Journal of Infrastructure, Policy and Development 2024, 8(6), 4462.
https://doi.org/10.24294/jipd.v8i6.4462

Article

The impact of greenhouse gas emissions and economic growth on health expenditure of EU countries: A panel data analysis

Melina Dritsaki[1,*], Chaido Dritsaki[2], Vasileios Argyriou[3], Panagiotis Sarigiannidis[4,5]

[1] Department of Economics, University of Western Macedonia, 52100 Kastoria, Greece
[2] Department of Accounting and Finance, University of Western Macedonia, Kila Kozanis, 50100 Kozani, Greece
[3] Department of Networks and Digital Media, Kingston University, KT1 2EE Kingston upon Thames, United Kingdom
[4] R&D Department, MetaMind Innovations P.C., 50100 Kozani, Greece
[5] Department of Electrical and Computer Engineering, University of Western Macedonia, 50100 Kozani, Greece
*** Corresponding author:** Melina Dritsaki, mdritsaki@uowm.gr

CITATION

Dritsaki M, Dritsaki C, Argyriou V, Sarigiannidis P. (2024). The impact of greenhouse gas emissions and economic growth on health expenditure of EU countries: A panel data analysis. Journal of Infrastructure, Policy and Development. 8(6): 4462. https://doi.org/10.24294/jipd.v8i6.4462

ARTICLE INFO

Received: 29 January 2024
Accepted: 7 March 2024
Available online: 18 June 2024

Abstract: The increase in energy consumption is closely linked to environmental pollution. Healthcare spending has increased significantly in recent years in all countries, especially after the pandemic. The link between healthcare spending, greenhouse gas emissions and gross domestic product has led many researchers to use modelling techniques to assess this relationship. For this purpose, this paper analyzes the relationship between per capita healthcare expenditure, per capita gross domestic product and per capita greenhouse gas emissions in the 27 EU countries for the period 2000 to 2020 using Error Correction Westerlund, and Westerlund and Edgerton Lagrange Multiplier (LM) bootstrap panel cointegration test. The estimation of model coefficients was carried out using the Augmented Mean Group (AMG) method adopted by Eberhardt and Teal, when there is heterogeneity and cross-sectional dependence in cross-sectional units. In addition, Dumitrescu and Hurlin test has been used to detect causality. The findings of the study showed that in the long run, per capita emissions of greenhouse gases have a negative effect on per capita health expenditure, except from the case of Greece, Lithuania, Luxembourg and Latvia. On the other hand, long-term individual co-integration factors of GDP per capita have a positively strong impact on health expenditure per capita in all EU countries. Finally, Dumitrescu and Urlin's causality results reveal a significant one-way causality relationship from GDP per capita and CO_2 emissions per capita to healthcare expenditure per capita for all EU countries.

Keywords: European countries; climate change; CO_2 emissions; health expenditures; economic growth; panel data
JEL Classification: C22; C23; I10

1. Introduction

The last decades, the relationship between the quality of environment, economic growth and health expenditure has drawn the attention of many researchers. It is undeniable that there are many papers regarding the relationship between health expenditure and dioxide carbon emissions CO_2 or the relationship between health expenditure and economic growth. However, there are very few papers that examine the relationship of all the three variables together. In our paper we examine the consequences of CO_2 emissions and growth of 27 EU countries on health expenditure.

The quality of human capital significantly relies on the paramount importance of health, as it relates to its sustainability and well-being. CO_2 emissions cause climate change which influences public health care and total economic production (Abdullah et al., 2017). According to Portney (2013), human capital promotes economic growth.

Thus, it is necessary to examine how CO_2 dioxide emissions can cause damage on quality of life and how it can change productivity and the cost of health care.

United Nations (UN) in 2015 suggested Sustainable Growth Goals that should be achieved until 2030 reporting that the main objectives are good health and prosperity. Good health is a fundamental human right. However, past and recent pandemics and epidemic diseases call for the re-examination for particular issues regarding health worldwide. Nowadays, people are forced to pay a high price for their health and their life due to ignorance and lack of suitable examination of various factors related to health such as energy, environment and private and public health expenditure. The challenges from COVID-19 have made the implementation of these goals compulsory (United Nations, 2015).

Climate change is a very serious threat, and its consequences affect many different aspects of our lives. Global warming, mainly from the use of fossil fuels, adds carbon dioxide and methane to greenhouse gases, among other things. Extreme weather events are increasingly occurring in many regions of the world, posing a serious threat to human survival.

It is well known that climate and weather conditions affect human health. This means that global climate change is altering the conditions related to economic growth, environmental degradation, healthcare spending and the overall well-being of populations. This is a considerable effect, which is not taken into account with due care.

CO_2 emissions from OECD countries represent half of world CO_2 emissions. However, CO_2 emissions in OECD countries have reduced from 2001. CO_2 emissions per GDP unit reduced from 4.9 kg/USD in 2001 to 2.7 kg/USD in 2015. The share of CO_2 emissions on worldwide CO_2 emissions also reduced from 54% in 2001 to 38% in 2015 (Liu et al., 2019). The average per capita CO_2 emissions of 27 EU countries for the year 2020 is 5.84 tons.

After the validation of Kyoto Protocol, EU member countries had to comply with the treaty's commitments. The protocol gave a significant latitude regarding the accomplishment of the common goal for European Union for the reduction 8% of GHG emissions until 2012 in relation to the levels in 1990. EU member countries already agreed for the internal distribution per country on carbon reduction in 1999 (Dritsaki and Dritsaki, 2023).

European Union Emissions Trading System (EU ETS) began in 2005 and operates in phases. The first phase, from 2005 until 2007, was a pilot phase in order for the system to be put into action. The second phase covered the commitment period of Kyoto Protocol from 2008 until 2012. Finally, the third phase begun in 2013 until 2020. **Figure 1** presents these three phases of CO_2 emissions for EU for the cost of 1ton CO_2 on EU ETS from 2005 until 2016 (see Bayera and Aklin (2020, p. 8805)).

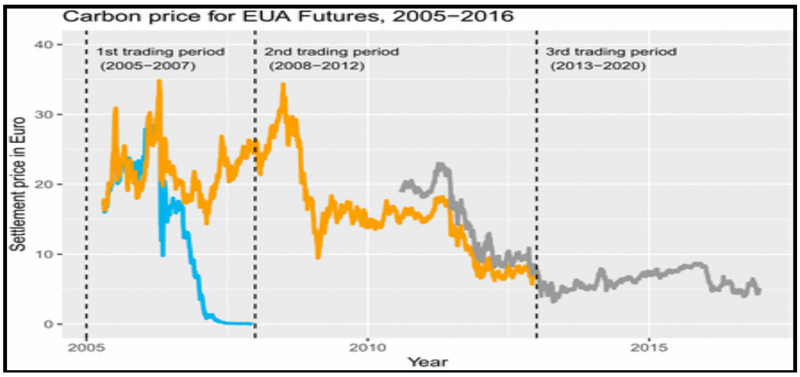

Figure 1. Carbon price for European Union Allowance (EUA), from 2005–2016 (Source: Intercontinental Exchange (ICE Futures Europe), accessed through Quandl (CZ2007, CZ2012, and CZ2016)).

The graph on **Figure 1** shows EU Allowance (EUA) settlement prices on future markets at maturity December 2007 (blue), December 2012 (yellow) and December 2016 (grey). The dotted vertical lines signify transaction period. Due to the fact that the licenses could not be transferred from the first to the second negotiation period, the prices reduced to zero in December 2007 (see Bayera and Aklin (2020, p. 8805)).

A common characteristic in all European countries (and generally in OECD countries), apart from their economic structure and health care systems, is the gradual gradation on GDP's share heading to health care during time. Expenditure for health care has increased from 8.6% of GDP on EU in 1998 to 9.7% in 2010 and 10.7% in 2020. The forecast in 2030 is 11.8% according to OECD. The rapid progress on medical technology, population ageing and the increase of public expenditure push for further growth **(**Dritsaki and Dritsaki, 2023).

