmental quality. However, Hassan et al. (2023), Nathaniel et al. (2024) and Wei et al. (2023) report that it increases environmental quality.

FDI flows are an important way of bringing technological innovation, especially to middle-income countries, and have favorable impacts on clean energy consumption. It is also identified as the driving force of technological diffusion in developing countries. It is known to be a tool to raise local environmental standards and reduce primary energy consumption (PEC) by transferring clean technology and management practices (Yasmeen et al., 2022). In the literature, it is seen that the intercourse among FDI and environmental quality is mostly examined within the scope of the pollution halo hypothesis and pollution haven hypothesis. In this context, Chishti (2023), Xu et al. (2022a), Yasmeen et al. (2022) found that the pollution haven hypothesis for the favorable intercourse among FDI and EF, but Zafar et al. (2019) are studies in which the pollution halo hypothesis for the unfavorable intercourse among FDI and EF is confirmed.

2.2. Natural Resource Dependency and Ecological Footprint Nexus

NR are an important determinant of growth by increasing economic vitality and industrial development. However, extracting, processing and consuming materials from nature leads to a decrease in environmental quality (Satrovic et al., 2024). The impact of NR on EF largely depends on how the resources are managed and used (Kang et al., 2023). In this context, if NR balances EF with the use of renewable resources, it affects environmental quality positively, and in case of aggressive and unconscious natural resource extraction and aggressive use of fossil-based fuels, it negatively affects environmental quality (Uzar, 2024). Ahmad et al. (2024), Ali et al. (2022), He et al. (2024), Jahanger et al. (2022), Kang et al. (2023), Li and Xu (2023), Luo and Mabrouk (2022), Ma et al. (2024), Qing et al. (2024), Satrovic et al. (2024), Usman and Radulescu (2022), Xia and Liu (2024), Xu et al. (2022a), Zhang and Chen (2023), Zhang et al. (2022) found in their study that NR accelerate environmental degradation. Gupta et al. (2022), Uzar (2024), Xu et al. (2022b), Yasmeen et al. (2022), Zafar et al. (2019) reveals that NR prevent environmental degradation.

2.3. Energy and Ecological Footprint Nexus

The historical trajectory shows that developed and developing countries have used energy intensively to facilitate production processes and other development activities. At the same time, one of the fundamental aspects of the global warming debate is increasing carbon emissions and the relationship of these emissions with PEC. Therefore, the intensity of PEC provides evidence that EF is increasing in almost all world regions (Appiah et al., 2023; Yasmeen et al., 2022). In studies examining the connection among energy use and environmental degradation, there is an increasing interest in non-renewable resources. Empirical studies also range from single country analysis to panel data analysis, as well as total and discrete energy use (Hassan et al., 2023). Ali et al. (2022), Appiah et al. (2023), Bashir et al. (2023), Dogan et al. (2022), Ma et al. (2024), Nketiah et al. (2024), Qing et al. (2024), Saqib et al. (2023), Ullah et al. (2021), Usman and Makhdum (2021), Usman and Radulescu (2022), Wei et al. (2023), Xu et al. (2022a), Xu et al. (2022b), Yasmeen et al. (2022) documents in their studies that renewable energy reduces the ecological footprint.

Conversely, Bashir et al. (2023), Dogan et al. (2022), Georgescu and Kinnunen (2024), Gupta et al. (2022), Kang et al. (2023), Shahzad et al. (2021), Ullah et al. (2021), Usman and Makhdum (2021), Usman and Radulescu (2022), Uzar (2024), Zafar et al. (2019) provide evidence in their studies that primary energy and/or non-renewable energy sources decrease environmental quality.

The literature selection also includes information on the direction of the causality intercourse among the variables is non-feedback (one-way) and/or feedback (two-way). In this context, studies conducted by Ahmad and Wu (2022), Ali et al. (2022), Appiah et al. (2023), Bashir et al. (2023), Chishti (2023), Dogan et al. (2022), Hassan et al. (2023), Karimli et al. (2024), Nathaniel et al. (2024), Saqib et al. (2023), Shahzad et al. (2021), Usman and Makhdum (2021), Usman and Radulescu (2022), Uzar (2024), Wei et al. (2023), Xia and Liu (2024), Zafar et al. (2019), Zhang and Chen (2023) provide evidence of one-way and/or two-way causality among EF and innovation, natural resources, energy types, globalization and foreign direct investments.

