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ORIGINAL ARTICLE

The effect of macroeconomic and environmental factors on innovation in EU member countries

***Melina Dritsaki*[1], *Chaido Dritsaki*[2,*], *Eleni Tsianaka*[3]**

[1] *Department of Economics, University of Western Macedonia, Kastoria, 52100, Greece.*

[2] *Department of Accounting and Finance, University of Western Macedonia, Kila Kozanis, Kozani, 50100, Greece.*

[3] *Department of Applied Informatics, University of Macedonia, Thessaloniki, 54636, Greece.*

ABSTRACT

This paper examines the long-run relationship between innovation and macroeconomic and environmental factors in the EU during the period 1990–2020. In the paper, the patents are used as a proxy of the innovation index. The market openness, per capita GDP, foreign direct investment, and oil prices are used as proxies for macroeconomic factors whereas per capita energy consumption, per capita CO_2 emissions, and renewable energy sources are proxies for environmental factors. For the analysis of this relationship, two-panel count data models are used, the Poisson regression model and negative binomial model as well as the ARDL cointegration technique and the Dumitrescu and Hurlin causality test. The results of the negative binomial model showed that trade openness, renewable energy sources, and CO_2 emissions have a significant and negative relationship with innovation, while GDP, investment, energy consumption, and oil prices have a significant and positive relationship with innovation. Furthermore, the causality test of Dumitrescu and Hurlin showed the presence of an unidirectional causal relationship between per capita CO_2 emissions and per capita energy consumption towards innovation.

KEYWORDS

innovation; macroeconomic factors; environmental factors; Poisson regression model; negative binomial model; Dumitrescu and Hurlin causality; European countries

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*CORRESPONDING AUTHOR
Chaido Dritsaki,
Department of Accounting and Finance, University of Western Macedonia, Kila Kozanis, Kozani, 50100, Greece
cdritsaki@uowm.gr

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1. Introduction

Innovation is the application of ideas in a practical way that leads to the creation of new products and services. In terms of the economy, innovation is the creation and use of concepts and methods that enhance products and services and increase the effectiveness of their production. Information technology is a modern example of innovation that has altered how businesses produce and sell their goods and services, creating new markets and business models. The ability of innovation to contribute to economic growth is one of its most significant advantages. In other words, we could say that innovation leads to higher productivity, meaning that the same input generates a greater output.

Innovation is one of the key drivers that influence economic growth and contribute to the development and modernization of production methods. Expenditure for innovation and investments for research support the infrastructure development, employment, climate change and the quality of people's lives (Ulku, 2004; Maradana et al., 2017). Many countries have adopted strategies for promoting innovation and amplifying their economy. But most of the developing countries import the technology from developed countries which does not fit on their environment, so they do not benefit from technological innovation.

Europe is the birthplace of many innovations and continues to be an innovative region, with potential to further strengthen its innovation capacity. Yet only three EU countries are among the top ten countries in the world in the Global Competitiveness Index. There is also a persistent gap in spending on research and development among the 27 EU Member States. Recent studies by the European Central Bank show a significant difference in productivity between the most productive and the least productive countries. This means that well-performing countries are highly innovative, while so-called laggard countries do not benefit much from innovation.

Performance in innovation is now a crucial component of competitiveness and economic development. Additionally, innovation is crucial for addressing international issues like climate change and sustainable development. The role of innovation will increase in the coming years because industrial production will change in favor of high-tech industries, especially with the development of nanotechnology, genetic engineering and ecological industry. Competitiveness can be interpreted as the ability to attract intellectual capital. The stimulation of innovative entrepreneurship, science and education should be supported by the experts of the European Union. However, despite the value of innovation, many EU nations have trouble improving performance in this area. In spite of the increased opportunities provided by globalization and new technologies, productivity performance in many EU countries hasn't improved much in recent years. (Dritsaki and Dritsaki, 2023a). The factors that affect innovation are heterogeneous macro-economic, environmental, and social.

1.1. Macroeconomic factors

1.1.1 GDP per capita

There is a significant body of work concentrating on technological innovation and economic growth, and research has repeatedly demonstrated that technological innovation is a key driver of economic progress. The study of Freimane and Balina (2016), who employed research and development as a measure of innovative activities, is among the most significant works focusing on this subject. According to Schumpeter (1934), who also emphasized that entrepreneurs are able to carry out these innovations, entrepreneurship plays a crucial part in economic progress. Schumpeter viewed innovation to be one of the productive functions. The innovation-based growth hypothesis postulates that innovation and economic growth are positively correlated. This theory contends that research and development (R&D) is crucial to innovation, productivity increase, and economic expansion. (Romer, 1986).

Many studies focus on the impact of innovation on economic growth, indicating the driving force of the innovation-growth relationship. Public expenditure for research creates positive knowledge diffusion which can be used in the creation of new ideas and innovation. This means that there is a bilateral relationship between innovation and economic growth (Pradhan et al., 2016).

Recent economic growth theory recognizes many research paradigms based on complexity and scope, and claims that elements like human capital and the availability of intellectual services are the primary influences on technological advancement. Economic growth theory has a wide range of analytical techniques because it has undergone a protracted development cycle. There is consensus, however, that technical innovation is what propels economic development and growth, which are frequently interconnected as a result of cause-and-effect relationships, as well as stimulating and integrating one another. In other words, we would say that technological innovation and economic growth overlap, and this relationship indicates increased importance of innovation in driving economic growth (Mohamed et al., 2022).

1.1.2. Foreign direct investment

Foreign direct investment has impact on the performance of companies' innovation. Investment contributes to economic growth, job creation, competitiveness, exports, productivity and innovation bringing cutting-edge technology and knowledge transfer. Developing countries find it difficult to close the technology gap with developed countries on their own, and often seek to attract foreign direct investment (FDI) in order to stimulate domestic innovation (Liu and Wang, 2021).