On the diagram below (**Figure 2**), the progression of CO_2 emissions in 27 EU countries from 1800–2020 is presented.

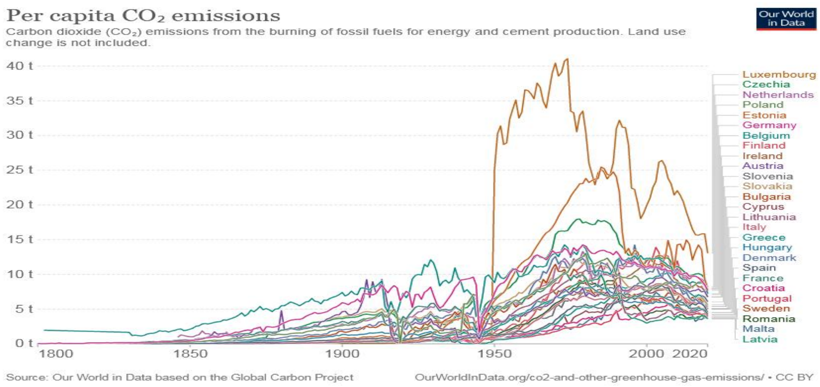

Figure 2. The progression of per capita carbon dioxide emissions (CO_2) on 27 EU countries from 1800–2020 (Source: Our World in Data based on the Global Carbon Project).

From **Figure 2** above we can see that there is a substantial decrease on per capita carbon dioxide emissions CO_2 in all 27 EU countries starting from 1980. The largest reduction occurs from 2002, the year after Kyoto's Protocol validation.

The aim of this paper is to examine the relationship between per capita healthcare expenditure, per capita CO_2 emissions and per capita GDP in the 27 EU countries during the period 2000–2020.The methods used in this paper are as follows:

- It uses the PVAR method that treats all variables as endogenous.
- Uses the test of Hausmam (1978), for the suitability between the fixed and random effects model.
- Uses the Breusch-Pagal (1980) LM, Pesaran Scaled (2004) LM_s, Pesaran (2004) CD_p, and Baltagi et al. (2012) test for the cross-sectional dependence of the residuals.
- Uses second generation unit-root tests Cross-Augmented Dickey-Fuller (CADF) and Cross Im-Pesaran-Shin (CIPS) Pesaran (2007) when cross-sectional unit dependence exists.
- For cointegration testing it uses the ECM test of Westerlund (2007), as well as the LM bootstrap test of Westerlund, and Edgerton (2007), for the long- and short-term relationship of variables.
- Uses the Augmented Mean Group (AMG) method adopted by Eberhardt and Teal (2010), for model estimation, as well as solutions to heterogeneity bias.
- Uses the Delta statistics test of Pesaran and Yamagata (2008) for the homogeneity of the slope of cointegration coefficients.
- Finally, it uses the causality test of Dumitrescu and Hurlin (2012) that takes into account cross-sectional independence-dependence, and heterogeneity of coefficients.

The main motivation of this study is based on: 1) Investigating the influence of CO_2 emissions and the growth of the 27 EU nations between 2000 and 2020 on health expenditure. This involves conducting panel cointegration tests to assess the long-term and short-term relationships among variables as well as performing causality analysis to examine cross-sectional dependence and analyze the heterogeneity of coefficients. 2) The effect of per capita greenhouse gas emissions on per capita health expenditure in the 27 EU countries. 3) The impact of greenhouse gas emissions per capita on GDP per capita of EU countries. 4) The impact of GDP per capita on health expenditure per capita in the 27 EU countries.

The paper is organized as follows: Section 2 introduces a recent literature review. Section 3 presents the data and methodology follows in section 4. Section 5 specifies the main results of the paper and finally, conclusion is given in section 6.

2. Literature review

Research on the environment, economic growth and healthcare spending has stood out as a popular subject of research in economy literature in recent years. Studies covering both developed and developing countries can be categorized into four groups. The initial group concentrates on the correlation between economic growth and CO_2 emissions (the environmental Kuznets curve hypothesis). The second group includes studies investigating the relationship between CO_2 emissions and healthcare expenditure. The link between healthcare spending and economic development has been the main interest of the third group. The fourth group consists of papers investigating environmental pollution, economic development and healthcare expenditure.

2.1. CO_2 emissions and economic growth

Many studies showed that in countries that use traditional energy sources, economic growth increases CO_2 emissions. According to the Kuznets environmental curve (inverted U-shaped curve) there is a hypothetical nexus between environmental degradation and economic development that suggests that the intensity of environmental degradation tends to increase as average income increases up to a certain point (Seker et al., 2015). Recent models of economic growth show that countries that consume more energy to promote economic growth, bring changes on CO2 emissions and end up with conflicting evidence (i.e., positive or negative correlations).

Kong and Khan (2019) in their work for 15 developing and 14 developed countries using panel data and the generalized method of moments (GMM) confirmed the Kuznets environmental curve hypothesis.

For the relationship between economic growth energy consumption, and CO_2 emissions in Thailand, Adebayo and Akinsola (2021) used wavelet coherence method for the period 1971 until 2018. The findings of their study indicated a positive correlation between CO_2 emissions and GDP growth in both the short and long term.

Using data and the ARDL model from 1985 until 2019 for China, Kong (2021) examined the relationship between economic growth, foreign direct investment and energy consumption, and concluded that real GDP has a positive impact on CO_2 emissions.

Cheikh et al. (2021) using a regime-switching model examined the link between energy consumption and economic growth in the Middle East and North Africa, discovering that economic growth has asymmetric effects on CO_2 emissions.

Isik et al. (2020) employed panel bootstrap cointegration to investigate the impact of increased consumption of renewable energy sources and international tourism income in G7 countries from 1995 to 2015. Their findings revealed that the augmented consumption of renewable energy sources positively influenced the growth of tourism income in countries like France, Italy, and the United Kingdom, while it had a negative impact on carbon dioxide emissions in the USA.

Phrakhruopatnontakitti et al. (2020), through the Environmental Kuznets Curve (EKC) and a VAR model, investigate the relationship between CO_2 emissions, energy consumption, and economic growth in four Asian countries during the period 1971–2005. Using the Error-Correction-Model, they found that energy consumption has a positive long-term impact on CO_2 emissions. The causality results through the error-correction model indicated a bidirectional long-term causal relationship between energy consumption and CO_2 emissions, as well as between energy consumption and economic growth. Additionally, the research showed a unidirectional short-term causal relationship from CO_2 emissions and energy consumption towards economic growth.

Meirun et al. (2021) explore the relationship between green technology innovation and economic development in Singapore from 1990 to 2018. For their analysis, they employ the bootstrap autoregressive-distributed lag-BARDL technique to examine the long-term and short-term relationship of these variables. The results of their study demonstrated a positive and significant relationship between innovation in green technology and economic development, both in the long term and short term. Furthermore, their findings indicate a negative and significant relationship, both in the long term and short term, between carbon dioxide emissions and economic development in Singapore during the period under examination.

2.2. CO_2 emissions and health expenditure

Most of the papers which have investigated the relationship between CO_2 emissions and health care expenditure have ended up in similar conclusions where the increase of CO_2 emissions, increase medical expenses.

Alimi et al. (2019) studied the linkage between the quality of environment and expenditure in health in 15 West African countries over the period 1995–2014. Using the generalized method of moments (GMM) they found that there is no link between private healthcare spending and environmental pollution, but there is a positive effect of environmental pollution derived from public healthcare spending.

Apergis et al. (2020) investigated relationship between environment pollution and health care expenditure in the long-run for 178 countries from 1995 until 2017. Their paper determined that for 1% of increase of CO_2 emissions, health expenditure will increase by 2.5%.