Table 1 reports a comprehensive summary of the timely literature on the effects of innovation, natural resources, and energy on the ecological footprint. A selection of empirical literature shows that there are differences among countries. The stated difference varies depending on the revenue levels and development stages of the countries. For example, Adekoya et al. (2022) state that FD accelerates environmental degradation in oil-importing countries and slows it down in oil-exporting countries. Similarly, Wang and Uctum (2024) state that FDI increases EF in poor countries and decreases it in rich income countries. However, it appears that the results are asymmetrical depending on the method used and the time period.

Table 1: Literature Summary

Researcher/s	Timeframe	Country/s	Technique/s	Results
Adekoya et al. (2022)	1990-2014	14 Oil-importing and 14 oil-exporting countries	AMG, CCEMG	G, NRE ≠ EF In oil-importing countries: FD → EF ↑ & RE → EF ↓ In oil-exporting countries: FD → EF ↓ (mostly) RE ≠ EF
Ahmad & Wu (2022)	1990-2017	20 OECD countries	PQR, causality	EI, HC → EF ↓ FD → EF ↑ G → EF (mixed) EI, G ↔ EF
Ahmad et al. (2024)	1990-2020	25 EU countries	FMOLS	EI → EF ↓ G, NR → EF ↑
Akram et al. (2023)	1997-2019	G7 countries	AMG, CCEMG, CS-ARDL, PQR, causality	EI, RE → CO_2 ↓ FD, NR → CO_2 ↑
Alfalih & Hadj (2024)	1998-2017	G20 countries	PQR, PTM	EI, HC → EF ↓
Ali et al. (2022)	1990-2016	Economic Community of West African States	AMG, CCEMG, causality	FD, NR → EF ↑ RE, HC → EF ↓ NR ↔ EF
Appiah et al. (2023)	1990-2020	29 OECD countries	CS-ARDL, causality	RE, EI → EF ↓ EI, RE ↔ EF
Aytun et al. (2024)	1980-2016	19 Middle-income countries	CS-ARDL	EI ≠ EF FD, HC → EF ↓
Bashir et al. (2023)	1990-2018	Newly industrialized countries	CS-ARDL, causality	EI, GE → EF ↓ CE → EF ↑ CE, EI, GE ⇒ EF
Chishti (2023)	1976Q1-2020Q4	Pakistan	Wavelet method, causality	FDI → EF ↑ FDI ⇒ EF
Dai et al. (2023)	1995-2018	Six ASEAN countries	CuP-BC, CuP-FM	EI → EF ↓
Dao et al. (2024)	2009-2019	31 OECD countries	MMQR	EI → EF ↓ NR → EF ↑ (mostly)

