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Exploring Innovation Performance in OECD Countries: The Impact of Economic, Institutional, and Social Factors[1]

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Abstract

This study analyses the economic, institutional and social factors affecting innovation performance by using a panel data set covering 38 OECD countries between 2013-2023 with a Panel Quantile regression model. Innovation is recognised as one of the key drivers of economic growth and competitiveness; however, the factors determining this performance vary significantly from country to country. According to the results of the analyses, economic growth has a positive and significant effect on the global innovation index. In addition, carbon emissions, green technology diffusion and government stability also have positive and significant effects on innovation. In this context, it can be said that high levels of carbon emissions encourage the development of innovative technologies by increasing the need to find solutions to environmental problems. On the other hand, foreign direct investments and urban population ratio have negative and significant effects on innovation. Variables such as foreign trade deficit, logistics performance index and income inequality have no statistically significant effect on innovation. The Pseudo R^2 value of the model was calculated as 0.7169, which shows that 71.69% of the variance in the dependent variable is explained by the model. In conclusion, it is emphasised that economic, social and institutional dynamics should be addressed with a holistic approach in order to increase innovation performance. In particular, increasing investments in green technology, supporting economic growth and strengthening political stability can increase the effectiveness of innovation processes. Moreover, in order to reduce the negative effects of urban population on innovation, it is important to manage urbanisation with more innovative and sustainable policies.

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1. Introduction

The rapidly changing and increasingly competitive structure of the global economy has made innovation performance an indispensable element for economic growth, sustainable development, and social welfare. For instance, the World Economic Forum (2023) report states that the contribution of global innovation to economic growth is 25-30%. Innovation not only transforms production processes but also plays a crucial role in creating new markets, accelerating

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technological progress, and ensuring the more efficient use of resources (Schumpeter, 1934). The vital role of innovation in economic growth is further underscored by the OECD (2022), where it is noted that OECD countries account for approximately 70% of global R&D expenditures and have patent applications per capita 50% higher than other nations.

The factors shaping innovation performance are multifaceted and closely tied to economic, institutional, and social structures. For instance, studies on the impact of education levels have shown that a 1% increase in the education index leads to a 0.8% increase in innovation outputs (Hanushek & Woessmann, 2010). Furthermore, global macroeconomic trends such as digital transformation, the shift to a green economy, and the fight against climate change have reshaped the dynamics of innovation. In 2022 alone, investments in green technology rose by 15%, reaching $1.1 trillion, emphasizing that innovation is critical for sustainable development (IRENA, 2023).

The Global Innovation Index (GII), published by the World Intellectual Property Organization (WIPO), INSEAD, and Cornell University, assesses the innovation capacity and performance of countries. It helps measure how countries use resources and the results achieved in their innovation processes. The GII is composed of two main components: Innovation Inputs and Innovation Outputs. Innovation Inputs evaluate resources and infrastructure, including institutional structures, R&D investments, education levels, technological infrastructure, and market complexity. Innovation Outputs, on the other hand, measure concrete results such as patents, scientific articles, and technology transfers, as well as outputs related to creativity and new designs.

The GII also highlights the importance of innovation in achieving sustainable development goals. The 2023 GII emphasized efforts to reduce carbon emissions and innovations in green technologies, which are essential for fostering both economic growth and environmental sustainability. Switzerland, Sweden, and the Netherlands lead the GII rankings, thanks to their high R&D investments, strong education systems, and innovative markets. Conversely, emerging economies like China and India have strengthened their innovation by ramping up R&D expenditures and accelerating digital transformation, positioning themselves more prominently in global innovation rankings.

The GII serves as an essential tool for both developed and developing countries. It provides concrete data for identifying strengths and weaknesses in innovation and helps guide policy decisions for improving competitiveness and fostering sustainable development. Moreover, it is a valuable resource for investors and policymakers to understand global innovation trends and opportunities.

The Innovation Input Sub-Index evaluates factors that facilitate innovation, including the Institutions pillar, which assesses political, regulatory, and business environments; the Human Capital and Research pillar, focusing on education and R&D activities; the Infrastructure pillar, which captures ICT, general infrastructure, and ecological sustainability; the Market Development pillar, examining financial systems and investment flows; and the Business Sophistication pillar, which highlights skilled labor and innovation collaboration. Meanwhile, the Innovation Output Sub-Index measures the tangible results of innovation, such as the Knowledge and Technology Output pillar, which looks at knowledge creation and technology diffusion, and the Creative Output pillar, which evaluates intangible assets like digital creativity and the production of creative goods and services.

In this context, the study aims to analyze the economic, institutional, and social factors influencing the innovation performance of OECD countries. For example, in 2023, the average GII value for OECD countries stood above 50, while it was around 35 for other nations (WIPO, 2023). The Education Index plays a critical role, as countries with higher education levels exhibit a 60% higher number of patents per capita (UNESCO, 2023). Additionally, R&D expenditures in OECD countries account for 2.4% of their GDP, compared to less than 1% in developing nations, which is considered a key factor behind the innovation performance gap (OECD, 2022). Foreign Direct Investment (FDI) also supports innovation by facilitating knowledge and technology transfer. For example, countries like China and South Korea have experienced more than a 10% increase in innovation output due to FDI (UNCTAD, 2022).

In studies on foreign direct investments, academic studies on the macroeconomic determinants of innovation capacity by Baykul (2022) generally focus on factors such as trade openness, infrastructure required for innovation, R&D activities, foreign direct investments, quality of human capital, supportive business environment and policy practices that encourage innovation. In this context, the impact of foreign direct investments on innovation has an important place in the literature. In this study, the relationship between these determinants and innovation performance is examined by using the Global Innovation Index (GII), which provides a comprehensive analysis in terms of inputs and outputs of innovation.