The relationship between carbon emissions, energy consumption and public health expenditure in various USA states was studied by Eckelmam et al. (2020). With their study, they concluded that there is no relationship between CO_2 emissions and public health expenditure.

Oyelade et al. (2020) studied the relationship between CO_2 emissions and public health expenditure for West Africa countries from 1990 until 2013 using panel quantile regression analysis. Their results showed that the increase of CO_2 emissions will increase public health expenditure.

Akbar et al. (2021) investigated the link between expenditure in health, carbon dioxide emissions and human development index (HDI) in 33 OECD countries from 2006 until 2016. The study's results suggest a two-way causal relationship between healthcare expenses and carbon emissions.

2.3. Healthcare expenditure and economic growth

Many researchers are claiming that there is a positive relationship between economic growth and healthcare expenses. Several studies have shown that improvements in healthcare can lead to GDP growth and vice versa (Fuchs, 2013; Ozturk and Topcu, 2014). Moreover, Piabuo and Tieguhong (2017) showed that increased spending on health increases human capital productivity and contributes positively to economic growth.

Gok et al. (2018) examined the connection between the efficiency of health expenditure and economic growth in emerging economies during the period from 2008 to 2012. The study revealed that economic growth can substantially enhance the efficiency of health expenditure in the countries analyzed. Atems (2019) studied the relationship between public health expenditure and economic growth in various states of USA from 1963 until 2015 ended up with a positive correlation between the two variables under examination.

Modibbo and Saibu (2020) studied the impact of healthcare expenditure on economic growth using the Generalized Method of Moments (GMM) in 45 African countries during 2000–2017. The results suggested that health expenses have a positive and significant impact on the economic growth of Africa.

Beylik et al. (2022) examine the relationship between healthcare spending and economic growth in 21 OECD countries over the period 1990–2019, using the Driscoll-Kraay standard error approach to panel data. In their study, they used GDP and income per capita as dependent variables and as independent variables refer to healthcare expenditure. The results of their work on the first model showed that a 1% increase in private health spending would bring a GDP increase of 0.04%, while a 1% increase from public healthcare services would bring a GDP increase of 0.09%. In the second model, a 1% increase in private health spending will have a diminishing effect on per capita income, while a 1% increase in public health services will bring an increase in per capita income of 0.06%.

2.4. CO_2 emissions, health expenditure, and economic growth

The literature on the relationship between CO_2 emissions, healthcare spending and economic growth is very limited. Most authors have examined relationships between two variables only. There are only a few papers referring to all three variables. The most recent of them are presented below.

Wang et al. (2020) applied the Bootstrap ARDL test to explore the connection between healthcare expenditure and carbon dioxide emissions in China within the context of economic development. The study's findings indicated that, over the long term, both carbon dioxide emissions and health expenditures exert a notable influence on China's economic development.

Atuahene et al. (2020) used the generalized method of moments (GMM) and data from 1690 to 2019 in order to examine the relationship between CO_2 emissions, economic development and healthcare expenses for China and India. Their conclusion highlighted a noteworthy correlation among the three variables. To elaborate, carbon dioxide emissions exhibited a substantial positive influence on healthcare expenditure, while economic growth demonstrated a negative impact on healthcare expenditure.

Li et al. (2022) used a Fourier ARDL model to examine the correlation between healthcare expenditure, CO_2 emissions and GDP variations for BRICS countries between 2000–2019. On their results, they noted that in the long run, Brazil and China depict cointegration relationships between health expenditure, CO_2 emissions and economic growth.

Qehaja et al. (2023) investigate the impact of healthcare spending on economic growth in the Western Balkan countries in the period 2000–2020. Their analysis is conducted using three econometric models: the ordinary least squares (OLS), the fixed effects (FEM) and the random effects (REM). The results showed that healthcare spending has a positive and significant impact on the economic development of all Western Balkan countries.

Haseeb et al. (2019) examine the impact of energy consumption, economic growth, and environmental pollution on healthcare expenditures, as well as on research and development (R&D) expenditures in Asian countries from 2009 to 2018. To analyze the short-term and long-term relationships of these variables, they utilized the ARDL approach in both models. Their study results indicated that, at the long-term level, energy consumption, economic growth, and environmental pollution have a positive impact on healthcare expenditures. Additionally, at the long-term level, energy consumption and economic growth positively influence expenditures on research and technology. Furthermore, findings revealed that environmental pollution and economic growth have a significant impact on short-term research and technology expenditures. Finally, they show that environmental pollution has an insignificant effect on short-term healthcare expenditures.

3. Research methods

3.1. Data

The annual data used in this study cover the period 2000–2020 for the 27 EU countries. Source of data is the database of the World Bank. The variables used in are health expenditure per capita (HEC), GDP per capita (GDPC) as an indicator of the level of economic development and, per capita greenhouse gas emissions (GHGC). Greenhouse gas emissions per capita were measured in metric tons, GDP per capita was calculated based on current prices expressed in US dollars on PPP, and healthcare expenditure per capita is expressed in US dollars on PPP. At this point we should clarify that greenhouse emissions including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O). In this framework, they are converted in an index which is expressed in CO_2 units evenly using the dynamic of global warming of each of the aforementioned gas (see Anwar et al. (2021)).

The sample study consists of 27 member countries of EU particularly 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) and the study period is from 2000 until 2020. EViews 13.0 and Stata 14.0 softwares were used to estimate the models. All variables and their symbols together with data sources are presented on the following **Table 1**.

Table 1. Data description.

Variables	Description	Source
HEC	Current health expenditure per capita (PPP current international $)	World Development Indicators database, World Bank
GDPC	GDP per capita, PPP (current international $)	World Development Indicators database, World Bank
GHGC	Greenhouse gas emissions per capita (in metric tons per capita)	World Development Indicators database, World Bank

3.2. Random effects vs. fixed effects estimation

The selection between the model of fixed effects and random effects is made by applying Hausman's (1978) control test. The null hypothesis of the model suggest that there is no difference between the estimated coefficients (fixed and random models). Specifically, the test of null hypothesis is accomplished with the following statistical criterion:

$$H = (\hat{\beta}_{FE} - \hat{\beta}_{RE})'\left[Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})\right]^{-1}(\hat{\beta}_{FE} - \hat{\beta}_{RE}) \tag{1}$$

which follows the χ^2 distribution with degrees of freedom equal to the rank of variance matrix $Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})$. The $\hat{\beta}_{FE}$ and $\hat{\beta}_{RE}$ are estimated coefficients of fixed and random effects respectively (see Dritsakis et al. (2021, p. 404)). For values larger than the critical values of χ^2 distribution, on a given level of significance, the hypothesis that the random estimation, does not differ from fixed estimation is rejected.

In other words, we could say that for the selection of models between fixed and random effects we apply the following hypotheses:

H_0: The random effects model is suitable.

H_1: The fixed effects model is suitable.

The empirical model used in our paper using the logarithms of variables is the following:

$$LHEC_{i,t} = b_0 + b_1 LGDPC_{i,t} + b_2 LGHGC_{i,t} + u_{i,t} \tag{2}$$

where t indicates time period $t = 1, \ldots, T$, i indicated the cross-sectional unit $i = 1, \ldots, N$ and $\mu_{i,t}$ is the error term (idiosyncratic error) and incorporates the unobserved factors that affect the dependent variable and change over time. LHEC, LGDPC and LGHGC are the natural logarithms of the corresponding variables.

In Equation (2) β_1 coefficient is expected to be positive. β_1 measures the effect of per capita GDP on the per capita health care expenditure. If β_1 is between 0 and 1, $0 \leq \frac{\partial LHCE_{i,t}}{\partial LGDPC_{i,t}} = \beta_1 \leq 1$ then per capita expenditure for health care is a necessity good. If β_1 is greater than 1, $\frac{\partial LHCE_{i,t}}{\partial LGDPC_{i,t}} = \beta_1 > 1$ then per capita expenditure for health care is a luxury good (see Abdullah et al. (2017)).