Dogan et al (2022)	1990-2017	South Asian countries	DOLS, FMOLS, FE, PMG, causality	RE → EF ↓ NRE → EF ↑ NRE, RE ⇒ EF
Georgescu & Kinnunen (2024)	1990-2021	Finland	ARDL	EC → EF ↑ FDI ≠ EF
Gupta et al. (2022)	1990-2016	Bangladesh	ARDL	EI, NR → EF ↓ PEC → EF ↑
Hassan et al. (2023)	1990-2019	15 OECD countries	AMG, CCEMG, CS-ARDL, causality	G, NE → EF ↓ G ↔ EF
He et al. (2024)	1973-2019	High emitting countries	GLM	NR → EF ↑
Jahanger et al. (2022)	1990-2016	73 Developing countries	PMG-ARDL	EI, HC → EF ↓ FD, G, NR → EF ↑
Kang et al. (2023)	1971-2019	US	ARCH	NR, EC → EF ↑
Karimli et al. (2024)	1970-2020	35 European countries	Causality	G ⇒ EF (mostly)
Li & Xu (2023)	1990-2020	BRICS countries	CS-ARDL	EI → EF ↓ NR → EF ↑
Luo & Mabrouk (2022)	1990-2018	Resource-rich economies	CS-ARDL	EI → EF ↓ G, NR → EF ↑
Ma et al. (2024)	1990-2021	Top and least green growth economies	CS-ARDL, MMQR	EI, RE → EF ↓ NR → EF ↑
Nathaniel et al. (2024)	1975-2018	Bangladesh	DARDL, causality	RE ≠ EF FD, G → EF ↓ G, FD ⇒ EF
Nketiah et al. (2024)	1990-2022	Ghana	ARDL, NARDL	EI, R&D, RE → EF ↓
Özarslan Doğan (2023)	1985-2020	Türkiye	ARDL, FMOLS	EI, FD → EF ↑
Qing et al. (2024)	1990-2020	Six South Asian countries	AMG, CCEMG	EI, RE → EF ↓ NR, G → EF ↑
Saqib et al. (2023)	1990-2019	E11 countries	AMG, CCEMG, CS-ARDL, causality	EI, RE → EF ↓ FD → EF ↑ EI, RE, FD ↔ EF
Satrovic et al. (2024)	1990-2018	Seven most innovative countries	MMQR, OLS	EI, R&D → EF ↓ NR → EF ↑
Shahzad et al. (2021)	1965Q1-2017Q4	US	QARDL, causality	NRE → EF ↑ NRE ⇒ EF
Ullah & Lin (2024)	1990-2018	Pakistan	CCR, FMOLS, NARDL	NR, RE → EF (asymmetric)
Ullah et al. (2021)	1996-2018	Top 15 renewable energy consumption countries	PSTR	RE → EF ↓ NRE → EF ↑
Usman & Makhdum (2021)	1990-2018	BRICS-T countries	AMG, CCEMG, FMOLS, MG, causality	NRE, FD → EF ↑ RE → EF ↓ FD ↔ EF NRE, RE ⇒ EF
Usman & Radulescu (2022)	1990-2019	Highest nuclear energy-producing 10 countries	AMG, CCEMG, causality	EI, NR, NRE → EF ↑ NE, RE → EF ↓ EI, NR, NRE, RE ↔ EF NE ⇒ EF
Uzar (2024)	1993-2017	E7 countries	AMG, causality	PEC → EF ↑ NR → EF ↓ PEC ⇒ EF NR ↔ EF
Wang & Uctum (2024)	1980-2016	82 countries by income groups	PTM	FDI → EF ↑ (low-income countries) FDI → EF↓ (high-income countries)
Wang et al. (2024)	2002-2016	BRICS countries	GMM, PCSEs	EI → EF ↑
Wei & Lihua (2023)	1995-2018	Six ASEAN countries	AMG, CCEMG, CS-ARDL	EI → CO_2 ↓
Wei et al. (2023)	1990-2018	Brazil	Bayern and Hank cointegration, DARDL, causality	EI, RE, G → EF ↓ FD ≠ EF EI, G, RE ⇒ EF

Xia & Liu (2024)	2000-2020	G7 countries	MMQR, causality	NR → EF ↑ EI → EF ↓ EI ⇒ EF NR ↔ EF
Xu et al. (2022a)	1992-2020	E7 countries	AMG, DOLS, FMOLS	NR → EF ↑ RE → EF ↓
Xu et al. (2022b)	1990-2017	China	CCR, DOLS, FMOLS	FDI → EF ↑ (long-time) EI, NR, RE → EF ↓ EI, FDI, NR, RE ⇒ EF (long-time)
Yasmeen et al. (2022)	1992-2017	52 Belt & Road countries	CS-ARDL, Driscoll-Kraay	BE, EI, NR → EF ↓ FDI → EF ↑
Zafar et al. (2019)	1970-2015	US	ARDL, causality	EC → EF ↑ NR, HC, FDI → EF ↓ EC ↔ EF NR ⇒ EF
Zhang & Chen (2023)	1998Q1-2020Q4	China	CCR, DOLS, FMOLS, causality	NR → EF ↑ R&D → EF ↓ NR, R&D ↔ EF
Zhang et al. (2022)	2000-2018	China	NARDL	EI, NR → EF ↑

Source: Edited by the authors.

Note[5]**:** Definition and direction of the relationship: Cointegration; ↑ increase, ↓ decrease, ≠ statistically insignificant. Causality: ⇒ one-way causality, ↔ two-way causality.

3. Methodology and Research Methods

The goal of this article is to evaluate the connections among ecological footprint and innovation, natural resource dependency, primary energy use, globalization and foreign direct investments in the top ten countries in the global innovation index ranking, namely Switzerland, Sweden, USA, United Kingdom, Singapore, Finland, Netherlands, Germany, Denmark and South Korea in the period 2009-2021 within the framework of panel data methodology.

3.1. Model and Dataset

The model established within the scope of the objective is as follows:

$$EF_{it} = \partial_0 + \gamma_1 GII_{it} + \gamma_2 NR_{it} + \gamma_3 PEC_{it} + \gamma_4 KOF_{it} + \gamma_5 FDI_{it} + \mu_{it} \quad (1)$$

The parameters EF, GII, NR, PEC, KOF and in the model represent ecological footprint, global innovation index, natural resource dependency, primary energy consumption, globalization index and foreign direct investments, respectively. ∂_0 is the constant coefficient; $\gamma_1, \gamma_2, \gamma_3, \gamma_4\ ve\ \gamma_5$ are the slope coefficients; μ_{it} indicates the error terms. Subscript i denotes cross-section of country and t explains the time dimension. Explanatory and descriptive information of the variables are represented in Table 2.