Özkul (2022), on the other hand, states that in the Turkish economy with limited natural resources, the inability of the public authority to provide sufficient domestic savings and to develop foreign exchange earning policies in a sustainable manner severely restricts firms' access to cost-effective financing sources. This situation has made Turkey's need for external financing more evident. In this context, the study emphasises that foreign direct investment (FDI) is one of the most effective instruments to meet the foreign exchange need in a stable manner. FDI has a strategic importance not only in terms of providing financing but also in terms of its potential to increase the technological capacity, productivity and international competitiveness of the country. However, as Özkul underlines, not only the quantity but also the quality of FDI is of great importance. Investments concentrated especially in sectors such as mergers and acquisitions, construction and real estate have limited effects in terms of technology transfer and high value added creation. On the other hand, ‘greenfield investments’ in the manufacturing industry or R&D-oriented service sectors have more positive and lasting effects on the technological development and innovation capacity of domestic firms.

In another study, Gündüz (2022), when the result of his study is evaluated from an economic perspective, it is seen that foreign direct investments, which are included in the model to reflect the effects of globalisation, have a significant effect on economic growth. The economic development process directly affects the international competitiveness of countries. As frequently emphasised in the literature, FDI not only provides capital inflows to developing countries, but also creates long-term competitive advantage by contributing to technology transfer, knowledge accumulation and development of management skills. (Dunning, 1993; Borensztein et al., 1998). The fact that the country groups analysed in the scope of the analysis are still not among the developed economies limits the competitiveness of these countries on a global scale. While increasing competitiveness is a strategic priority for developed countries, the main objective for developing countries is generally to raise their level of development. In this context, every economic step taken towards development also contributes to the process of gaining competitive advantage over countries with similar levels of development. Foreign direct investments, especially in high value-added sectors, play a decisive role in this process. On the other hand, Akyol (2022) examined the effects of technological innovation, financial development, economic growth and foreign direct investments on renewable energy consumption. Khan et al. (2021). In the study using the data of 69 countries within the scope of the Belt and Road Initiative for the period 2000-2014, estimates were made with the Generalised Method of Moments (GMM) within the scope of dynamic panel data analysis. The findings reveal that technological innovation, economic growth and foreign direct investment have a statistically significant and negative effect on renewable energy consumption. On the other hand, financial development has a positive and significant effect on renewable energy consumption. These results indicate that the impact of FDI on environmental sustainability may vary depending on the nature of the investment. Bakkal (2022), on the other hand, aims to analyse the effects of economic development, foreign direct investments and financial development on environmental degradation. The findings reveal that more widespread use of environmentally friendly technologies and renewable energy sources in production processes can make significant contributions to sustainable global growth. The study was conducted with the data for the period 1980-2018; unit root tests, ARDL cointegration approach, Toda-Yamamoto and Fourier Toda-Yamamoto causality tests were used in the analysis process.

Kırıkkaleli and Adebayo (2021) analysed the environmental effects of financial development in a study conducted with global data covering the years 1990-2018. Econometric methods such as DOLS (Dynamic OLS) and FMOLS (Fully Modified OLS) were used in the study and the results showed that the development in the financial system can be effective in reducing carbon emissions In their study, Süt and Çetin (2018) evaluated the advantages and limitations of indicators commonly used in the measurement of innovation such as R&D expenditures, patent numbers and researcher employment. The extent to which these indicators accurately reflect the level of innovation is critically analysed, and alternative indices that can reflect innovation in a more inclusive manner are also discussed. In this framework, the European Innovation Index and the Global Competitiveness Innovation Index were used and it was emphasised that the selection of appropriate variables in innovation analyses is decisive for the results of the analysis.

In another study, Rahman et al. (2021) found that economic growth has a positive and statistically significant effect on carbon emissions. In addition, significant and positive relationships were also found between energy consumption, human capital and foreign trade. These findings indicate that sustainable development policies should be formulated by taking into account the environmental impacts of economic growth and energy use. Studies indicate that these factors affecting innovation performance vary across quantiles. For example, the Endogenous Growth Model developed by Grossman and Helpman (1991) posits that R&D investments directly boost economic growth and innovation output. Panel quantile regression analysis offers more precise insights in the presence of extreme values, thus providing clearer representations of innovation dynamics across countries.

Among previous studies, Çoban and Özkan (2022) examined the impact of globalization and economic growth on the environment in Turkey using a dynamic ARDL simulation model with data from 1970 to 2020. The results indicate that as foreign direct investment (FDI) and energy use increase, environmental quality decreases, while trade openness positively affects the environment. Similarly, Sertçelik and Gökmen (2021) analyzed the impact of innovation and human capital on economic growth using data from OECD countries for the period 1991-2017 and found significant effects from these variables. Rahman et al. (2021) discovered that economic growth increases carbon emissions, and positive relationships exist between energy consumption, human capital, and foreign trade. Lastly, Bakkal (2022), using data from 1980 to 2018, emphasized the importance of environmentally friendly technologies and renewable energy in reducing environmental damage, applying ARDL and Toda-Yamamoto tests.

In this study, the focus is on analyzing economic, institutional, and social factors affecting innovation performance by using the panel quantile regression method with data from 38 OECD countries for the period 2013-2023. OECD countries, with their high income levels and developed infrastructures, play a significant role in innovation activities. However, there are notable differences in innovation performance across these countries. Understanding the underlying reasons for these differences and how they affect innovation is crucial for effectively guiding innovation processes and developing relevant policies.