The relationship between foreign direct investment and innovation is not clear from a theoretical point of view. On the one hand, the entry of a large capacity of foreign capital will seize high-quality sources in the domestic market thus intensifying market competitiveness. On the other, foreign companies will train local workers and create new jobs. Furthermore, the presence of foreign direct investment could reduce the cost of innovation for domestic firms. Fons-Rosen et al. (2017) on their paper establish that foreign direct investment can enhance the productivity and innovation of domestic firms if foreigners enter sectors that are technologically close to domestic firms. On the other hand, Aghion et al. (2005), claim that foreign direct investment can harm the performance of domestic firms through the effect of increased competition that can discourage innovation in domestic firms. Finally, the impact of foreign direct investment remains a matter for investigation.

1.1.3. Trade openness

International technology transfer can also take place through trade. The importance of market opening is emphasized by both Adam Smith and Ricardo. As a result, countries will specialize in the production of goods and services and benefit from the ability to export these goods and services. On the other hand, nations without these benefits will import from them and focus on different kinds of products and services. According to internal growth theory, developing nations will gain from the transfer of advanced technology through an open-trade policy because this technology will be used in production processes and result in high output, which will directly influence economic growth (Romer, 1986).

Importers can improve their technologies by incorporating into their production procedures a state-of-the-art imported capital, goods and services, which are not available in the domestic market (Grossman and Helpman, 1991). A country that imports goods with a higher composition than the one that provides, it will be able to improve the effectiveness and quality of produced goods. The effect of market openness on innovation is not related only with capital imports and technology imports but also with exports. When companies enter the market, they may be exposed to more competitive markets and may therefore be forced to improve their technology more frequently. Also, they will have access to state-of-the-art production methods (Lazzarotti et al., 2017). In conclusion, the impact of market openness is valid, not only in innovation increase and technology adoption, but it leads the market to more effective productive procedures and improvement in source distribution (Almeida and Fernandes, 2008).

1.1.4. Crude oil prices

Oil plays a dominant role in the global energy market and its price volatility has significant economic and environmental consequences. After 2014 oil prices fell from US$100 per barrel to US$50 in a matter of months, surprising many analysts. Meanwhile, many articles have been written about the causes of depression as well as the role of supply and demand factors. This decline in oil prices disrupted the stability in many countries, creating economic pressure in oil-productive countries and providing economic boost in importing countries. Conversely, the increase of oil price amplifies the sectoral innovation systems, both politically and economically allowing entities to invest on new energy technologies. The crude oil market is a globalized market, so shocks in market conditions can occur on both sides and the market may lead to intense price volatilities. Moreover, a link between global economic uncertainty and world crude oil market integration exists (Kuck and Schweikert, 2017).

Energy prices can also trigger the development of environmentally clean technologies. Popp (2005) uses patent data to study the bond between environmental policy and technological change. The findings of his paper present the positive impact that energy prices have on patents. Also, the paper presents that Higher energy prices lead to a shift towards environmentally friendly innovation. From an environmental perspective, oil-producing countries benefit from global emissions reductions, but are also harmed, to varying degrees, by demand reductions, as oil prices affect global oil production and actual industrial commodity activity (Guo et al., 2021).

1.2. Environmental factors

1.2.1. CO_2 emissions

Energy is essential for the survival and the development of society. However, the dioxide carbon emissions are the main driver of global warming. In order to avoid the worst consequences of climate change and global warming, humans must reduce emissions. More than 180 countries have announced greenhouse gas emissions reduction targets. However, the way that responsibilities are distributed among countries has become a point of contention. Countries have to draw their attention to renewable energy sources which are cleaner and safer than fossil fuels.

Climate change causes extended damages to the environment. CO_2 emissions are the main cause of global warming and in turn is expected to cause widespread extinctions due to warming and more extreme weather events. Initiatives for reducing greenhouse gas emissions have helped to stimulate global action and prompted the adoption of an international protocol. According to the Climate

Transparency Report (2020), data from G20 countries show that developing countries suffer the greatest vulnerability to climate change. On the contrary, developed countries boost climate finance to support developing countries in their efforts to combat climate change (Yu et al., 2022; Dritsaki and Dritsaki, 2023b).

1.2.2. Renewable energy

In recent years, and especially after the war in Ukraine, there has been a strong pressure to achieve security for energy supply, given the political instability in the countries with the largest energy reserves. Concerns about energy security and climate change are fueling the search for alternative energy technologies. Technological innovation provides a solution to mitigate the problem, with alternative forms of energy such as solar, wind, geothermal and biomass, which also bring a healthier climate. Alternative energy sources are mainly developed in industrialized countries with a high number of patent applications. A positive driver of technological innovation in the energy sector is the price of energy. Increased fossil fuel prices create incentives for innovation in the production of electricity from renewable energy sources. An increase in oil prices may allow energy use to move away from fossil fuels, while on the other hand low oil prices may threaten renewable energy sources. Therefore, high energy prices cause technological advances which increases the political feasibility of changes in the energy economy (Cheon and Urpelainen, 2012). As noted by Xia et al. (2019), the growth and long-term sustainability prospects of the renewable and alternative sectors cannot be isolated from the fossil fuel sector. Therefore, the following questions arise:

Countries are indeed committed to invest and develop alternative energy sources as a substitute for fossil fuels.

Is a long-term transition to sustainability being made or are countries simply encouraging innovation in alternative energies in a short-term approach, when necessary, given the conditions of fossil fuel markets?