[5] Parameters: BE: Biomass energy, CE: Coal energy, EC: Energy consumption, EF: Ecological footprint, EI: Eco-innovation, FD: Financial development, FDI: Foreign direct investment, G: Globalization, GE: Geothermal energy, HC: Human capital, NE: Nuclear energy, NR: Natural resource, NRE: Non-renewable energy, PEC: Primary energy consumption, RE: Renewable energy, R&D: Research & Development.
Technique/s: AMG: Augmented Mean Group, ARCH: Autoregressive Conditional Heteroskedasticity, ARDL: Autoregressive Distributive Lag, CCEMG: Common Correlated Effects Mean Group, CCR: Canonical Cointegrating Regression, CS-ARDL: Cross-Sectional ARDL, CuP-BC: Continuously Updated-Biased Corrected, CuP-FM: Continuously Updated-Fully Modified, DARDL: Dynamic ARDL, DOLS: Dynamic Ordinary Least Square, FE: Fixed Effects, FMOLS: Fully Modified Ordinary Least Squares, GLM: Generalized Linear Model, GMM: Generalised Method of Moments, MG: Mean Group, MMQR: Method of Moments Quantile Regression, NARDL: Nonlinear ARDL, OLS: Ordinary Least Squares, QARDL: Quantile ARDL, PCSEs: Panel-corrected Standard Errors, PMG: Pooled Mean Group, PMG-ARDL: Pool Mean Group-ARDL, PQR: Panel Quantile Regression, PSTR: Panel Smooth Transition Regression, PTM: Panel Threshold Model.

Table 2: Variable Descriptions

Abb.	Explanation	Source
EF	Ecological footprint of consumption (in global hectares) divided by the population of the country	Global Footprint Network
GII	Global innovation index score	World Intellectual Property Organization
NR	Total natural resources rents (% of GDP)	World Bank
PEC	Primary energy consumption per capita, gigajoule per capita	Energy Institute
KOF	Globalization index calculates the social, economic and political dimensions of globalization	ETH Zürich KOF Swiss Economic Institute
FDI	Foreign direct investment, net (BoP, current US$)	World Bank

The hypotheses established within the context of the theoretical framework are as follows:

Hypothesis 1. The effect of the global innovation index on the ecological footprint is unfavorable.

Hypothesis 2. The link among natural resource dependency and ecological footprint points in a favorable direction.

Hypothesis 3. It is assumed that primary energy use raises the ecological footprint due to its possible relationship with natural resource use.

Hypothesis 4. Globalization has mixed effects on environmental degradation, depending on its intensity and degree.

Hypothesis 5. Depending on the characteristics of the sample set, the relationship among FDI and EF is attributed to the pollution halo hypothesis.

Hypothesis 6. There are one-way and/or two-way causal connections among the variables in the model.

3.2. Panel Data Analysis

In the analyses conducted with panel data sets, it is important to first obtain information about the stationarity of the data since the data also include a time dimension. In order to ensure that the models to be estimated do not contain spurious relationships, the stationarity of the variables should be tested with unit root tests. Regression models to be constructed with variables that are stationary or stationarized at the level value will not contain spurious relationships. Panel data regression models for stationary series can be estimated using different estimation techniques. The types of models used in panel data analyses vary according to the structure of the data set and the effects it contains. In this context, there are three different types of models used in panel data methodology. These models are pooled model, fixed effects (FE) and random effects (RE) models. In the pooled model, the constant and slope parameters do not change according to time and unit. When the error term satisfies the desired assumptions, this model is estimated using the ordinary least squares (OLS) technique and is used for panel data sets that do not include time and unit effects. However, for data sets where the error term does not meet the desired properties and time and unit effects are observed, FE model or RE model is preferred depending on the relationship among time and unit effects and the error term (Güriş, 2015). The choice of one of the mentioned model types is decided by conducting various systematic tests. Although there are more than one test for model selection in the panel data literature, in this article, F test is used to choose among fixed and pooled models, Score test is used to choose among polled and random models and Hausman test is used to decide among FE model and RE model. After the tests, it was concluded that FE model is the appropriate model. The estimated model is examined for the presence of variance, autocorrelation and inter-unit correlation and FE model is estimated with the technique developed by Driscoll and Kraay (1998) to overcome the assumption violations. The details of the unit root test and the FE model estimation technique used for the model are discussed in the subsections below.