The study aims to explore the economic, institutional, and social factors contributing to the disparities in innovation performance across countries. These factors include economic growth, education levels, research and development expenditures, government stability, foreign direct investment, urban population density, and environmental factors. The impact of these factors on innovation is shaped not only by economic variables but also by social structures and institutional practices.

The contribution of this study to literature lies in its multifaceted analysis of the factors influencing innovation performance. In particular, the use of the panel quantile regression method, quantile regression, unlike classical regression models, allows to estimate not only the mean of the dependent variable, but also its values in certain percentiles (e.g. 10%, 50%, 90%). This approach provides more detailed and robust results, especially in cases where the data set contains outliers or the distribution is not symmetric. This approach helps analyze how the determinants of innovation performance vary among countries and which factors are most pronounced in low, medium, and high-performing countries. This contributes to a more nuanced understanding of innovation, enabling policymakers to design more targeted strategies that consider varying economic and social structures. Ultimately, this study underscores the need for a deeper understanding of the interaction between economic, institutional, and social factors to promote and support innovation more effectively.

2. Data and Methodology

The main objective of this study is to investigate the impact of global innovation, which is the dependent variable, on the independent variables in 38 Organisation for Economic Co-operation and Development (OECD) member countries (Australia, Austria, Belgium, Canada, Chile, Costa Rica, Colombia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States); global innovation index, economic growth, carbon emissions, education index, foreign direct investments, research and development (R&D) investments, green technology diffusion, government stability, urban population, foreign trade deficit, logistics performance index, income inequality index. Table 1 provides explanations and sources of the variables.

Table 1. Variable Descriptions

Variables	Definitions	Source
Global Innovation Index	Average of input and output sub-indices	World Intellectual Property Organisation (WIPO)
Economic Growth	GDP per capita growth (annual %)	World Bank
Carbon Emissions	Carbon emissions (metric tonnes per capita)	World Bank
Foreign Direct Investment	Foreign Direct Investment, net (Balance of Payments, current US$)	World Bank
Green Technology	Diffusion Diffusion of environmentally relevant technologies, % all technologies (%)	OECD Statistics
Government Stability	Index values between 1 and 10	Political Risk Services (PRS) Group
Urbanisation	Urban population (% of total population)	World Bank
Trade Deficit	Trade (% GDP)	World Bank
Logistics Performance Index	Total LPI score	World Bank
Income Inequality Index	Share of TOP1 income (%)	World Income Database (WID)

Source: Author

In this study, the Global Innovation Index (GII) is taken as the dependent variable. Independent variables are selected to cover economic, environmental, social and governance dimensions. The variables used in the model and their definitions are presented below:

- LGII (Global Innovation Index): It is the dependent variable of the study. It is a comprehensive index that measures the innovation capacity and output of countries.
- LGDP (Economic Growth): It is represented by taking the logarithm of real Gross Domestic Product per capita.
- LCO (Carbon Emissions): Per capita carbon dioxide emissions (in metric tonnes) expressed logarithmically.
- LFDI (Foreign Direct Investment): Logarithmic value of foreign direct investments received as a percentage of GDP.
- LGTD (Green Technology Diffusion): It is an index expressing the level of adoption of green technologies and is included in the model by taking its logarithm.
- GOV (Government Stability): It is a composite indicator reflecting political stability and government effectiveness.
- LURB (Urban Population): It is the logarithm of the ratio of urban population in total population.
- LTO (Foreign Trade Deficit): Reflects the impact of trade in goods and services on external balance; expressed in logarithmic terms.
- LPI (Logistics Performance Index): An index based on World Bank data that measures the trade logistics infrastructure and efficiency of countries.
- INEQ (Income Inequality Index): It is an index that measures the inequality in income distribution; it is generally based on the Gini coefficient.

Through these variables, the impact of economic, environmental, institutional and social dynamics determining innovation capacity has been empirically analysed.

Table 2. Variable Abbreviations

Variable Type	Variable Abbreviations	Description
Dependent Variable	LGII	Global Innovation Index
Independent Variable	LGDP	Economic Growth
Independent Variable	LCO	Carbon Emissions
Independent Variable	LFDI	Foreign Direct Investment
Independent Variable	LGTD	Green Technology
Independent Variable	GOV	Government Stability
Independent Variable	LURB	Urbanisation
Independent Variable	LTO	Trade Deficit
Independent Variable	LPI	Logistics Performance Index
Independent Variable	INEQ	Income Inequality Index

Source: Author

This study utilizes a panel dataset encompassing 38 OECD countries from 2013 to 2023, enabling a long-term assessment of economic, environmental, social, and innovation performance across nations. By integrating data from multiple years, the panel structure allows for a more comprehensive analysis, capturing both temporal trends and cross-country variations.