3.3. Cross sectional dependence

In order to test for cross sectional dependence (correlation) among residuals we apply tests by Breusch-Pagan (1980) *LM*, Pesaran Scaled (2004) LM_s, Pesaran (2004) CD_p, and Baltagi et al. (2012). Based on Ari and Senturk (2020) these tests can be used both for balanced and unbalanced panels. The above cross-sectional dependence tests follow the equation below:

$$y_{i,t} = \alpha_i + \beta'_{i,t} x_{i,t} + u_{i,t} \tag{3}$$

The null hypothesis (H_0) for the equation above is: H_0: $\hat{\rho}_{ij} = Corr\left(u_{it}, u_{jt}\right) = 0$ for $i \neq j$ (there are no cross-sectional relationships between units).

Breusch-Pagan test for panel dependence is given with the Lagrange statistic from the following equation:

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{4}$$

The *LM* follows asymptotically the χ^2 distribution with $\frac{N(N-1)}{2}$ degrees of freedom.

The Scaled LM_s of Pesaran is given from the following equation.

$$LM_s = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T_{ij}\hat{\rho}_{ij}^2 - 1\right)} \quad (5)$$

The LM_s follows asymptotically the normal distribution $N(0,1)$.

The *CD* test of Pesaran (2004) is given from the following equation:

$$CD_p = \sqrt{\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T_{ij}\hat{\rho}_{ij}^2\right)} \quad (6)$$

The CD_p follows asymptotically the normal distribution $N(0,1)$.

The bias-corrected scaled LM test of Baltagi et al. (2012) is given by the equation below:

$$LM_{BC} = \sqrt{\frac{1}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\left(T_{ij}\hat{\rho}_{ij}^2 - 1\right)} - \frac{N}{2(T-1)} \quad (7)$$

The LM_{BC} follows asymptotically the normal distribution $N(0,1)$.

In the Equations (4)–(7) *N* denotes the cross-sectional units, *T* displays the time period and $\hat{\rho}_{ij}$ indicates the coefficient of pair-wise correlation obtained from OLS estimation for each cross-section dimension *i*.

3.4. Slope homogeneity tests

In order to test the slope homogeneity of coefficients' in cointegration equation, we use the Delta test of Pesaran and Yamagata (2008). Pesaran and Yamagata (2008) improved the slope homogeneity coefficient tests of Swamy (1970) and formed two new Delta statistics $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ as follows:

$$\tilde{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \quad (8)$$

where: *N* is the number of cross-section unit, $\tilde{S}$ denotes the statistical test of Swamy (1970) and *k* are the independent variables of the model.

If the *p* value of the test is larger than 5%, the null hypothesis and cointegration coefficients are regarded as homogenous.

If the errors are normally distributed, then the bias adjustment of mean variance $\tilde{\Delta}$ can be expressed as: (see Dritsaki and Dritsaki (2023)).

$$\tilde{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\tilde{z}_{iT})}{\sqrt{Var(\tilde{z}_{iT})}}\right) \quad (9)$$

where $E(\tilde{z}_{iT}) = k$ and $Var(\tilde{z}_{iT}) = \frac{zk(T-k-1)}{T+1}$.

Panel estimation methods that don't consider the panel dependence and heterogeneity between units, may lead to biased and inconsistent estimates. Therefore, the cross sections dependencies are one for the primary diagnostic tests to be conducted prior to any panel data analysis.

3.5. Panel unit root tests

In order to conduct a unit root test for panel data, we apply the Cross-Augmented Dickey-Fuller (CADF) test and Cross Im-Pesaran-Shin (CIPS) second generation test of Pesaran (2007) when a dependence between cross-sectional units exist. CADF test is given by the following equation:

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{j=0}^{p} \delta_{i,j} \Delta \bar{y}_{t-j} + \sum_{j=0}^{p} \lambda_{i,j} \Delta y_{i,t-j} + \varepsilon_{i,t} \quad (10)$$

where $i = 1, \ldots, N$, $t = 1, \ldots, T$, $\bar{y}_{t-1}$ is the mean of the lags at their levels, $\Delta\bar{y}_{t-1}$ is the mean of lags at their first differences, and $e_{i,t}$ are the error terms.

CIPS test is a modification of the first-generation Im-Pesaran-Shin (2003) test. It is calculated based on the mean value of *t* statistics of the lagged variables of *CADF* regressions and is given by:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_i \quad (11)$$

where $CADF_i$ represents the cross-sectional *ADF* statistics for *i* cross-sectional unit.

The null hypothesis of *CADF* test implies that the series has unit root. The alternative hypothesis suggests that there is stationarity in at least one series. The *CADF* test furthermore examines the dependence both inside and between the cross-sectional units and operates also in small samples.

3.6. Panel cointegration tests

If the unit root hypothesis is rejected for all variables, then there is cointegration. The cointegration test of Westerlund (2007) is the most suitable for the following reasons. This test can be used not only when there are cross-sectional dependencies but also when these dependencies are absent. If there is a dependency among units, the bootstrap distribution is used, whereas when there is no dependency, the asymptotic normal distribution is used. The cointegration test of Westerlund (2007) is employed through an error correction model which has the following form (see Persyn and Westerlund (2008, p. 233)).

$$\Delta y_{i,t} = \delta_i' d_t + \alpha_i \left(y_{i,t-1} + \beta_i' x_{i,t-1}\right) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \vartheta_{ij} \Delta x_{i,t-j} + e_{i,t} \quad (12)$$

where *t* denotes the time period $t = 1, \ldots, T$, and *i* the cross-sectional unit $i = 1, \ldots, N$, $y_{i,t}$ is an endogenous variable, $x_{i,t}$ are vector of exogenous variables, α_i is the adjustment coefficient (error correction parameter), d_t shows the deterministic factors, δ_t' are the vector parameters, and $e_{i,t}$ are the residuals of white noise.

The above function can be written as follows:

$$\Delta y_{i,t} = \delta_i' d_t + \alpha_i y_{i,t-1} + \lambda_i' x_{i,t-1} + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,t-j} + \sum_{j=0}^{p_i} \vartheta_{ij} \Delta x_{i,t-j} + e_{i,t} \quad (13)$$

where $\lambda_i' = -\alpha_i \beta_i'$ (see Persyn and Westerlund (2008, p. 233)).

The parameter a_i denotes the speed adjustment. If $a_i < 0$ then there is error correction, meaning that the variables of the model are cointegrated. If $a_i = 0$ then there is no error correction thus there is cointegration.

Westerlund (2007) for the error correction model suggested two different types of tests for the examination of null hypothesis of non-cointegration. The statistic tests of group-mean tests G_t and G_α, based on weighted amounts of a_i and estimated for individual countries, belong to the first category. In the second category, panel tests

P_t and P_α, are based on estimation of a_i for the total of panel data. The four test statistics of Westerlund (2007) are the following:

$$G_t = \frac{1}{N}\sum_{i=1}^{N}\frac{\hat{a}_i}{s.e(\hat{a}_i)},\quad G_a = \frac{1}{N}\sum_{i=1}^{N}\frac{T\hat{a}_i}{\hat{a}_i(1)},\quad P_t = \frac{\hat{a}}{s.e(\hat{a})},\quad P_\alpha = T\hat{\alpha}$$

Another test that can be employed when there are and when there are not cross sectional dependencies is the LM bootstrap test of Westerlund and Edgerton (2007). The LM bootstrap test of Westerlund and Edgerton (2007) differs from the Westerlund test (2007) on the null hypothesis and the autocorrelation test. On the null hypothesis, Westerlund and Edgerton (2007) tests the cointegration existence and allows autocorrelation to differ from cross section to another.