3.2.1. Cross-sectional Dependence Test

Pesaran (2004) recommended a cross-sectional dependence (CD) test with strong small sample properties even in the case of small N and T to investigate CD. This test is robust even in the case of N>T. The test developed by Pesaran is based on the LM test statistic recommended by Breusch and Pagan (1980). The two different CD_{LM} test statistics developed by Breusch and Pagan to test the null hypothesis of no CD in the event of T>N and when both T and N are large are formulated as follows (Pesaran, 2004):

In the event of T>N:

$$CD_{LM} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{2}$$

Both T and N are large:

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

Where $\hat{\rho}_{ij}^2$ is the estimate of the partial correlation coefficient of the errors. This test statistic was modified by Pesaran (2004) for T>N and for both small T and small N cases as follows (Pesaran, 2004):

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{4}$$

3.2.2. Stationarity Tests

In this study, we use the IPS unit root test recommended by Im, Pesaran and Shin (2003), which is a first generation unit root test for variables without CD, and the CADF unit root test recommended by Pesaran (2007), which is a second generation unit root test for variables with CD. The IPS unit root test is based on averaging the ADF test statistics measured separately for all units. The model recommended for the IPS test is as follows (Yerdelen Tatoğlu, 2012):

$$\Delta Y_{it} = \rho_i Y_{it-1} + \sum_{L=1}^{p_i} \phi_{iL} Y_{it-L} + \mu'_i \gamma + u_{it} \tag{5}$$

The null hypothesis of the IPS test is $H_0: \rho_i = 1$ and the alternative hypothesis is $H_a: \rho_i \neq 1$. The test statistic is calculated as follows (Yerdelen Tatoğlu, 2012):

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_{\rho_i} \tag{6}$$

t_{ρ_i}, represents the ADF test statistic calculated for units.

The IPS test, which provides robust results when the panel data set does not contain CD, is not used for series with CD due to the decrease in its power properties. In case of CD, second generation unit root tests that take this dependence into account should be preferred. The CADF unit root test that takes into account CD recommended by Pesaran (2007) is a test based on ADF equations. The data generation process of the test is as follows (Pesaran, 2007):

$$y_{it} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + u_{it} \qquad i = 1, \dots, N;\ t = 1, \dots, T \tag{7}$$

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \tag{8}$$

f_t are unobserved common effects and u is the individual-specific (identical) error.

The model (7) can be rewritten as follows:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \tag{9}$$

Where $\alpha_i = (1-\phi_i)\mu_i$, $\beta_i = -(1-\phi_i)$ ve $\Delta y_{it} = y_{it} - y_{i,t-1}$

Here, the null hypothesis implies a unit root process and is shown as follows:

$H_0: \beta_i = 0$ for all i (10)

In order to test the H_0, the t-ratio of OLS estimation of the parameter b_i obtained from the following cross-sectional ADF (CADF) regression is used (Pesaran, 2007):

$$\Delta y_{it} = a_i + b_i + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it} \tag{11}$$

$\bar{y}_t = N^{-1} \sum_{j=1}^{N} y_{jt}$ and their lagged values are $\bar{y}_{t-1}, \bar{y}_{t-2}, \ldots$

The test statistic for the CADF test is calculated as follows:

$$t_i(N,T) = \frac{\Delta \mathbf{y_i}' \bar{\bar{\mathbf{M}}}_{\mathbf{w}} \mathbf{y}_{\mathbf{i},-\mathbf{1}}}{\hat{\sigma}_i (\mathbf{y_i}' \bar{\bar{\mathbf{M}}}_{\mathbf{w}} \mathbf{y}_{\mathbf{i},-\mathbf{1}})^{1/2}} \tag{12}$$

The necessary definitions in the CADF test statistic formula are given in detail in Pesaran (2007).