The regression of this model is expressed as follows:

$$LNGII_{1_{it}} = \alpha_{it} + \alpha_{2i}LNGDP_{it} + \alpha_{3i}LNCO_{it} + \alpha_{4i}LNFDI_{it} + \alpha_{5i}LNGTD_{it} + \alpha_{6i}GOV_{it} + \alpha_{7i}LNURB_{it} + \alpha_{8i}LNTO_{it} + \alpha_{9i}LPI_{it} + \alpha_{10i}INEQ_{it} + \varepsilon_{it} \quad (1)$$

Including LNGII, except for the GOV and INEQ variables, which are taken at the natural logarithmic level. The error term is denoted as ε_it, with i and t representing countries and time, respectively. This paper builds an empirical model by combining the form of the quantile approach as follows:

$$Q_{\tau}(LNGII_{1_{it}}) = \alpha_{\tau} + \alpha_{2\tau}LNGDP_{it} + \alpha_{3\tau}LNCO_{it} + \alpha_{4\tau}LNFDI_{it} + \alpha_{5\tau}LNGTD_{it} + \alpha_{6\tau}GOV_{it} + \alpha_{7\tau}LNURB_{it} + \alpha_{8\tau}LNTO_{it} + \alpha_{9\tau}LPI_{it} + \alpha_{10\tau}INEQ_{it} \quad (2)$$

Table 3, presents the descriptive statistics of the variables used in the study, including the mean, standard deviation, minimum, and maximum values. The logarithmized dependent variable, the Global Innovation Index (GII), has an average value of 1.55 across the 38 OECD countries during the study period, with a minimum of 1.46 and a maximum of 1.65. Among the independent variables, the Economic Growth Index (GDP) shows an average of 2.29, ranging from a low of -11.16 to a high of 24.47.

Table 3. Descriptive Statistics

Variable	Number of Observations	Average	Standard Deviation	Min.	Max.
LGII	418	1.553	0.0395	1.4684	1.6457
LGDP	418	2.298	3.3185	-11.167	24.475
LCO	418	0.805	0.2347	0.2265	1.335
LFDI	418	9.889	0.7583	7.7364	11.538
LGTD	418	1.943	0.8331	0.301	3.7840
GOV	418	7.008	0.9224	4.75	10.333
LURB	418	1.888	0.0650	1.726	1.9921
LTO	418	4.493	0.5386	3.140	5.9769
LPI	418	3.611	0.3671	2.612	4.2259
INEQ	418	0.3743	0.0844	0.249	0.6419

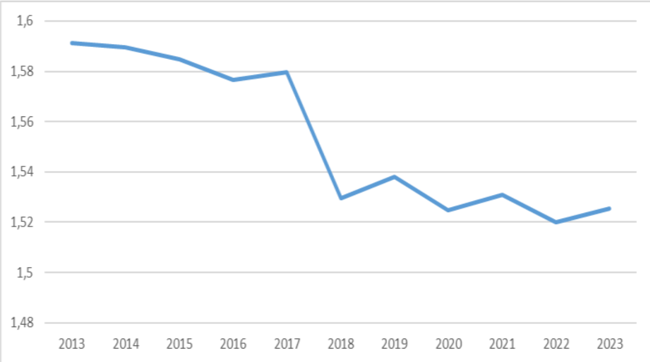
Source: Author

Figure 2 illustrates distinct trends in the Global Innovation Index (GII) averages of OECD countries between 2013 and 2023. During the 2013-2017 period, the index exhibited a slight decline, starting at approximately 1.59, followed by a partial recovery in 2017. This trend suggests that innovation performance in OECD countries remained relatively stable throughout these years. However, a sharp drop in the index is observed in 2018, indicating a major shift or shock in the factors influencing innovation. Potential reasons for this decline include economic slowdowns, political instability, or reductions in R&D investments.

After 2018, the index continued to fluctuate at lower levels. Although a temporary recovery was seen in 2019, the index declined once again in 2020, largely due to the effects of the COVID-19 pandemic. The pandemic significantly disrupted innovation activities, slowing down investments and research efforts. The index remained subdued until 2022, after which it began to show signs of recovery in 2023. However, despite this recent improvement, innovation performance in OECD countries has yet to fully return to pre-decline levels.

Overall, to gain deeper insight into these trends, a detailed examination of economic growth, R&D expenditures, environmental factors, political stability, and technology policies during this period is essential.

Figure 1. Global Innovation Index, 2013-2023



The results of the correlation analysis, presented in Table 3, provide insights into the linear relationships between variables and their interaction (positive or negative). Additionally, Table 4 displays the correlation coefficients, illustrating the strength and significance of these relationships.

A positive and significant correlation was found between the Global Innovation Index (GII) and economic growth (LGDP), suggesting that economic expansion is associated with higher innovation performance. Conversely, the negative and significant relationship between GII and carbon emissions (LCO) implies that innovation may contribute to reducing environmental degradation.

The results also indicate a positive and significant correlation between GII and government stability (GOV), highlighting that a stable political environment fosters innovation. However, the negative and significant relationship between GII and trade openness (LTO) suggests that higher trade openness might constrain local innovation capacities. Similarly, a negative and significant correlation between GII and the Logistics Performance Index (LPI) indicates that logistical challenges may hinder innovation progress.

Furthermore, urbanization (LURB) and green technology diffusion (GTD) both exhibit negative correlations with GII, suggesting that rapid urbanization and certain aspects of green technology adoption may not directly translate into enhanced innovation performance. The negative relationship between foreign direct investment (FDI) and GII implies that foreign capital inflows might have adverse effects on domestic innovation capacity, potentially due to dependency on external technologies rather than fostering indigenous R&D.