1.2.3. Energy consumption

Energy consumption and economic growth are variables that are usually assumed to be correlated. Energy is considered a key input to production, which in turn contributes to economic development. High energy use causes greenhouse gas emissions (GHG), which in turn contribute to climate change and global warming. It is necessary to take precautions to separate carbon emissions from energy consumption by substituting energy derived from renewable sources for energy derived from fossil fuels in order to combat global warming and climate change. Due to the fact that developed countries are more responsible for carbon emissions, they must adhere to the Kyoto Protocol’s restrictions on energy consumption (Murad et al., 2019).

Energy consumption is impacted by technological innovation both directly and indirectly, as improved technological innovation lowers energy consumption through the development of green and energy efficient technologies. Furthermore, technological innovation increases energy supplies and energy security through the development of alternative renewable energy sources and that better technological innovation can enable both sustainable economic growth and environmental security at the same time by reducing dependency on fossil fuel (Wang, 2022).

In recent years, researchers have paid increasing attention to exploring the relationship between innovation and entrepreneurship. However, in this paper, we examine the link between innovation and macroeconomic and environmental factors in EU countries. Therefore, the main objective of this paper is to examine the relationship between innovation and macroeconomic and environmental factors. In summary, we would like to assess the importance of the innovation-factor link by investigating whether the level of innovation has contributed to these factors or whether the expansion of innovation is simply a consequence of only some factors.

The rest of this paper is organized as follows: Section 2 presents the literature review. In Section 3 data, variables, and descriptive statistics are presented. Section 4 describes the econometric methods while Section 5 introduces preliminary tests. The empirical results are given on Section 6 and the Discussion follows in Section 7. Finally, in Section 8 we provide the conclusions together with some policy implications.

2. Literature review

As energy became an important growth factor, many attempts have been made and still becoming more intense from scientists on modelling innovation's impact on energy. Literature illustrates that innovation contributes to economic growth directly and indirectly through other macroeconomic and environmental factors. But it is also likely that innovation can be affected from economic growth and other macroeconomic and environmental factors. This means that both innovation and also macroeconomic and environmental factors can cause one another and so there is the possibility of feedback relationship. Several papers have developed this issue. Some of them are referred below:

Pece et al. (2015) examined if the long run economic growth is affected by the dynamic innovation performing the multiple regression models estimated on Central European Countries. On their analysis, they used economic growth, number of patents, number of trademarks, R&D expenditures to estimate the relationship between economic growth, investment and innovation. Their findings provide evidence for a strong connection between human, money and economic growth.

Murad et al. (2019) investigated the dynamic relationships between technological innovation, energy consumption, energy prices and economic growth for Denmark during the period 1970 until 2012. In order to test both the short run and the long run dynamic between variables, they used the autoregressive distributed lag model (ARDL) for time series analysis. Additionally, in their paper, they used the Granger procedure within the VAR framework to identify the causal relationship between variables. According to the ARDL approach for cointegration, while energy prices and technological advancement have a negative and significant impact on energy consumption, real GDP growth has a positive short- and long-term impact on energy consumption. The findings demonstrate that energy use and economic growth are unrelated, supporting the neutral hypothesis for Denmark. Furthermore, it has been established that energy consumption is a result of both technological advancement and rising energy prices. Consequently, the paper recommends that Denmark implement a conservative energy policy.

Nunes and Catalão-Lopes (2020) examined the effect of oil price on innovation during the period 2000–2018 with the use of negative binomial regression for the ten most innovative countries. The empirical findings show that the effect of oil prices on the applications patents for renewable energy sources is asymmetric. When the prices decrease, the reduction in innovation is more pronounced than the expansion when prices are rising. This result denotes some absence of commitment to find sustainable alternatives to the use of fossil fuels.

Mohamed et al. (2022) analyze the effects of innovation and economic growth on developing nations between 1990 and 2018. They employ the Granger causality test and the error correction model (ECM) method in their analysis. The test results demonstrated that the increase of the indices of technological innovation leads to the increase of economic growth both in the short and the long run. Also, the findings of their paper showed a bilateral causal relationship between technological innovation and GDP and a short-run unilateral causal relationship expanding from technological innovation to GDP.

Mongo et al. (2021) using an Autoregressive Distributed Lag model (ARDL), analyze the impact of environmental innovations, consumption of renewable energy sources, GDP per capita and the degree of economic openness on CO_2 emissions for 15 European countries for the period 1991–2014. The results of the paper showed that, in the long run, environmental innovations tend to reduce CO_2 emissions, while in the short run the observed effect is the opposite, suggesting the existence of a rebound effect.

Using an Autoregressive Distributed Lag model (ARDL) and Granger causality based on a vector error correction model, Vetsikas and Stamboulis (2021) investigate the effects of innovation activity (measured by R&D expenditure and patent applications) and economic growth (GDP per capita) on trade openness in 10 European countries from 1983 to 2018. The empirical results show that all of the countries looked at have a significant long-term relationship between the variables. Most nations have statistically significant and positive long-run coefficients for R&D spending, patent applications, and GDP per capita. For each nation, error correction models produce intriguing results in short-run dynamics. Finally, different countries have different Granger causal relationships between variables.