2.2.3. Fixed Effects Model Estimation Method

There are three distinct types of models in linear panel data analysis: Pooled model, FE and RE models. In the pooled model, both fixed and slope parameters do not change depending on the unit and time. The OLS method is used to estimate the pooled model. If there are unit and time effects in the model and the pooled model is to be estimated, the model can be estimated by using the first differences method by removing the unit and time effects. However, since the first differences method causes loss of information, other methods can be used when unit and time effects are present. In the presence of unit and time effects, estimating the model with a FE model or a RE model will yield more explanatory results. The model to be estimated varies according to the way unit and time effects are included in the model. If the effects are included in the model as a random component such as the error term, such models are called RE models, and if these effects are included in the model as a parameter to be estimated for each unit, they are called FE models. Which of these model types to choose is based on certain assumption tests. Model selection tests are essentially tests that conclude by conducting assumption tests for different models. For example, the test that chooses among the pooled model and the FE model is based on the evaluation of the statistical significance of the effects in the FE model. The Hausman test, which allows the choice among RE and FE models, is a test of the assumption of the RE model that the correlation among unit effects and explanatory variables must be zero. If this assumption is violated, then the FE model, which allows the relationship among unit effects and explanatory variables, can be preferred. There are four different types of models that can be used for FE models where the effect of time and unit effects on the constant term and slope parameter differ:

$$Y_{it} = \beta_{0i} + \textstyle\sum_{k=1}^{K} \beta_k X_{kit} + u_{it} \qquad i = 1, \ldots, N;\ t = 1, \ldots, T \tag{13}$$

$$Y_{it} = \beta_{0it} + \textstyle\sum_{k=1}^{K} \beta_k X_{kit} + u_{it} \qquad i = 1, \ldots, N;\ t = 1, \ldots, T \tag{14}$$

$$Y_{it} = \beta_{0i} + \textstyle\sum_{k=1}^{K} \beta_{ki} X_{kit} + u_{it} \qquad i = 1, \ldots, N;\ t = 1, \ldots, T \tag{15}$$

$$Y_{it} = \beta_{0it} + \textstyle\sum_{k=1}^{K} \beta_{kit} X_{kit} + u_{it} \qquad i = 1, \ldots, N;\ t = 1, \ldots, T \tag{16}$$

Model (13) is a unit effects model where the slope parameter is fixed and the fixed parameter is variable across units. It is also called the model with dummy variables or covariance model. Model (14) is a unit and time effects model in which the slope parameter is fixed and the fixed parameter varies with respect to both units and time. In model (15), both the fixed and the slope parameter are variable with respect to units and constant with respect to time. In model (16), all parameters vary with respect to both units and time. For the estimation of model (13), many methods can be used such as error correction model (ECM) with shadow variables, within-group estimation, between-group estimation, pooled ECM, maximum likelihood, generalized ECM and flexible generalized ECM. In studies, the model (13) is usually estimated and the within-group estimation method is preferred to estimate the FE model. The within-group estimator is also referred to as the FE estimator in the literature (Güriş, 2015).

The within-group estimator method first tries to eliminate the unit effect. The first model is as follows (Güriş, 2015):

$$Y_{it} = \beta_0 + X_{it}\beta + \mu_i + u_{it} \qquad i = 1, \dots, N;\ t = 1, \dots, T \tag{17}$$

For this model, averages are taken based on the time dimension:

$$\bar{Y}_i = \beta_0 + \bar{X}_i\beta + \mu_i + \bar{u}_i \tag{18}$$

The difference of the first model is taken from the averages model with respect to this time:

$$(Y_{it} - \bar{Y}_i) = (X_{it} - \bar{X}_i)\beta + (u_{it} - \bar{u}_i) \tag{19}$$

The model (19) can also be rewritten as:

$$\ddot{y}_{it} = \ddot{x}_{it}\beta + \ddot{u}_{it} \quad \text{i=1,…,N;} \quad \text{t=1,…,T} \tag{20}$$

The following FE estimator is obtained by applying Pooled ECM to the transformed regression:

$$\hat{\beta}_{SE} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{x}_{it}'\ddot{x}_{it}\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\ddot{x}_{it}'\ddot{y}_{it}\right) \tag{21}$$

There are assumptions that the FE model must meet. These are that the error terms are constant, non-autocorrelated and there is no correlation among units. These assumptions are tested and if any of these assumptions are not met, then these problems can be overcome by estimation methods using robust standard errors (Yerdelen Tatoğlu, 2012). The estimators recommended by Driscoll and Kraay (1998) provide consistent estimators in case of assumption violations. In this study, since the assumptions are not met as a result of the tests performed for FE models, the estimation results using robust standard errors recommended by Driscoll and Kraay are used.