Also, a positive and significant relationship is observed between GII and income inequality (INEQ), indicating that while innovation drives economic advancements, it may also contribute to widening income disparities, emphasizing the need for inclusive policies. Lastly, the correlation analysis underscores the potential risk of multicollinearity among independent variables, which must be carefully addressed in further econometric modeling

Table 4. Correlation Test

	LGII	LGDP	LCO	LFDI	LGTD	GOV	LURB	LTO	LPI	INEQ
LGII	1.000									
LGDP	0.092*	1.000								
LCO	-0.293*	-0.068	1.000							
LFDI	-0.232*	-0.021	0.230*	1.000						
LGTD	-0.208*	-0.102*	0.445*	0.574*	1.000					
GOV	0.143*	0.038	0.066	0.114*	0.047	1.000				
LURB	-0.159*	-0.074*	0.041	0.289*	0.343*	0.057	1.000			
LTO	-0.113*	0.142*	0.122	-0.254*	-0.349*	-0.054	-0.225*	1.000		
LPI	-0.322*	-0.097	0.316*	0.343*	0.330*	0.100*	0.333*	-0.071	1.000	
INEQ	0.338*	0.067	-0.352	0.168*	-0.136*	0.116*	0.201*	-0.451*	-0.170*	1.000

Notes: *, ** and *** indicate 1%, 5% and 10% significance levels, respectively

3. Empirical Findings

In this study, the horizontal cross-sectional dependence test is first conducted to determine whether there is interdependence among countries in the panel dataset. The presence of such dependence suggests that economic, social, or policy-related factors in one country may influence others, potentially affecting the predictive accuracy of the model. If cross-sectional dependence exists, failing to account for it could lead to biased estimations and reduced model reliability.

Table 5 presents the test statistics and probability values for the Pesaran CSD Test, Friedman CSD Test, and Frees CSD Test, which are used to assess cross-sectional dependence. Since the p-values of all tests are below 0.05, the null hypothesis of cross-sectional independence is rejected. This confirms the existence of cross-sectional dependence among the countries

Table 5. Cross Sectional Dependence Test

CSD Test			
Model*	**Pesaran CSD Test**	**Friedman CSD Test**	**Frees CSD Test**
Test statistic	29.231	126.263	6.961
Probability Value	0.000	0.000	0.000

Notes: Model indicated by *; LGII=f (LGDP, LCO, LFDI, LGTD, GOV, LURB, LTO, LPI, INEQ).

Following the detection of cross-sectional dependence, the study proceeds with second-generation unit root tests to enhance analytical accuracy by accounting for heterogeneity and common shocks. Given the presence of cross-sectional dependence, the Pesaran CADF and CIPS tests, which belong to the second-generation unit root testing methods, are applied to assess the stationarity of the variables. Table 6 presents the results of these tests, evaluating the stationarity levels of the panel dataset variables. The analysis considers the results under both the Constant and Constant & Trend model specifications, ensuring a comprehensive assessment of the unit root properties of the variables.

According to the unit root test results, most variables are stationary under constant and trend models. According to the CADF test level results, LFDI, LGTD are stationary only at constant level. According to the results of both unit root tests, LFDI, LURB, and LTO variables contain unit root (I(1)) at level. However, LGII, LGDP, LCO, LGTD, GOV, LPI, and INEQ variables are stationary (I(0)) when both unit root tests are evaluated together. According to the results of the second generation unit root test, all variables are stationary when the first difference is taken in the constant and in the constant and trend. Therefore, the findings indicate that all series are stationary in their first differences. From these findings, it is seen that the variables in the model have a mixed stationary level (I(0) and I(1)).

Table 6. Unit Root Test Results

Variable	Model	CIPS^{a}	CIPS^{b}	CADF^{a}	CADF^{b}
LGII	Fixed	-2.495***	-3.790***	-2.787***	-3.589***
	Fixed & Trend	-2.964***	-3.673***	-3.528***	-3.751***
LGDP	Fixed	-2.334**	-3.311***	-1.388	-2.310***
	Fixed & Trend	-2.594*	-3.325***	-1.978*	-3.088***
LCO	Fixed	-2.563**	-2.925***	-3.239***	-2.895***
	Fixed & Trend	-2.517	-2.863**	-3.001***	-3.082***
LFDI	Fixed	-1.269	-3.624***	-2.110	-2.342***
	Fixed & Trend	-1.931	-3.329***	-2.084	-2.960***
LGTD	Fixed	-2.975***	-3.743***	-2.008*	-2.724***
	Fixed & Trend	-2.938***	-3.707***	-1.757	-2.689***
GOV	Fixed	-2.368***	-3.363***	-2.107**	-2.203***
	Fixed & Trend	-2.614**	-3.563***	-2.383	-2.860***
LURB	Fixed	-1.624	-2.934***	-1.416	-2.556***
	Fixed & Trend	-2.050	-4.071***	-1.634	-2.601***
LTO	Fixed	-1.518	-2.493***	-1.469	-2.169***
	Fixed & Trend	-1.881	-2.597**	-2.395	-2.878***
LPI	Fixed	-1.508	-3.235***	-2.031**	-2.432***
	Fixed & Trend	-1.388	-4.105***	-2.884***	-2.962***
INEQ	Fixed	-2.459***	-3.406***	-1.956*	-2.487***
	Fixed & Trend	-2.924***	-3.510***	-2.408***	-3.070***

Notes: a denotes the unit root test model at level and b denotes the unit root test model at first difference level. *, ** and *** denote 10%, 5% and 1% significance level, respectively.

Table 7 presents the results of the panel cointegration test, confirming the presence of a long-run relationship between the variables. In all cointegration tests, p-values below 0.05 (here 0.0000) lead to the rejection of the null hypothesis of no cointegration, providing strong evidence that the variables move together in the long run. The Pedroni, Kao, and Westerlund tests yield consistent results, further reinforcing the existence of a long-run equilibrium among the variables. This finding indicates that the economic, environmental, and innovation-related factors examined in the study are interconnected over time. The confirmation of a cointegration relationship suggests that additional analyses, such as error correction models (ECM) or causality tests, can be employed to explore the long-run dynamics in greater depth.