The impact of foreign direct investment and trade openness on the relationship between innovation and energy for 24 OECD countries from 1996 to 2015 is examined by Osabuohien-Irabor and Drapkin, (2022). This study uses the cross-sectionally augmented autoregressive distributed lags (CS-ARDL), augmented mean group estimator (AMG), and system generalized methods of moments (SYS-GMM) techniques to address econometric issues like cross-sectional dependence, endogeneity, and heterogeneity in the panel estimation process. The relationship between technological innovation and energy demand is characterized by an inverted U-shape curve, which is supported by data on foreign direct investment and trade openness. In particular, the study discovers that the influence of technological innovation on energy use via the reverse technology spillover effect from outward FDI reinforces OECD countries towards an energy-saving environmental sustainability both in the short-run and long-run. Additionally, the coefficients are larger at small quantiles, indicating that countries like India and South Africa, which produce fewer renewable energy sources per capita than nations like Brazil and Russia, have a higher likelihood of experiencing a renewable energy innovation. Analyzed by Solarin et al., (2022), real GDP, the producer price index, and CO_2 emissions are taken into account as they assess the effect of technical innovation on green growth in the BRICS countries from 1993 to 2018. The empirical results show that the influence of renewable energy innovation on renewable energy production is significantly positive across all quantiles using a new panel quantile regression enhanced with the method of moments. Additionally, the coefficients are larger at small quantiles, indicating that countries like India and South Africa, which produce fewer renewable energy sources per capita than nations like Brazil and Russia, have a higher likelihood of experiencing a renewable energy innovation.

Boonman et al. (2023) used the EXIOMOD Computable General Equilibrium model to estimate the economic and environmental impacts of a series of different circular economy scenarios developed by the European Commission. The results of their work showed that innovation-focused circular policies can have strong positive economic and environmental impacts in a wide-ranging portfolio of measures that can address a wide range of pollutants. Furthermore, they argue that policies that stimulate innovation and result in efficiency or the development of recycling technologies are key to the transition to a circular economy.

3. Data

For the analysis of the paper, we use annual data for the period 1990–2020 for 27 countries of EU. The indices of World Development of World Bank in 2022 are used for the data. The missing observations are covered using the mean average or trend. For the measuring of innovation, we used the number of patents. There is a close relationship between innovation, macroeconomic and environmental variables. In the framework of macroeconomic variables, we use market openness (the total of imports and exports to gross domestic product), per capita GDP in constant prices 2015 in US dollars, foreign direct investment in US dollars and crude oil prices in Europe (Brent-Europe) in dollars per barrel. For the environmental variables, we use the per capita energy consumption in kilos equivalent to oil, the per capita CO_2 emissions in metric tons, and the renewable energy sources as a percentage of the total energy consumption. The paper consists of 27 countries of EU (Austria (AUT), Belgium (BEL), Bulgaria (BGR), Cyprus (CYP), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), Greece (GRC), Croatia (HRV), Hungary (HUN), Ireland (IRL), Italy (ITA), Lithuania (LTU), Luxembourg (LUX), Latvia (LVA), Malta (MLT), Netherlands (NLD), Poland (POL), Portugal (PRT), Romania (ROU), Slovak Republic (SVK), Slovenia (SVN), Sweden (SWE). For the analysis of the paper, the econometric software packages of Stata 14.0 and EViews 12.0 were used. All the variables, with the description and sources, are presented below (**Table 1**).

Table 1: Variables and sources.

Variable	Description	Sources
INN	Number of resident patent applications	WDI
OPEN	Trade openness (as the total of exports and imports divide GDP)	WDI
GDP	Per capita (constant 2015 US$)	WDI
ENER	Energy use (kg of oil equivalent per capita)	WDI
FDI	Foreign direct investment (net inflows, US$)	WDI
CO_2	CO_2 emissions (metric tons per capita)	WDI
REN	Renewable energy (% of total final energy use)	WDI
OIL	Crude oil prices (Brent-Europe) (US$ per Barrel)	U.S. Energy Information Administration

On **Table 2** the descriptive statistics of the examined variables are provided.

Table 2: Descriptive statistics.

	INN	OPEN	GDP	ENER	FDI	CO2	REN	OIL
Mean	3304	108.1	26442	3449	1.58×10^{10}	7.85	14.9	48.09
Std.Deviation	8733	59.58	19767	1487	4.87×10^{10}	3.81	11.6	29.97
Maximum	51736	380.1	112418	9428	7.34×10^{11}	30.3	54.1	109.9
Minimum	2.00	27.1	3379	1578	-3.44×10^{11}	2.93	0.00	12.86
Skewness	4.25	1.72	1.73	1.39	5.62	2.27	0.87	0.67
Kurtosis	21.03	6.61	7.23	5.12	74.59	11.09	3.03	2.25
Jarque-Bera	13872	866.2	1047.3	428.7	183193	3010	107.8	83.34
Probability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Observations	837	837	837	837	837	837	837	837

Source: author's calculations.

The average of patents for 27 EU countries is 3304 with std. deviation 8733. The estimation of std. deviation show that the average of patents has larger volatility from the rest of the model's variables examined. In all variables there is a positive asymmetry (right-skewed), implying that the distribution is right-skewed and most of the observations are on the right. Also, all variables have up-spread peaks (> 3) meaning that the distribution is leptokurtic with most of the observations to be in the middle of the distribution. Finally, based on the results, the variables don't follow the normal distribution according to the test of Jarque and Bera (1987).

4. Econometric methods

For the relationship between innovation and macroeconomic and environmental variables, we choose innovation as a dependent variable, and we define this variable with the number of applications for patents. For independent variables, we use market openness, the per capita GDP, foreign direct investment, and crude oil prices in the framework of macroeconomic variables. At the same time, the per capita energy consumption, renewable energy sources (percentage of total energy consumption) and per capita CO_2 emissions are used in the framework of environmental variables. The model employed for the above relationship is provided below:

$$INN_{it} = \beta_{i0} + \beta_{i1}OPEN_{t} + \beta_{2i}GDP_{t} + \beta_{3i}ENER_{t} + \beta_{4i}FDI_{t} + \beta_{5i}O\ \ 2_{t} + \beta_{6i}OIL_{t} + \beta_{7i}REN_{t} + \varepsilon_{t} \quad (1)$$

where $t = 1,\ldots,T$ and $I = 1,\ldots, N$ index the time-series and cross-sectional units, respectively.