2.2.4. Causality Test

The causality test recommended by Juodis, Karavias and Sarafidis (2021) is a Granger-type test. This test is applicable to panel models with both homogeneous and heterogeneous coefficients. The null hypothesis states that all Granger-causality parameters are equal to zero. To account for dynamic panel bias, referred to as Nickell bias by Juodis et al. (2021), we utilize the Split Panel Jackknife test procedure recommended by Dhaene and Jochman (2015). Then, a Wald test based on a bias-corrected FE estimator is recommended. This test is valid as long as T is (at least moderately) large, regardless of whether the H_a is homogeneous or heterogeneous, or whether the autoregressive parameters vary across individuals (Juodis et al., 2021).

4. Results

In the first methodological stage, the CD test recommended by Pesaran (2004) was applied. In line with the results, IPS, the first generation unit root test, was applied for the FDI variable, which does not include CD. For all other variables containing CD, the CADF unit root test, which is the second generation unit root test, was used. Unit root test findings showed that all variables were stationary at their level values. The results are presented in Table 3.

Table 3: CD and Stationarity Tests

Variables	EF	GII	NR	PEC	KOF	FDI
Pesaran (2004) CD test statistics	12.30	24.11	12.75	8.50 (0.000)	11.20	-0.05
(p-val.)	(0.000)	(0.000)	(0.000)		(0.000)	(0.961)
		CADF				IPS
Stationarity test statistics	-2.779	-2.437	-2.905	-2.886	-2.305	-4.6521
(p-val.)	(0.001)	(0.017)	(0.000)	(0.000)	(0.042)	(0.000)

Before performing panel data regression analysis, model selection tests were conducted to determine the estimation method. According to the findings in Table 4, the FE model was found to be the appropriate model when comparing the classical model with the FE model, the RE model when comparing the classical and RE models, and the FE model when comparing the FE and RE models.

Table 4: Model Selection Tests

Tests	Statistics values	Model selection
F test	F(21,103) = 78.40 (p-val. = 0.000)	Classic model? FE model?
Score test	$\chi^2(1)$ = 34000000 (p-val. = 0.000)	Classic model? RE model?
Hausman test	$\chi^2(2)$= 33.69 (p-val. = 0.000)	FE model? RE model?

Before the FE model estimation process, model diagnostic tests were performed and the model was tested according to econometric criteria. Model diagnostic test findings are summarized in Table 5. The findings indicated that there were autocorrelation, heteroskedasticity and correlation among units problems in the model.

Table 5: Model Diagnostic Tests

Diagnostic tests	Test type	Statistical values
Autocorrelation	Bhargava et al. Durbin Watson	DW = 0.97144527
	Baltagi-Wu	LBI = 1.3021083
Heteroscedasticity	Modified Wald test	$\chi^2(10)$ = 112.22 (p-val. = 0.000)
Correlation among units	Pesaran test	CD = 4.892 (p-val. = 0.000)

According to the findings in Table 6, GII, NR and PEC variables were found to be statistically significant. The model analysis process was redone by removing the statistically insignificant FDI and KOF variables. In order to correct deviations from the assumptions, the FE model was estimated using the estimator recommended by Driscoll and Kraay (1998), which gives strong results in cases of autocorrelation, heteroskedasticity and correlation among units. The findings obtained are presented in Table 4. In this context, under statistical significance, the GII variable affects the EF variable negatively, while the NR and PEC variables affect it positively. A one unit increase in the GII variable reduces the EF variable by 0.003 units. A one unit increase in the NR variable increases the EF variable by 0.292 units; however, a one unit increase in the PEC variable increases by 0.024 units.

Table 6: FE Model Prediction Results

Variables	Coeff.	Robust S. E.	t-statistic	p-val.
GII	-0.0028	0.0014	-2.01	0.075
NR	0.2727	0.1265	2.16	0.060
PEC	0.0237	0.0037197	6.40	0.000
KOF	-0.0195	0.0351	-0.55	0.593
FDI	1.70e-13	1.21e-13	1.40	0.194
Constant	2.2148	3.042637	0.73	0.485
Within group R^2 = 0.5996		F (5, 9) = 96.91 (p-value = 0.000)		
Result of estimation with significant variables				
Variables	Coeff.	Robust S. E.	t-statistic	p-val.
GII	-0.0032	0.0009	-3.29	0.009

NR	0.2919	0.1278	2.28	0.048
PEC	0.0238	0.0037	6.48	0.000
Constant	0.5595	0.8165	0.69	0.510
Within group $R^2 = 0.5979$		F (3, 9) = 103.04 (p-val. = 0.000)		

In addition, the causality test results of this study, which examines the causality relationship among variables, are presented in Table 7. According to the results of Juodis, Karavias ve Sarafidis (2021) Granger causality test in Table 7, there is a causality relationship among GII and FDI variables and EF. This means that the prior period values of GII and FDI variables contain important information for estimating the EF variable.