Let the following cross sectional panel be:

$$y_{it} = \alpha_i + x_{it}^{'}\beta_i + z_{it} \tag{14}$$

where t denotes the time period t = 1, …, T, and i the cross sectional unit i = 1, …, N, $z_{it} = u_{it} + v_{it}$ and $v_{it} = \sum_{j=1}^{t} n_{ij}$.

where n_{it} is ($i.i.d$) and $Var(n_{it}) = \sigma_i^2$.

The vector $w_{it} = (u_{it}\ \Delta x_{it}^{\prime},)$ is a linear procedure given as:

$$w_{it} = \sum_{j=0}^{\infty}\alpha_{ij}e_{it-j} \tag{15}$$

where e_{it} is an error with zero mean and $i.i.d$, whereas the parameter a_{ij} we assume that satisfies the sum conditions.

The two hypotheses test are:

H_0: $\sigma_i^2 = 0$ for all i.

H_1: $\sigma_i^2 > 0$ for some i.

In the case of non-existing panel dependence on the above model, hypotheses testing can be done with LM test as follows: (see Westerlund and Edgerton (2007, p. 186)).

$$LM_{NT^2}^{+} = \sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\omega}_{it}^{-2}S_{it} \tag{16}$$

where S_{it} is part of the sum of $\hat{z}_{it}$ procedure which is a fully modified estimation of z_{it} whereas $\widehat{\omega}_{it}^2$ is an estimator of long run variance u_{it} on conditional Δx_{it}.

In case of the existence of cross sectional dependence, the LM test cannot be used as it provides deviations on the results. To overcome this problem, the bootstrap method of Ari and Senturk (2020) is used instead of the typical normal distribution. The bootstrap method follows the procedure of automatic regression as detailed below (see Westerlund and Edgerton (2007, p. 187)):

$$\sum_{j=0}^{\infty}\phi_{ij}w_{it-j} = e_{it} \tag{17}$$

The first stage on bootstrap method is the ϕ_{it} estimation from the above equation using $\widehat{w}_{it} = (\hat{z}_{it}, \Delta x_{it}^{\prime})^{\prime}$ instead w_{it} and p_i lags. The residuals can be calculated as follows: (Senturk et al., 2014).

$$\hat{e}_{it} = \sum_{j=0}^{\infty}\widehat{\phi}_{ij}w_{it-j} \tag{18}$$

On the second stage, the e_i^* is taken from the empirical distribution from the following residuals $\hat{e}_t - \frac{1}{T}\sum_{j=1}^{T}\hat{e}_j$. After that, instead of $\widehat{w}_{it}$ and $\hat{e}_{it}$ on Equation (18), we used e_{it}^* and w_{it}^* to be calculated.

On the last stage, the w_{it}^* is divided as $w_{it}^* = (z_{it}^*, \Delta x_{it}')'$ and the bootstrap sample which is x_{it}^* and y_{it}^* is formed with the following procedure: (Senturk et al., 2014).

$$y_{it}^* = \hat{\alpha}_i + x_{it}^*\hat{\beta}_i + z_{it}^* \text{ and } x_{it}^* = \sum_{j=1}^{T}\Delta x_{ij}^* \quad (19)$$

3.7. Augmented Mean Group (AMG) estimator

If there is cross sectional dependence and the variables are cointegrated on the examined model, we can estimate the model using the Augmented Mean Group (AMG) adopted by Eberhardt and Teal (2010). The AMG estimator tests the unobservable joint factors through the weighted cross sectional mean of independent variables of the regression. The means are included in assisting the removal of bias due to the unobservable factors hence there is no empirical interpretation. The AMG estimator was adopted by Eberhardt (2012) and is estimated on the following model:

$$y_{it} = \beta_i x_{it} + u_{it} \text{ for } i = 1, \ldots, N \text{ and } t = 1, \ldots, T \quad (20)$$

where,

$$u_{it} = \alpha_{1i} + \lambda_i f_t + \varepsilon_{it} \quad (21)$$

and

$$x_{it} = \alpha_{2i} + \lambda_i f_t + \gamma_i g_t + e_{it} \quad (22)$$

where y_{it} and x_{it} are observable series, β_i is the slope of a particular unit on the observable regressor, u_{it} is the sum of unobservable joint factors and ε_{it} are the error terms.

The unobservable series on Equation (21) consist of a group of fixed effects α_{1i} which capture the timely fixed heterogeneity in all groups, as well as an observable common factor f_t, with heterogeneous factor loadings λ_i, that control heterogeneity and cross sectional dependence. The factors f_t and g_t can be nonlinear and non-stationary with consequences for cointegration.

3.8. Causality test

The causality test of Dumitrescu and Hurlin (2012) can be used both on cross sectional independence and cross sectional dependence as well as on heterogeneity of coefficients with effective results. Also, another characteristic of the Dimitrescu and Hurlin (2012) test is that it operates with the presence and the absence of a cointegrating relationship.

Dumitrescu and Hurlin (2012) for the causality on panel data test adopt the following regression:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K}\gamma_{ik}y_{i,t-k} + \sum_{k=1}^{K}\beta_{ik}x_{i,t-k} + e_{i,t} \quad (23)$$

$$\text{with } i = 1, \ldots, N \text{ and } t = 1, \ldots, T$$

where $y_{i,t}$ and $x_{i,t}$ are observations of two stationary variables for individual i on period t. The coefficients γ_{ik} and β_{ik} can differ between individual units. $e_{i,t}$ are the cross sectional residuals and K is the lag order which is the same for all cross sectional units.

Dumitrescu and Hurlin test assumes that there is causality for some individuals, not necessarily for all. So, the null and alternative hypothesis is:

H_0: $\beta_{i1} = \cdots = \beta_{ik} = 0 \; \forall i = 1, \ldots, N_1$.

H_1: $\beta_{i1} \neq 0$ or... or $\beta_{ik} \neq 0 \; \forall i = N_1 + 1, N_1 + 2, \ldots, N$.

The process of Dimitrescu and Hurlin (2012) test is the following: We estimate N individual regressions on the above regression and conduct the F test of K linear hypotheses $\beta_{i1} = \ldots = \beta_{ik} = 0$ to retrieve the individual Wald statistic W_i and to calculate the average Wald statistic $\overline{W}$ as below:

$$\bar{W} = \frac{1}{N} \sum_{i=1}^{N} W_i \quad (24)$$

4. Research results

The Hausmam test, (1978) shows whether the model is of fixed or random effects. The null hypothesis test, as it is mentioned, claims that there is no difference between the estimated coefficients (in both fixed effects model and random effects model). So the random effect model is suitable.

From the Hausmam test (1978) we use the X^2 distribution. The results of this test are presented on **Table 2**.

Table 2. Results of the Hausman test (Source: Author's calculations).

Test summary	X^2 statistic	X^2 d.f.	p-value
Cross-section random	12.983473	2	0.0015

The results of **Table 2** reject the null hypothesis, so we conclude that the fixed effects model is the most suitable.

For the panel cross dependence tests among residuals we use four different tests.

Moreover, the homogeneity of the coefficients of cointegration was investigated applying the adjusted delta test of Pesaran and Yamagata, (2008). The results of these tests are shown on **Table 3**.

According to the results of **Tables 3** and **4**, the tests for cross-sectional dependence used, reject the null hypothesis. So, we can assert that there is cross sectional dependence (correlation) among residuals. Also, the results of **Table 4** show that the null hypothesis of coefficients' homogeneity is rejected. Thus, we sum up that the cointegration coefficients are heterogeneous. The results of the above table guide us to use the tests of Cross-Augmented Dickey-Fuller (CADF) of Pesaran (2007), the second generation unit root test as they take account the panel dependence and heterogeneity.

Table 3. Cross-sectional dependence and homogeneity test results (Source: Author's calculations).