Since the dependent variable on the above model (number of applications for patents) is measurable and non-negative, we use two-panel count data models. First, we use the Poisson regression model developed by Palmgren (1981) to examine the relationship between the applications for patents and macroeconomic and environmental independent variables. In other words, the Poisson regression is a generalized linear form of a model regression analysis used for modelling Poisson count data. As Cameron and Trivedi (2013) mentioned, even though the most common starting point on count data is Poisson regression, the results of Poisson regression model can be misleading due to the overdispersion. For this reason, we test the overdispersion using the likelihood ratio test-LR. Secondly, according to the results of LR test, in the case of overdispersion, we use the negative, binomial regression introduced by Hausman et al. (1984) to analyze the relationship between variables of the model (1).

5. Preliminary tests

This section presents the preliminary tests of panel data for the suitability of model used.

5.1. Multicollinearity test

For multicollinearity test we use the Variance Inflation Factor—*VIF*. $VIF = \frac{1}{1-R^2}$ showing the speed of increase of variance when there is a multicollinearity problem. It is obvious that the larger the value of *VIF*, the bigger the problem of multicollinearity. There is no critical value to compare it with the value of *VIF*. A rule of thumb is when the value is larger than 10, then the corresponding variable generates multicollinearity.

The Variance Inflation Factor is $VIF = \frac{1}{1-R^2}$ = 1.27 on variables' level and 1.006 on first differences correspondingly (less than 10). So, we can conclude the absence of multicollinearity (R^2 is the coefficient of determination which indicate the degree where a prognostic factor can explain the shift to the response variable).

5.2. Hausman test (random effects vs. fixed effects estimation)

The panel data econometric modeling often applies two basic approaches, one is fixed effects and the second is random effects. For the suitability between fixed and random effects the Hausman (1978) test is used. The null hypothesis show that the preferred model is that of random effects whereas the alternative hypothesis indicates the fixed effects model. On the following table, the results of Hausman (1978) test are provided.

The results of **Table 3** do not reject the null hypothesis. Thus, we conclude that the most suitable model is the random effects model.

Table 3: Hausman test.

Test summary	Chi-Sq. statistic	Chi-Sq. d.f.	Prob.
Cross-section random	0.000	7	1.000

Source: Author's calculations.

5.3. Cross sectional dependency

To use the panel unit root tests, we should examine the existence of cross-sectional dependency on panel data. If cross-sectional dependency does not exist, then we can use the first-generation unit root test. If there is a cross-sectional dependency, then the second-generation unit root tests (SURADF, CADF and CIPS) can be employed which take into account the cross-sectional dependency.

For the cross-sectional dependency among residuals, we use the Breusch and Pagan (1980), LM, Pesaran (2004) Scaled, LM, and Pesaran (2004), CD tests. The results of these tests are showed on table 4.

Table 4: Cross-sectional dependence and homogeneity test results.

Cross-sectional dependence test (H_0: No cross-sectional dependence)			
Test	**Statistic**	**d.f**	***p*-value**
Breusch-Pagan LM	2802.844	351	0.000
Pesaran scaled LM	92.53890		0.000
Pesaran CD	14.41960		0.000

Source: Author's calculations.

The findings from the above table indicate that the null hypothesis of no cross dependency is rejected on 1% level of significance. Thus, we can continue with tests and estimation techniques that consider cross dependency.

5.4. Homogeneity-Hheterogeneity test for random effects

On a sample of panel data, it is necessary to examine the panel homogeneity or heterogeneity on the specification generator process data.

The model of random effects can be formulated as follows:

$$Y_{it} = \alpha_0 + \beta X_{it} + u_{it} \qquad \mu\varepsilon \; u_{it} = \alpha_i + e_{it} \tag{2}$$

where u_{it} is considered a complex error (idiosyncratic error) consisted of two random components, α_i (non-observable individual effects) and e_{it} (non-observable time effects) and for this reason this model is called two error component model. The Lagrange Multiplier (LM) test assume that the non-observable individual effects are normally distributed $N\left(0,\sigma^2_{\alpha_i}\right)$, likewise the idiosyncratic errors $N\left(0,\sigma^2_{u_i}\right)$. The null hypotheses on the previous assumptions can be expressed as follows:

$H_o : \sigma^2_{\alpha_i} = 0$ (no individual effects).

$H_o : \sigma^2_{e_i} = 0$ (no time effects).

$H_o : \sigma^2_{u_i} = 0$ (no individual and time effects).

For the above hypothesis and for balanced samples, Breusch and Pagan (1980) created three statistics of Lagrange multiplier, LM_{α_i}, LM_{e_i} and LM_{u_i}.

The existence of individual heterogeneity can be tested with the null hypothesis as follows:

$H_0 : \sigma^2_{\alpha_i} = 0$ (there is no individual heterogeneity on data).

$H_0 : \sigma^2_{\alpha_i} > 0$ (there is an individual heterogeneity on data).

If we reject the null hypothesis, then we conclude that there is an individual heterogeneity meaning that the model of random effects is the most suitable. **Table 5** presents the three statistics of Lagrange multiplier.

Table 5: Lagrange multiplier tests for random effects.

	Test hypothesis		
	Cross-section	Time	Both
Breusch-Pagan	10876.99 (0.0000)	3.392534 (0.0655)	10880.38 (0.0000)

Source: Author's calculations.

The results of the above table denote that the null hypothesis of non-heterogeneity is rejected. Meaning that the first-generation unit root tests provide inefficient results. Thus, we can use the second-generation unit root test of Pesaran (2007) CIPS which considers both the cross-sectional dependency and heterogeneity.