Table 7. Panel Co-integration Tests Results

Test	Statistic Value	Probability Value
Phillips–Perron t (Pedroni)	-10.0761	0.0000
Dickey-Fuller t(Kao)	4.0517	0.0000
Augmented Dickey-Fuller t (Kao)	6.0366	0.0000
Modified Dickey–Fuller t (Kao)	4.7585	0.0000
Variance ratio (Westerlund)	7.4430	0.0000

Notes: Model indicated by *; LGII=f (LGDP, LCO, LFDI, LGTD, GOV, LURB, LTO, LPI, INEQ).

In Table 8, the results of the panel quantile regression highlight the effects of explanatory variables across different quantiles of the dependent variable. Quantile regression enables the examination of how independent variables influence the dependent variable at various levels of distribution, such as low, medium, and high values. It also reveals how the impact of these independent variables changes from quantile 10 to quantile 90.

According to McFadden (2000), Pseudo R^2 values between 0.2 and 0.4 indicate a very good model fit. Pseudo R^2 measures the explanatory power of the quantile regression model. For instance, in the 10th quantile, the Pseudo R^2 is 0.2018, and in the 90th quantile, it is 0.3387. These values suggest that the model's explanatory power improves as the quantile values increase. Specifically, the model can account for 20% of the variability in the dependent variable at the 10th quantile, indicating a moderate fit at lower quantiles, while it performs better at higher quantiles.

The results show that LGDP (Economic Growth) is positively and significantly related to the dependent variable at all quantiles (at the 1% significance level). The coefficients range from 0.0011 at the 10th quantile to 0.0016 at the 90th quantile, indicating a positive effect that slightly strengthens as the quantile value increases. Similarly, LCO (Carbon Emission) also exhibits a positive and significant effect across all quantiles (at the 1% significance level). The coefficients for LCO are 0.1853 at the 10th quantile and 0.1201 at the 90th quantile. While LCO maintains a strong positive influence on the dependent variable, its effect diminishes slightly as the quantile increases, suggesting that the impact of carbon emissions on innovation performance is more pronounced at lower quantiles.

LFDI (Foreign Direct Investment) has a negative and significant effect on the dependent variable across all quantiles at the 1% significance level. The coefficients range from -0.0101 at the 10th quantile to -0.0133 at the 90th quantile, indicating a slight yet consistent negative influence. LGTD (Green Technology Investment), on the other hand, shows a positive and significant effect at all quantiles. Coefficients increase from 0.0068 at the 10th quantile to 0.0163 at the 90th quantile, demonstrating a stronger impact of green technology investment on innovation, especially in higher quantiles. This suggests that green technology investments have a positive effect on the dependent variable, with their impact intensifying at higher quantile levels.

LGOV (Government Stability) shows a positive effect on the dependent variable, but it is only significant at the 10% level in the medium and high quantiles. The coefficients for government stability are 0.0015 at quantile 10 and 0.0039 at quantile 90. These results imply that government stability becomes a significant factor in influencing innovation performance at higher levels of the distribution, but its impact is not substantial at lower quantiles. LURB (Urban Population Ratio) is negative and significant at the 1% level across all quantiles. Coefficients range from -2.4439 at the 10th quantile to -2.3756 at the 90th quantile, suggesting that a higher urban population has a consistent negative impact on innovation, which is somewhat consistent across quantiles. LTO (Trade Deficit), however, exhibits a negative but insignificant effect at all quantiles. The coefficients are -0.0109 at quantile 10 and -0.0226 at quantile 90, indicating a small, statistically insignificant effect of trade deficit on innovation performance.

LPI (Logistics Performance Index) shows insignificant effects across both low and high quantiles. The coefficients are -0.0104 at quantile 10 and 0.0171 at quantile 90, indicating that logistics performance does not have a statistically significant impact on innovation. This may suggest that the effect of logistics performance on innovation is either limited or mediated by other factors.

Finally, INEQ (Income Inequality) shows a positive but statistically insignificant effect on the dependent variable across all quantiles, with coefficients ranging from 0.0041 at the 10th quantile to 0.0058 at the 90th quantile. This indicates that while income inequality may have a positive impact, its direct effect on innovation performance is weak and insignificant.

In the panel fixed effects (FE) model, economic growth (LGDP) shows a positive and significant effect on innovation, confirming its importance for fostering innovation at the 1% significance level. Both carbon emissions (LCO) and green technology diffusion (LGTD) also have significant positive effects, suggesting their roles in enhancing innovation performance. Government stability (GOV) positively influences innovation but with a lesser impact at the 5% significance level. In contrast, foreign direct investment (LFDI) and urban population ratio (LURB) have negative and significant effects on innovation. The negative coefficient of urban population suggests that dense urbanization may hinder innovation, possibly due to overcrowded or inefficient urban systems. The effects of foreign trade (LTO), logistics performance index (LPI), and income inequality (INEQ) are not statistically significant in the model. The Pseudo R^2 value of 0.7169 indicates that the model explains 71.69% of the variation in the dependent variable, showing a strong explanatory power.