Cross-sectional dependence test (H_0: No cross-sectional dependence)		
Test	**Statistic**	***p*-value**
Breusch-Pagan LM	1497.451	0.000
Pesaran scaled LM_s	43.27001	0.000
Bias-corrected scaled LM_p	42.52001	0.000
Pesaran CD_{BC}	23.97770	0.000
Homogeneity test (H_0: Slope coefficients are homogeneous)		
Test	**Statistic**	***p*-value**
$\tilde{\Delta}$	12.436	0.000
$\tilde{\Delta}_{adj}$	15.893	0.000

Note: $\tilde{\Delta}$ and $\tilde{\Delta}_{adj}$ test denote the slope homogeneity tests proposed by Pesaran and Yamagata (2008).

Table 4. Panel unit root test.

	Pesaran-CADF			
	Constant		**Constant and trend**	
Variable	***t*-bar**	**Prob.**	***t*-bar**	**Prob.**
LHEC	−1.495	>0.01	−1.222	>0.01
LGDPC	−1.931	>0.10	−1.729	>0.10
LGHGC	−1.735	>0.10	−1.181*	>0.01
ΔLHEC	−15.194*	<0.01	−2.658***	<0.10
ΔLGDPC	−2.635*	<0.01	−2.780**	<0.05
ΔLGHGC	−7.031*	<0.01	−3.869*	<0.01

Critical values: −2.36, −2.18, −2.08 (constant), and −2.88, −2.70, −2.60 (constant and trend) for *t*-bar statistics. *, ** and *** indicates 1%, 5%, and 10% level of significance respectively, Δ is first difference, the lag lengths from cross-sections were selected using Modified Akaike Information Criterion (MAIC).

The null hypothesis of the test denotes that there is unit root in all series.

The results on **Table 4** show that the variables are stationary in first differences. Thus, the Westerlund (2007) cointegration test via error correction model.

On the following table, we use the Westerlund (2007) cointegration test to define if there is cointegration between the examined variables.

Table 5. ECM panel cointegration test (Westerlund, 2007).

Statistic	**Value**	***Z*-value**	***P*-value**
G_t	−2.221	−3.324	0.028**
G_a	−8.964	−4.174	0.047**
P_t	−8.221	−4.253	0.004*
P_a	−7.729	−5.023	0.001*

Note: * and ** indicates 1% and 5% level of significance respectively.

Table 5 shows the Westerlund cointegration results via error correction model. The results present that the null hypothesis of non-cointegration is rejected from all 4 test statistics. Afterwards we examine the cointegration variables using the LM bootstrap Westerlund and Edgerton (2007) test which allow the autocorrelation to differ between cross sections and also it operates well also in small samples.

Table 6. LM bootstrap panel cointegration test (Westerlund and Edgerton, 2007).

	Constant			**Constant and trend**		
	LM statistic	**Asymptotic *p*-value**	**Bootstrap *p*-value**	**LM statistic**	**Asymptotic *p*-value**	**Bootstrap *p*-value**
LM bootstrap	1.426	0.227	0.569	0.735	0.253	0.678

Note: The bootstrap *p*-value was generated with 10.000 replications.

The results of cointegration from LM bootstrap test in **Table 6** above show the acceptance of null hypothesis. So, there is a cointegrating relationship between examined variables.

Afterwards, we examine the cointegration coefficients with AMG procedure as adopted from Eberhardt and Teal (2010). This procedure takes into consideration the heterogeneity and cross sectional dependence of cross sectional unit. Furthermore, it allows one unbiased and efficient estimator for different cross sectional units and time series.

The AMG procedure is implemented in three steps: (see Eberhardt (2012, p. 64)).

1) *"A pooled regression augmented model with year-dummies is estimated on first differences with OLS and the dummies coefficients are collected in the different years. In other words, they represent an estimated average cross-group of the development of the non-observable series during time. This is referred as a ¨common dynamic procedure".*

$$\Delta y_{it} = \alpha_{1t} + \beta_i \Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + \varepsilon_{it} \tag{25}$$

where x_{it} is a vector of regressors and D_t are the year dummies.

2) *"Next, the regression model for this group, is augmented with this estimated average of cross group and is estimated with OLS, with the coefficient dummies to substitute the non-observable common factors".*

$$y_{it} = \alpha_i d_t + \beta_i x_{it} + \lambda_i \hat{c}_t + \varepsilon_{it} \tag{26}$$

where $\hat{c}_t$ is the coefficient of year-dummy replacing the non-observable common factor f_t from Equation (21)

3) The β_{AMG} panel coefficient as the average of coefficients' estimations from the previous equation (Kaya, 2021):

$$\hat{\beta}_{AMG} = \frac{1}{N}\sum_{i=1}^{N} \beta_i \tag{27}$$

On **Table 7** the results of long-run cointegrating coefficients with Augmented Mean Group (AMG) approach are presented.

Table 7. Long-run cointegrating coefficients by AMG approach.

Country	LGDPC	LGHGC
Austria (AUT)	0.911*	−0.643*
Belgium (BEL)	0.916*	−0.619*
Bulgaria (BGR)	0.959*	−1.224*
Cyprus (CYP)	0.896*	−0.887*
Czech Republic (CZE)	0.946*	−0.892*
Germany (DEU)	0.968*	−0.817*
Denmark (DNK)	0.861*	−0.410*
Spain (ESP)	0.873*	−0.624*
Estonia (EST)	1.079*	−1.429**
Finland (FIN)	0.876*	−0.485*
France (FRA)	0.887*	−0.584*
Greece (GRC)	0.748*	0.034
Croatia (HRV)	0.743*	−0.091
Hungary (HUN)	0.775*	−0.239**
Ireland (IRL)	0.903*	−0.646*
Italy (ITA)	0.815*	−0.281*
Lithuania (LTU)	0.499*	1.492
Luxembourg (LUX)	0.663*	0.334*
Latvia (LVA)	0.610*	0.737
Malta (MLT)	0.814*	−0.343*
Netherlands (NLD)	1.000*	−1.009*
Poland (POL)	1.166*	−2.072*
Portugal (PRT)	0.825*	−0.361*
Romania (ROU)	0.826*	−0.935*
Slovak Republic (SVK)	0.939*	−1.076*
Slovenia (SVN)	0.858*	−0.515*
Sweden (SWE)	0.927*	−0.967*
Panel European Union (EUU)	0.744*	−0.059

Notes: *, **, and *** are respectively significant at 1%, 5%, and 10%.

As listed on **Table 7**, the individual cointegration coefficients revealed that per capita carbon dioxide emissions have positive impact on per capita health expenditure to Greece, Lithuania, Luxembourg and Latvia and a negative impact in all other countries of EU. Conversely, individual cointegration coefficients of per capita GDP received from AMG estimator have a strong positive impact on per capita health expenditure for all EU countries. It is worth noting that on counties like Estonia, Netherlands and Poland, the per capita health expenditure is regarded as luxury good. Our study confirms the results of the papers of Gok et al. (2018), Atems (2019), and Modibbo and Saidu (2020) which claim that economic growth has positive impact on health expenditure. As far as the impact of per capita carbon dioxide emissions is concerned on health expenditure, our result is confirmed from mixed results from papers such as Oyelade et al. (2020) showing a positive relationship, whereas the paper of Akbar et al. (2021) show a bilateral relationship between these two variables.

Table 8 presents the short-term causality tests.

Table 8. Results of causality test.

Country	ΔLGDPC, ΔLHEC	ΔLHEC, ΔLGHGC	ΔLGHGC, ΔLGDPC
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)	⇒***	⇐*	⇐***

Notes: *, **, *** indicates the rejection of the null hypothesis at 1%, 5%, and 10% significance level. (⇒) or (⇐) are unidirectional causal relations and (⇔) are bidirectional.