6. Empirical results

6.1. Panel Unit Root tests

For the second-generation unit root test, we use the Pesaran (2007) test CIPS which considers the cross-sectional dependency and heterogeneity. On the following table 6, the results of Pesaran second generation unit root test are presented.

Table 6: Pesaran CADF panel unit root test.

	Pesaran-CIPS			
	Intercept		Intercept and trend	
Variable	t-stat	Prob.	t-stat	Prob.
INN	–2.307**	< 0.05	–3.675*	< 0.01
OPEN	–1.741	> 0.10	10.553	> 0.10
GDP	–0.114	> 0.10	–3.169*	< 0.01
ENER	–1.551	> 0.10	–1.889	> 0.10
FDI	–2.493*	< 0.01	–14.288*	< 0.01
CO_2	–2.350*	< 0.01	–2.377	> 0.10
OIL	0.000	> 0.10	0.000	> 0.10
REN	–1.662	> 0.10	–4.046*	< 0.01
ΔINN	–3.334*	< 0.01	–3.313*	< 0.01
ΔOPEN	–3.489*	< 0.01	–3.751*	< 0.01
ΔGDP	–2.449*	< 0.01	–3.103*	< 0.01
ΔENER	–2.231**	< 0.05	–2.311**	< 0.05
ΔFDI	–9.708*	< 0.01	–4.563*	< 0.01
ΔCO_2	–2.654*	< 0.01	–2.156**	< 0.05
ΔOIL	–2.165**	< 0.05	–2.213**	< 0.05
ΔREN	–3.614*	< 0.01	–5.807*	< 0.01

*Critical values: –2.33, –2.17, –2.08 (Intercept), and –2.83, –2.68, –2.60 (Intercept and Trend) *, ** and ***Indicates 1% ,5% and 10% level of significance respectively, Δ is first difference, The lag lengths from cross-sections were selected using Akaike Information Criterion (AIC).*

6.2. Panel ARDL cointegration test

The variables are integrated I(0) and I(1) order, as can be seen in the previous table. As a result, we employ the autoregressive distributed lag (ARDL) for cointegration testing which can be written as follows:

$$\Delta INN_{it} = a_i + \beta_1 INN_{i,t-1} + \beta_2 OPEN_{i,t-1} + \beta_3 GDP_{i,t-1} + \beta_4 ENER_{i,t-1} + \beta_5 FDI_{i,t-1}$$
$$+ \beta_6 O\ \ 2_{i,t-1} + \beta_7 OIL_{i,t-1} + \beta_8 REN_{i,t-1} + \sum_{i=1}^{p-1} \alpha_{1i} \Delta INN_{i,t-1} = \sum_{i=0}^{q-1} \alpha_{2i} \Delta OPEN_{i,t-1}$$
$$\sum_{i=0}^{q-1} \alpha_{3i} \Delta GDP_{i,t-1} + \sum_{i=0}^{q-1} \alpha_{4i} \Delta ENER_{i,t-1} + \sum_{i=0}^{q-1} \alpha_{5i} \Delta FDI_{i,t-1} + \sum_{i=0}^{q-1} \alpha_{6i} \Delta O\ \ 2_{i,t-1} \quad (3)$$
$$+ \sum_{i=0}^{q-1} \alpha_{7i} \Delta OIL_{i,t-1} + \sum_{i=0}^{q-1} \alpha_{8i} \Delta REN_{i,t-1} + \varepsilon_{it}$$

where Δ is the first difference of variables. Also, α_1–α_8 are the short-run coefficients while β_1–β_8 are the long-run coefficients and ε_{it} is the error term.

Finding out whether there is cointegration between variables is necessary before estimating the cointegration test. We use the Wald F distribution to cointegrate the variables. The results of the cointegration test are shown in **Table 7**.

Table 7: Wald test.

Test Statistics	Value	df	Prob.
F-Statistic	1.5199	(8,766)	0.1463
Chi-square	12.159	8	0.1442

Source: Author's calculations.

If the cointegration is established, meaning there is a long run relationship among variables, then we can create an error correction model.

The results of table 8 indicate that the null hypothesis of non-cointegration is not rejected. So, we conclude that there is no long run relationship among variables. Hence, we proceed with the Pairwise Granger causality test.

6.3. Empirical results from Poisson regression and negative binomial

The results of estimation of Poisson regression and negative binomial regression are on **Tables 8 and 9** respectively.

Table 8: Poisson regression and LR results.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.616598	0.002486	3465.900	0.0000
GDP	6.32×10^{-5}	7.60×10^{-8}	831.7049	0.0000
OPEN	–0.038956	2.72×10^{-5}	–1430.021	0.0000
FDI	3.24×10^{-12}	6.91×10^{-15}	468.4154	0.0000
ENER	0.000234	8.61×10^{-7}	271.4079	0.0000
REN	–0.062313	8.63×10^{-5}	–721.7289	0.0000
CO_2	0.005812	0.000329	17.68167	0.0000
OIL	0.012409	2.32×10^{-5}	533.8467	0.0000
LR statistic	5157022			0.0000

Source: Author's calculations.

Table 9: Negative binomial results.

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	9.080031	0.164639	55.15108	0.0000
GDP	5.27×10^{-7}	3.04×10^{-6}	17.34664	0.0000
OPEN	–0.029359	0.000658	–44.60339	0.0000
FDI	4.13×10^{-12}	7.42×10^{-13}	5.560813	0.0000
ENER	0.000413	6.05×10^{-5}	6.824329	0.0000
REN	–0.069804	0.004329	–16.12596	0.0000
CO_2	–0.194600	0.023127	–8.414259	0.0000
OIL	0.014888	0.001363	10.92062	0.0000

According to Poisson regression, the results show that all independent variables (macroeconomic and environmental) are significantly related with innovation. Moreover, the LR test results reject the null hypothesis of the equality of average and variance. Hence, the data are extremely dispersed, and this dispersion creates problem on Poisson regression. To deal with this problem, we use the negative binomial model.