Table 8. Panel Quantile Regression Results

Variable	FE	Quantile Regression								
		10th	20th	30th	40th	50th	60th	70th	80th	90th
C	6.884*** (0.537)	1.908*** (0.142)	1.967*** (0.101)	2.010*** (0.123)	1.993*** (0.146)	2.059*** (0.118)	2.112*** (0.105)	2.132*** (0.076)	2.060*** (0.068)	1.997*** (0.107)
LGDP	0.0013*** (0.0003)	0.0011** (0.001)	0.0011** (0.001)	0.0012*** (0.001)	0.0013*** (0.001)	0.0013*** (0.001)	0.0014*** (0.001)	0.0015*** (0.001)	0.0015*** (0.002)	0.0016*** (0.001)
LCO	0.1535*** (0.035)	0.1853*** (0.050)	0.1778*** (0.040)	0.1722*** (0.042)	0.1634*** (0.031)	0.1536*** (0.031)	0.1422*** (0.033)	0.1355*** (0.041)	0.1284*** (0.052)	0.1201*** (0.061)
LFDI	-0.011*** (0.003)	-0.0101** (0.001)	-0.0105*** (0.001)	-0.0108*** (0.001)	-0.0112*** (0.005)	-0.0117*** (0.003)	-0.0122*** (0.002)	-0.0125*** (0.003)	-0.0129*** (0.004)	-0.0133*** (0.001)
LGTD	0.0114*** (0.005)	0.0068** (0.012)	0.0079** (0.002)	0.0087** (0.001)	0.0100** (0.007)	0.0114*** (0.001)	0.0131** (0.006)	0.0140** (0.004)	0.0151*** (0.007)	0.0163** (0.011)
GOV	0.0027** (0.005)	0.0015 (0.001)	0.0018 (0.002)	0.0020 (0.001)	0.0023 (0.007)	0.0027* (0.001)	0.0031* (0.004)	0.0033* (0.004)	0.0038 (0.005)	0.0039 (0.003)
LURB	-2.410*** (0.292)	-2.4439 (0.432)	-2.4360*** (0.371)	-2.4302*** (0.332)	-2.4209*** (0.288)	-2.4107*** (0.262)	-2.3987*** (0.307)	-2.3917*** (0.353)	-2.3843*** (0.414)	-2.3756*** (0.493)
LTO	-0.0166 (0.011)	-0.0109 (0.012)	-0.0122 (0.011)	-0.0132 (0.013)	-0.0148 (0.017)	-0.0166 (0.012)	-0.0186 (0.015)	-0.0198 (0.012)	-0.0211 (0.015)	-0.0227 (0.025)
LPI	0.002 (0.011)	-0.0104 (0.011)	-0.0073 (0.011)	-0.0049 (0.0141)	-0.0012 (0.013)	0.0029 (0.012)	0.0077 (0.014)	0.0106 (0.012)	0.01360 (0.015)	0.0172 (0.023)
INEQ	0.0049 (0.102)	0.0041 (0.161)	0.0043 (0.142)	0.0044 (0.122)	0.0047 (0.103)	0.0049 (0.102)	0.0052 (0.114)	0.0054 (0.132)	0.0056 (0.156)	0.0061 (0.183)
Pseudo R^2	0.7169	0.2018	0.2105	0.2111	0.2155	0.2517	0.2273	0.2633	0.2898	0.3387
Observation	418	418	418	418	418	418	418	418	418	418

Notes: *, ** and *** indicate 1%, 5% and 10% significance levels, respectively.

Table 9 shows the results of Dumitrescu-Hurlin panel causality test to investigate the causal relationship between the variables. The probability value for the causal relationship of the global innovation index on economic growth: 0.0906, which indicates a significant causal relationship at the 10% significance level. However, there is no significant causal relationship between economic growth and global innovation index as the probability value is 0.4759.

There is a significant bidirectional causality effect between the global innovation index and carbon emissions. On the contrary, while there is a causality from the global innovation index to FDI, there is no causality from FDI to the global innovation index. The global innovation index is not a cause of green technology diffusion, while green technology diffusion is a cause of global innovation. Similarly, there is no significant causal relationship between government stability and global innovation, while global innovation is a cause of government stability. Moreover, there is a bidirectional causality between global innovation and urbanization rate. There is a significant bidirectional causal relationship between global innovation and foreign trade deficit and logistics performance index and income inequality at 10% significance level

Table 9. Panel Causality Test Results

Null Hypothesis	W-istat.	Zbar-istat.	Probability Value
LGII → LGDP	0.5852	-1.8081	0.0906
LGDP → LGII	0.8365	-0.7129	0.4759
LGII → LCO	1.6384	2.7827	0.0054
LCO → LGII	3.7643	12.0492	0.0000
LGII → LFDI	1.7908	3.4470	0.0006
LFDI → LGII	1.3298	1.4374	0.1506
LGII → LGTD	1.1969	0.8583	0.3907
LGTD → LGII	3.0842	9.0848	0.0000
LGII → GOV	1.8230	3.5875	0.0003
GOV → LGII	1.2554	1.1134	0.2655
LGII → LURB	1.6620	2.8854	0.0039
LURB → LGII	4.4685	15.1190	0.0000
LGII → LTO	1.4865	2.1206	0.0540
LTO → LGII	0.5408	-2.0016	0.0653
LGII → LPI	1.4077	1.7769	0.0756
LPI → LGII	2.1745	5.1196	0.0000
LGII → INEQ	4.7164	16.1993	0.0000
INEQ → LGII	2.4244	6.2087	0.0000

Notes: *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

4. Conclusion and Recommendations

This study examines the factors influencing global innovation performance using a panel quantile regression model, utilizing data from OECD countries. The analysis explores the impact of economic growth, carbon emissions, foreign direct investment (FDI), green technology investments, government stability, urbanization, trade deficit, logistics performance, and income inequality on innovation.

The results indicate that economic growth (LGDP) and green technology investments (LGTD) positively and significantly enhance global innovation. The consistently positive impact of LGDP across all quantiles highlights the crucial role of economic expansion in fostering innovation. Additionally, green technology investments demonstrate a strong positive effect, particularly in higher quantiles, suggesting that the advancement and diffusion of environmental technologies contribute significantly to innovation.