The results of the above table present a unilateral causal relationship from GDP per capita to health expenditure per capita for the countries Cyprus, Spain, Estonia, Finland, Greece, Croatia, and Sweden, unilateral causal relationship from health expenditure per capita to GDP per capita for countries Bulgaria, Slovak Republic and bilateral causal relationship for Austria and Slovenia.

Furthermore, the results show a unilateral causal relationship from greenhouse gas emissions per capita to health expenditure per capita for the countries Cyprus, Greece, Croatia, Italy, Lithuania, Romania, and Sweden and bilateral causal relation for Slovenia.

Also, the results of the above table show a unilateral causal relationship from greenhouse gas emissions per capita to GDP per capita for countries Estonia, Croatia, and Portugal, unilateral causal relation from GDP per capita to greenhouse gas emissions per capita for the countries of Austria, Finland, Netherlands, and Sweden, and bilateral causal relationship for Luxembourg.

Finally, for the countries of Belgium, Czech Republic, Germany, Denmark, France, Hungary, Ireland, Latvia, Malta, and Poland the results showed that there is no causal relationship.

The causality among three variables for all EU countries was analyzed through the Dumitrescu and Hurlin (2012) test and the findings are presented on **Table 9**. The causality test of Dumitrescu and Hurlin (2012) is calculated with three different statistical values. The mean statistic of Wald ($\overline{W}$) the standardized statistic ($\bar{Z}$) and the corresponding *p*-value.

Table 9. Dumitrescu and Hurlin test results.

Null Hypothesis	($\overline{W}$)	($\bar{Z}$)	*p*-value
DLGDPC does not homogeneously cause DLHEC	4.02997	2.68861	0.0072*
DLHEC does not homogeneously cause DLGDPC	2.91015	0.78971	0.4297
DLGHGC does not homogeneously cause DLHEC	4.67570	3.78359	0.0002*
DLHEC does not homogeneously cause DLGHGC	2.22475	−0.37254	0.7095
DLGHGC does not homogeneously cause DLGDPC	2.92095	0.80802	0.4191
DLGDPC does not homogeneously cause DLGHGC	3.08323	1.08320	0.2787

Note: *, **, and *** indicates 1%, 5% and 10% level of significance respectively. We used the test with lag = 2.

The causality results from Dumitrescu and Hurlin (2012) test revealed a significant unilateral causal relationship for all EU countries from per capita GDP and greenhouse gas emissions to per capita health expenditure. These findings are in line with those of Gok et al. (2018), Atems (2019), Kong (2021) and Adebayo and Akinsola (2021).

5. Conclusion and discussion

The study explores the relationship between health spending, environmental pollution and economic growth in the 27 EU countries between 2000 and 2020. In the beginning, the Hausman (1978) test was applied to investigate the most appropriate model. To test the cross sectional dependence and homogeneity of the slope between countries, we use, among others, the Pesaran (2004) CD and the Pesaran and Yamagata (2008) Delta tests respectively. The second generation unit root test is performed with the Pesaran (2007) CADF test, while cointegration is determined through tests, ECM by Westerlund (2007) and a bootstrap by Westerlund and Edgerton (2007). The long-term coefficients were estimated with Augmented Mean Group (AMG) method based on Eberhardt and Teal (2010) test while the control of causality was applied Dumitrescu and Hurlin (2012) test. Our findings from the econometric analysis revealed that all variables are stationary on first differences therefore we can confirm the existence of a long-run relationship between the examined variables.

By analyzing the individual coefficients of cointegration, we find that per capita CO_2 emissions have a negative strong effect on per capita health expenditure in most of the EU countries. One would expect that in cases where environmental pollution increases, per capita health expenditure would also increase. This result of our study is also confirmed by the findings of other researchers such as those Li et al. (2022).

On the contrary, the individual cointegration coefficients of per capita GDP have a strong positive impact on per capita health expenditure in all EU countries. This means that an increase on income in all EU countries will increase the public health expenditure. Our study confirms the results of the papers of Gok et al. (2018), Atems (2019) and Modibbo and Saidu (2020) claiming that economic growth has a positive effect on health expenditure. It should also be pointed out that in all EU countries, the per capita health expenditure is considered an essential good, except for Estonia, Netherlands and Poland which is considered a luxury good.

The Granger causality analysis for each EU member country separately showed mixed results with most countries having no causal relationship between the variables under consideration. Dumitrescu and Hurlin (2012) causality analysis for all EU members revealed a unidirectional causality starting from GDP per capita and from greenhouse gas emissions per capita to health expenditure per capita.

Climate change and its consequences are obvious on the agriculture production, on the availability and quality of water resources, on the quality of ecosystem and mainly on public health. Evidence that, human activity and expansiveness are considered the main reasons of climate change, is stronger than ever. Worldwide, the majority of people have already comprehend the consequences of the environmental degradation and global warming coming from the increasing energy consumption, thus encouraging government to deal with the causes of climate change. Most of the papers that involved with the relationship of greenhouse gas emissions and health expenditure have concluded that the increase of greenhouse gas emissions, increase health expenditure. So, it is important to determine those factors that increase health expenditure.

The contribution of this paper to the literature on the relationship between per capita CO_2 emissions, GDP per capita and per capita health care expenditure is manifold. First, since it used Hausman (1978) test to investigate whether the fixed effects model or random effects model is the most appropriate, analyzed the issue in a more rigorous manner in the sense of addressing the cross-sectional dependence (correlation) between residuals using the Breusch-Pagal LM (1980), Pesaran Scaled LM_s (2004), Pesaran CD_p (2004), and Baltagi et al. (2012). For the problem of heterogeneity that potentially exists in the panel data, it uses Pesaran and Yamagata (2008) Delta test. In addition, for the second-generation unit root tests he uses Pesaran (2007) CIPS test.

Second, the study has addressed the issue of cross-sectional dependence and heterogeneity, where the findings are more reliable. Third, the paper has examined the existence of a long-run relationship between per capita CO_2 emissions, per capita GDP and per capita health care expenditure using a cointegration technique of Westerlund (2007) which examines the existence of a cointegrated vector in panel data by applying the ECM, as well as the LM bootstrap panel cointegration approach introduced by Westerlund and Edgerton (2007) which is robust against cross-sectional correlation and panel heterogeneity. Fourth, the coefficients of cointegration are estimated with an AMG estimator of Eberhardt and Teal (2010), taking into account heterogeneity and cross-sectional dependence. Fifth, the causality test of Dumitrescu and Hurlin (2012) is applied as it considers both heterogeneity and cross-sectional dependence.

The innovation of this work lies in the recent methodology that provides more accurate results. Specifically, the panel data used in the study are examined for their cross-sectional dependence and heterogeneity to lead us to unbiased and consistent estimates. To test for unit root, CADF and second-generation CIPS tests are applied to the phenomenon of cross-sectional dependence. The Westerlund test is used for cointegration, performed through the error-correction model with bootstrap distributions (when there is dependence among cross-sectional units) and asymptotic normal distribution (when there is none). Additionally, cointegration is examined through the LM bootstrap test of Westerlund and Edgerton. The estimation of the model (if there is cross-sectional dependence and cointegration) is carried out using the Augmented Mean Group (AMG) method. Finally, the Dumitrescu and Hurlin causality test is employed because it is suitable for both cross-sectional dependence and coefficient heterogeneity. The methodology used provides results for both the entire EU set of countries and for each individual country separately for the variables under examination.

On our paper the impact of per capita greenhouse gas emissions and per capita GDP on per capita health expenditure was examined. The findings of our paper do not comply with the recent literature of health expenditure increase coming from the greenhouse gas emissions increase. In most EU countries, the results showed a negative relationship between these two variables. It should be clarified that the health expenditure are referred to the total per capita expenditure and are private not public. So, it is necessary to separate the health expenditure between private and public in order to ensure if all the EU countries agree with the policy concerning the reduction of greenhouse gas emissions and green development.