The results of the above table show that trade openness, renewable energy sources and dioxide emissions have significant and negative relationship with innovation, whereas GDP, investment, energy consumption and oil prices have significant and positive relationship with innovation.

6.4. Pairwise Dumitrescu Hurlin panel causality tests

The causal dynamic relationship among variables can be traced from the paper of Granger (1969) who developed a causality test based on time series data. A prerequisite of Granger's (1969) causality test is that the two-time series must be cointegrated. As the Wald test results showed that there is no cointegration and the test of Breusch and Pagan (1980) also showed that there is an individual heterogeneity on the random effects model, that is the reason we use the Dumitrescu and Hurlin (2012) test for variables' causality. Dumitrescu and Hurlin (2012) developed a procedure implementing pairwise the non-Granger causality test with heterogeneous panel data. Dumitrescu and Hurlin test can forecast the cross-section dependency and cross-section independence. The underlying regression is:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + e_{i,t} \quad \text{with } i = 1,\ldots,N \text{ and } t = 1,\ldots,T \tag{4}$$

where $y_{i,t}$ and $x_{i,t}$ are the observations of two stationary variables for individual i in period t. Coefficients are allowed to differ across individuals but are assumed to be time invariant. The lag order K is assumed to be identical for all individuals, and the panel must be balanced. To determine the outcome of Dumitrescu and Hurlin panel causality test hypotheses, use a W-statistic, which means of all test statistics of cross-sectional units as well as a harmonized Z-statistic accordingly if $T > N$ or $T < N$. On the following **Table 10**, the results of Dumitrescu and Hurlin, (2012) test are provided.

Table 10: Pairwise Dumitrescu Hurlin Panel Causality tests.

Null hypothesis:	W-Stat.	Zbar-Stat.	Prob.
ΔENER does not homogeneously cause ΔCO_2	2.13360	–0.12263	0.9024
ΔCO_2 does not homogeneously cause ΔENER	2.35591	0.35668	0.7213
ΔFDI does not homogeneously cause ΔCO_2	2.09870	–0.19788	0.8431
ΔCO_2 does not homogeneously cause ΔFDI	2.01290	–0.38285	0.7018
ΔGDP does not homogeneously cause ΔCO_2	1.97733	–0.45955	0.6458
ΔCO_2 does not homogeneously cause ΔGDP	2.60969	0.90383	0.3661
ΔINN does not homogeneously cause ΔCO_2	1.92117	–0.58063	0.5615
ΔCO_2 does not homogeneously cause ΔINN	**6.53096**	**9.35825**	**0.0000**
ΔOIL does not homogeneously cause ΔCO_2	**4.30025**	**4.54876**	**5×10^{-6}**
ΔCO_2 does not homogeneously cause ΔOIL	**1.05671**	**–2.44444**	**0.0145**
ΔOPEN does not homogeneously cause ΔCO_2	1.61141	–1.24848	0.2119
ΔCO2 does not homogeneously cause ΔOPEN	1.73214	–0.98818	0.3231
ΔREN does not homogeneously cause ΔCO_2	**3.07723**	**1.91188**	**0.0559**
ΔCO_2 does not homogeneously cause ΔREN	**3.94180**	**3.77591**	**0.0002**
ΔFDI does not homogeneously cause ΔENER	2.62886	0.94518	0.3446
ΔENER does not homogeneously cause ΔFDI	1.76686	–0.91334	0.3611
ΔGDP does not homogeneously cause ΔENER	2.79729	1.30832	0.1908
ΔENER does not homogeneously cause ΔGDP	1.53794	–1.40690	0.1595
ΔINN does not homogeneously cause ΔENER	2.24245	0.11206	0.9108
ΔENER does not homogeneously cause ΔINN	**4.53201**	**5.04844**	**4×10^{-7}**
ΔOIL does not homogeneously cause ΔENER	**3.99078**	**3.88152**	**0.0001**
ΔENER does not homogeneously cause ΔOIL	**1.16162**	**–2.21825**	**0.0265**
ΔOPEN does not homogeneously cause ΔENER	2.84635	1.41409	0.1573
ΔENER does not homogeneously causeΔOPEN	**1.27568**	**-1.97233**	**0.0486**
ΔREN does not homogeneously cause ΔENER	**3.76383**	**3.39220**	**0.0007**
ΔENER does not homogeneously cause ΔREN	**3.68470**	**3.22160**	**0.0013**
ΔGDP does not homogeneously cause ΔFDI	**4.02470**	**3.95465**	**8×10^{-5}**
ΔFDI does not homogeneously cause ΔGDP	2.85939	1.44219	0.1492
ΔINN does not homogeneously cause ΔFDI	1.60413	–1.26418	0.2062
ΔFDI does not homogeneously cause ΔINN	1.47241	–1.54818	0.1216
ΔOIL does not homogeneously cause ΔFDI	**3.23173**	**2.24498**	**0.0248**
ΔFDI does not homogeneously cause ΔOIL	**4.39068**	**4.74372**	**2×10^{-6}**
ΔOPEN does not homogeneously cause ΔFDI	2.16169	–0.06207	0.9505
ΔFDI does not homogeneously cause ΔOPEN	**3.83060**	**3.53616**	**0.0004**
ΔREN does not homogeneously cause ΔFDI	2.32805	0.29661	0.7668
ΔFDI does not homogeneously cause ΔREN	2.53674	0.74657	0.4553
ΔINN does not homogeneously cause ΔGDP	1.97035	–0.47459	0.6351
ΔGDP does not homogeneously cause ΔINN	1.74075	–0.96962	0.3322
ΔOIL does not homogeneously cause ΔGDP	1.81314	–0.81354	0.4159
ΔGDP does not homogeneously cause ΔOIL	2.24092	0.10875	0.9134
ΔOPEN does not homogeneously cause ΔGDP	1.77774	–0.88987	0.3735
ΔGDP does not homogeneously cause ΔOPEN	**4.19899**	**4.33044**	**1×10^{-5}**
ΔREN does not homogeneously cause ΔGDP	2.91278	1.55732	0.1194
ΔGDP does not homogeneously cause ΔREN	**4.43059**	**4.82977**	**1×10^{-6}**
ΔOIL does not homogeneously cause ΔINN	2.07728	–0.24405	0.8072
ΔINN does not homogeneously cause ΔOIL	1.95486	–0.50800	0.6115
ΔOPEN does not homogeneously cause ΔINN	2.24499	0.11754	0.9064
ΔINN does not homogeneously cause ΔOPEN	1.80477	–0.83159	0.4056
ΔREN does not homogeneously cause ΔINN	2.82208	1.36175	0.1733
ΔINN does not homogeneously cause ΔREN	2.01941	–0.36882	0.7123
ΔOPEN does not homogeneously cause ΔOIL	2.31646	0.27162	0.7859
ΔOIL does not homogeneously cause ΔOPEN	**0.80912**	**–2.97825**	**0.0029**
ΔREN does not homogeneously cause ΔOIL	2.05804	–0.28554	0.7752
ΔOIL does not homogeneously cause ΔREN	**6.14534**	**8.52683**	**0.0000**
ΔREN does not homogeneously cause ΔOPEN	2.19897	0.01831	0.9854
ΔOPEN does not homogeneously cause ΔREN	1.47099	–1.55125	0.1208