Table 7: Causality Test Results

Variables	Coeff.	z	prob>|Z|
GII	0.0132	7.32	0.000
NR	0.243	1.46	0.145
KOF	0.025	0.33	0.745
FDI	6.54e-13	2.12	0.034
PEC	-0.0022	-1.15	0.252

Null Hypothesis: The selected variables are not the Granger cause of EF.

HPJ Wald test statistic = 165.9441, p-val. = 0.000

Pesaran, Yamagata (2008) Slope parameter homogeneity test

Delta test statistics = 2.977, p-val. = 0.003

5. Discussion

In this study, the connections among innovation, natural resource dependency, energy and ecological footprint of the top ten countries in the global innovation index ranking in the period 2009-2021 were evaluated. The results obtained from the fixed effects model showed that the global innovation index, natural resources and primary energy use have favorable and/or unfavorable effects on the ecological footprint. In this direction, the results that the global innovation index increases environmental quality confirm the first hypothesis of the study. Achieved result is consistent with Ahmad and Wu (2022), Ahmad et al. (2024), Alfalih and Hadj (2024), Appiah et al. (2023), Aytun et al. (2024), Bashir et al. (2023), Dai et al. (2023), Dao et al. (2024), Gupta et al. (2022), Jahanger et al. (2022), Li and Xu (2023), Luo and Mabrouk (2022), Ma et al. (2024), Nathaniel et al. (2024), Nketiah et al (2024), Qing et al. (2024), Saqib et al. (2023), Satrovic et al. (2024), Wei et al. (2023), Xia and Liu (2024), Xu et al. (2022a), Yasmeen et al. (2022), Zafar et al. (2019), Zhang and Chen (2023). The second hypothesis, which is that the link among natural resource dependency and ecological footprint is favorable, is consistent with the results of the study. In the sample set considered, extracting, processing and using materials from nature increases environmental degradation. Empirical evidence is supported by the studies cited in the literature selection such as Ahmad et al. (2024), Ali et al. (2022), He et al. (2024), Jahanger et al. (2022), Kang et al. (2023), Li and Xu (2023), Luo and Mabrouk (2022), Ma et al. (2024), Qing et al. (2024), Satrovic et al. (2024), Usman and Radulescu (2022), Xia and Liu (2024), Xu et al. (2022b), Zhang and Chen (2023), Zhang et al. (2022). The conclusion that natural resources raise the ecological footprint is also valid in the case where primary energy use is high. This result is attributed to the literature examples where the third hypothesis is confirmed, namely, primary energy and/or non-renewable energy sources deteriorate environmental quality (see Adekoya et al., 2022; Bashir et al., 2023; Dogan et al., 2022; Georgescu & Kinnunen, 2024; Gupta et al., 2022; Kang et al., 2023; Shahzad et al., 2021; Usman & Makhdum, 2021; Usman & Radulescu, 2022; Uzar, 2024; Zafar et al., 2019).

The fourth hypothesis, which is established regarding the interaction among globalization and ecological footprint, indicates that this relationship is complex and dynamic, and points to the insignificant relationship of globalization on ecological footprint. The result reached is interpreted as there are many variables affecting the level of globalization, and Adekoya et al. (2022) is exemplified by the results of the study. The fifth hypothesis, which explains that the relationship among foreign direct investments, which are expressed as the driving force of technological diffusion, and environmental quality will confirm the pollution halo hypothesis, is not promoted by the empirical evidence of the study. The obtained result is evaluated within the framework of the development levels of the countries and is promoted by the empirical evidence of the study conducted by Georgescu and Kinnunen (2024).

The result regarding the one-way causality relationship among the global innovation index and the ecological footprint derives similarities with the results of the studies conducted by Bashir et al. (2023), Nathaniel et al. (2024), Wei et al. (2023), Xia and Liu (2024). However, the non-feedback relationship from foreign direct investments to the ecological footprint is exemplified by the study of Chishti (2023).

Policy proposals within the scope of empirical evidence indicate that as a way to reduce the ecological footprint, focus on and encourage innovations, support natural resource dependency with renewable energy sources and reduce non-renewable energy consumption within primary energy. With this, the use of low carbon technologies and clean energy sources in energy systems should be increased. According to the results, it is recommended that resources be managed effectively and efficiently, especially in natural resource dependency, which has the highest impact on the ecological footprint.

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