Conversely, FDI exhibits a negative effect on innovation, implying that foreign investments may not always support technological advancement, especially if they do not target high-value-added sectors. While green technology investments strongly influence innovation at higher quantiles, the urban population ratio negatively affects innovation, possibly due to infrastructure constraints or urban congestion. Moreover, trade deficit and logistics performance do not show significant impacts, indicating that innovation dynamics in OECD countries may be less sensitive to these factors.

To foster a more dynamic innovation ecosystem, governments should enhance collaboration between public institutions, private enterprises, and research organizations. Public-private partnerships (PPPs) can drive innovation by facilitating technology transfer, commercialization of research, and industry-academia linkages. Governments should establish innovation hubs and technology clusters where firms, universities, and startups can co-develop cutting-edge solutions. Moreover, regulatory frameworks should be designed to encourage venture capital investment in high-tech and green sectors, ensuring that innovative ideas receive sufficient funding to reach commercialization.

Access to funding remains a critical barrier to innovation, particularly for startups and small- and medium-sized enterprises (SMEs). In addition to traditional R&D grants and tax incentives, policymakers should introduce alternative financing models such as green bonds, innovation funds, and impact investment programs that support sustainable innovation. Governments can also incentivize corporate R&D investments by offering tax credits for companies that engage in research collaborations with universities or invest in emerging green technologies.

The digital economy plays an essential role in driving innovation across industries. Policymakers should prioritize investments in digital infrastructure, artificial intelligence (AI), and big data analytics to accelerate innovation. Expanding access to high-speed internet, 5G networks, and cloud computing services will create an enabling environment for businesses to adopt data-driven innovation strategies. Additionally, governments should support digital upskilling programs to equip workers with the necessary skills to thrive in an increasingly technology-driven economy.

The negative impact of urbanization on innovation suggests the need for smarter urban planning. Governments should implement smart city initiatives that leverage renewable energy, IoT-enabled infrastructure, and sustainable transport solutions to enhance urban innovation potential. Policies should focus on reducing congestion, improving air quality, and expanding green spaces, creating a healthier and more innovation-friendly environment. Public investments in sustainable urban infrastructure can further support the development of innovation districts, where research institutions and technology firms collaborate on new solutions.

A well-functioning intellectual property (IP) rights system is crucial for encouraging innovation, particularly in high-tech and knowledge-intensive industries. Policymakers should focus on enhancing IP laws, streamlining patent registration processes, and providing stronger legal protections for innovators. Additionally, international collaboration on IP protection agreements will help ensure that technological advancements are safeguarded across borders, promoting global knowledge sharing while maintaining fair competition. The study finds that trade openness can sometimes create constraints on domestic innovation. To address this, policymakers should design trade policies that protect emerging industries while still encouraging global knowledge exchange. Governments can implement strategic industrial policies that support local R&D efforts, incentivize domestic firms to adopt advanced technologies, and facilitate innovation-driven exports. Additionally, participation in international research collaborations should be encouraged to integrate local innovations into global supply chains.

Innovation should not only drive economic growth but also contribute to social equity and sustainable development. Policymakers should implement inclusive innovation policies that ensure marginalized communities, small businesses, and underrepresented groups have access to technology and funding opportunities. Encouraging women’s participation in STEM fields, supporting entrepreneurs from disadvantaged backgrounds, and creating regional innovation hubs in less-developed areas can help bridge the innovation gap and create a more inclusive economy.

One promising avenue for future research is the exploration of the role that artificial intelligence (AI) and machine learning play in driving innovation, especially in the context of green technologies and sustainable industries. Given the transformative potential of AI in various sectors, future studies could investigate how the integration of AI into R&D processes, product development, and decision-making contributes to innovation. Research could also explore how AI can enhance resource efficiency and reduce the environmental impact of industrial activities. Understanding the ways in which AI interacts with existing innovation ecosystems and policy frameworks would provide valuable insights into how to leverage technological advancements to achieve sustainable development goals.

Another important direction for future research is the relationship between technological innovation and social equity. While innovation can drive economic growth, it is essential to explore how it can also promote social inclusion. Studies could examine the impact of inclusive innovation policies on reducing inequality, particularly in developing regions or among underrepresented groups. Future work could investigate how social innovation and technological inclusion policies can be designed to ensure that the benefits of innovation are widely distributed, contributing to both economic and social development.

Moreover, the positive and significant effect of carbon emissions and green technology diffusion on innovation may be considered as a counter-intuitive or unexpected finding at first glance. However, there are some structural and political dynamics underlying this finding. Firstly, in countries with high carbon emissions, the pressure for environmental sustainability becomes a trigger for innovation in public policies and private sector strategies. High emission levels drive firms and governments towards cleaner production technologies, energy efficiency practices and environmentally friendly process innovations. In this context, environmental degradation can actually act as a "trigger stress factor" for innovation.

Similarly, the positive impact of green technology diffusion on innovation shows that the search for solutions to environmental problems is not only limited to technology transfer, but also encourages R&D activities at the local scale. Green technologies are often adopted in line with external pressures, international environmental norms and carbon emission targets, and this process may result in the introduction of new policies and incentive mechanisms to increase the innovation capacity of both the private sector and public institutions.

Therefore, this can be said that both variables represent structural dynamics that mobilise innovation indirectly rather than directly. This indicates that innovation is shaped not only by technological progress but also by environmental and institutional imperatives.

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