From the above results, we conclude that there is a unidirectional causal relationship from per capita CO_2 emissions and per capita energy consumption to innovation.

7. Discussion

Literature shows that imports and exports can improve technology. So, there is a positive correlation between market openness and innovation adoption (Lazzarotti et al., 2017). On the results of our paper there is a negative relationship between trade openness and innovation matching with that of Selcuk et al. (2022). The negative and significant relationship between trade openness and innovation as well as the non causal relationship between them can be explained from the high income of EU members that do not necessarily depend on high technology products. The impact of GDP on innovation is positive and significant as mentioned in the literature (Vetsikas and Stamboulis, 2021). In addition, the paper showed that there is a significant, positive and causal relationship between energy consumption and innovation. As energy consumption is increasing, countries allocate more sources for innovation providing energy efficiency. There is a negative and non causal relationship between renewable energy sources and innovation. This finding is confirmed from the small or minimal development of renewable energy sources on 27 EU countries. The effect of foreign direct investment is significant and positive. This result matches with the papers of Ghimire and Paudel (2019) and Osabuohien-Irabor and Drapkin (2022). There is a significant negative relationship between CO_2 emissions and innovation as well as unidirectional causal relationship from CO_2 emissions to innovation. These results consent to the papers of Su and Moaniba, (2017), and to the paper of Solarin et al. (2022) showing the negative relationship between the innovation on climate change and CO_2 emissions coming from fossil fuel consumption. Finally, the impact of oil price on innovation is positive and significant, according to the papers of Guillouzouic-Le Corff (2018) and that of Nunes and Catalão-Lopes (2020). The increase of oil price mainly after the war in Ukraine, will motivate the countries of EU to use alternative energy sources like sun and wind.

8. Conclusion

Strengthening innovation is considered a difficult policy objective in many countries because it prioritizes new high-level skills as it involves significant adjustment to new technologies. The strategy to promote and enhance innovation can contribute to the achievement of social and environmental goals, building a foundation for future economic growth (Gedikli and Derindag, 2023).

On the paper we examine how innovation has been affected from selected macroeconomic and environmental variables on EU member countries. The environmental variables used like CO_2 emissions and renewable energy sources affect negatively innovation while energy consumption has a positive impact on innovation. From the macroeconomic variables, trade openness negatively affects innovation whereas the other macroeconomic variables such as GDP, investment and oil prices have a positive impact on innovation.

The effect of macroeconomic and environmental variables on innovation differs across EU countries due to different economic structure and environmental approaches related with natural and energy sources of each country. Structural measures for the promotion of innovation consist of the increase of R&D expenditure and education investment, and enabling entrepreneurs to begin new enterprises and for failed businesses to exit the market more quickly. The results vary from country to country according to factors (macroeconomic and environmental) used in the empirical research. From 27 EU countries, only three of them are numbered among the ten best countries worldwide on the global competitiveness indicator. There is a gap in R&D expenditure among 27 member countries. Furthermore, the diffusion for innovation on EU countries seems to be quite slow. There is an important difference between innovation of productive and less productive countries. It must be highlighted that innovation is important on facing global challenges such as climate change and sustainable growth.

Government policies of EU member countries can support innovation with continuous reforms and update of the regulatory and institutional framework when the innovative activity takes place. On this framework, reforms are required and governments should make policy and enforce regulations that foster innovation more in a series of policy sectors to the entrepreneurial environment, to the services of industrial network, to international trade and international investments, financial markets, labor markets and education.

Author contributions

Conceptualization, MD and CD; methodology, MD; software, CD; validation, MD and CD; formal analysis, MD; investigation, CD; resources, CD; data curation, TE; writing — original draft preparation, CD; writing — review and editing, MD. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

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