On the contrary, causality test showed unilateral causal relationship in the short run from per capita greenhouse gas emissions to per capita health expenditure in countries Cyprus, Greece, Croatia, Italy, Lithuania, Romania, and Sweden. Besides, many researchers agree that the health sector plays a crucial role on moderating the consequences of climate change and is essential on a country's growth. Furthermore, the increase of per capita GDP can affect the investment on health positively. Environmental degradation with greenhouse gas emissions has serious impact on climate change and citizens' health. Therefore, EU government should prioritize the sustainable economic growth.

The decrease of greenhouse gas emissions should be a priority in all member countries of EU. All countries must establish policies for investments in renewable energy sources such as wind and solar parks as well as hydroelectric establishments. Moreover, policies like petrol taxes, subsidies and low interest loans for green energy will assist on achieving this target. These changes will boost life expectancy and reduce to a large extent health expenditure.

As far as the limitations of our research are concerned, we should mention the following:

- The results of our paper should be different if the sample size was larger for all used variables.

- The countries could have been divided into two groups. Those within the Euro zone and those that do not use euro and compare these two groups.
- Another country separation could have been on the basis of per capita GDP in purchasing power parity.

Furthermore, for a future research, asymmetry models can be used for a nonlinear cointegration on panel data that ignore the assumptions of linear models where joint factors are presented on residuals. Also, on the model more variables can be added like pollution measurement as well as social factors (life expectancy) that affect health expenditure on EU countries.

Author contributions: Conceptualization, MD and CD; methodology, MD; software, PS; validation, CD, PS and VA; formal analysis, CD; investigation, VA; resources, PS; data curation, CD; writing—original draft preparation, MD; writing—review and editing, MD; visualization, PS; supervision, CD; project administration, VA; funding acquisition, PS. All authors have read and agreed to the published version of the manuscript.

Acknowledgments: This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No. 101070181 (TALON).

Conflict of interest: The authors declare no conflict of interest.

References

Abdullah, S. M., Siddiqua, S., & Huque, R. (2017). Is health care a necessary or luxury product for Asian countries? An answer using panel approach. Health Economics Review, 7(1). https://doi.org/10.1186/s13561-017-0144-8

Adebayo, T. S., & Akinsola, G. D. (2021). Investigating the Causal Linkage Among Economic Growth, Energy Consumption and CO2 Emissions in Thailand: An Application of the Wavelet Coherence Approach. International Journal of Renewable Energy Development, 10(1), 17–26. https://doi.org/10.14710/ijred.2021.32233

Akbar, M., Hussain, A., Akbar, A., et al. (2020). The dynamic association between healthcare spending, CO2 emissions, and human development index in OECD countries: evidence from panel VAR model. Environment, Development and Sustainability, 23(7), 10470–10489. https://doi.org/10.1007/s10668-020-01066-5

Alimi, O. Y., Ajide, K. B., & Isola, W. A. (2019). Environmental quality and health expenditure in ECOWAS. Environment, Development and Sustainability, 22(6), 5105–5127. https://doi.org/10.1007/s10668-019-00416-2

Anwar, M. A., Madni, G. R., & Yasin, I. (2021). Environmental quality, forestation, and health expenditure: a cross-country evidence. Environment, Development and Sustainability, 23(11), 16454–16480. https://doi.org/10.1007/s10668-021-01364-6

Apergis, N., Bhattacharya, M., & Hadhri, W. (2020). Health care expenditure and environmental pollution: a cross-country comparison across different income groups. Environmental Science and Pollution Research, 27(8), 8142–8156. https://doi.org/10.1007/s11356-019-07457-0

Ari, I., & Şentürk, H. (2020). The relationship between GDP and methane emissions from solid waste: A panel data analysis for the G7. Sustainable Production and Consumption, 23, 282–290. https://doi.org/10.1016/j.spc.2020.06.004

Atems, B. (2019). Public health expenditures, taxation, and growth. Health Economics, 28(9), 1146–1150. Portico. https://doi.org/10.1002/hec.3894

Atuahene, S. A., Yusheng, K., & Bentum-Micah, G. (2020). Health Expenditure, CO2 Emissions, and Economic Growth: China vs. India. https://doi.org/10.20944/preprints202009.0384.v1

Baltagi, B. H., Feng, Q., & Kao, C. (2011). Testing for sphericity in a fixed effects panel data model. The Econometrics Journal, 14(1), 25–47. https://doi.org/10.1111/j.1368-423x.2010.00331.x

Bayer, P., & Aklin, M. (2020). The European Union Emissions Trading System reduced CO_2 emissions despite low prices.

Proceedings of the National Academy of Sciences, 117(16), 8804–8812. https://doi.org/10.1073/pnas.1918128117

Beylik, U., Cirakli, U., Cetin, M., et al. (2022). The relationship between health expenditure indicators and economic growth in OECD countries: A Driscoll-Kraay approach, Front Public Health, 10, https://doi.org/10.3389/ fpubh. 2022.1050550

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange Multiplier Test and its Applications to Model Specification in Econometrics. The Review of Economic Studies, 47(1), 239. https://doi.org/10.2307/2297111

Cheikh, N. B., Zaied, Y. B., Chevallier, J. (2021). On the nonlinear relationship between energy use and CO2 emissions within an EKC framework: Evidence from panel smooth transition regression in the MENA region. Research in International Business and Finance, 55, 101331. https://doi.org/10.1016/j.ribaf.2020.101331

Dritsakis, N., Dritsaki, C., and Dritsaki, M. (2021). Special topics in econometrics, Klidarithmos Publications, Athens, 2021.

Dritsaki, M., & Dritsaki, C. (2023). The Relationship Between Health Expenditure, CO2 Emissions, and Economic Growth in G7: Evidence from Heterogeneous Panel Data. Journal of the Knowledge Economy. https://doi.org/10.1007/s13132-023-01349-y

Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. Economic Modelling, 29(4), 1450–1460. https://doi.org/10.1016/j.econmod.2012.02.014

Eberhardt, M. (2012). Estimating Panel Time-Series Models with Heterogeneous Slopes. The Stata Journal: Promoting Communications on Statistics and Stata, 12(1), 61–71. https://doi.org/10.1177/1536867x1201200105

Eberhardt, M., Teal, F. (2010). Productivity analysis in global manufacturing production. University of Oxford Department of Economics Discussion Paper No. 515.

Eckelman, M. J., Huang, K., Lagasse, R., et al. (2020). Health Care Pollution And Public Health Damage In The United States: An Update. Health Affairs, 39(12), 2071–2079. https://doi.org/10.1377/hlthaff.2020.01247

Fuchs, V. R. (2013). The Gross Domestic Product and Health Care Spending. New England Journal of Medicine, 369(2), 107–109. https://doi.org/10.1056/nejmp1305298

Gok, M. S, Ongel, V., Altindag, E. (2018). Analysis the interplay between economic growth and health expenditures: the case of emerging economies. Journal of Global Strategic Management, 12(2), 53–62. https://doi.org/10.20460/jgsm.2019.268

Haseeb, M., Kot, S., Hussain, H., & Jermsittiparsert, K. (2019). Impact of Economic Growth, Environmental Pollution, and Energy Consumption on Health Expenditure and R and D Expenditure of ASEAN Countries. Energies, 12(19), 3598. https://doi.org/10.3390/en12193598

Hausman, J. A. (1978). Specification Tests in Econometrics. Econometrica, 46(6), 1251. https://doi.org/10.2307/1913827

Ibukun, C. O., Osinubi, T. T. (2020). Environmental quality, economic growth, and health expenditure: empirical evidence from a panel of African countries. African Journal of Economic Review, 8(2), 119-140.

Işik, C., Ahmad, M., Pata, U. K., et al. (2020). An Evaluation of the Tourism-Induced Environmental Kuznets Curve (T-EKC) Hypothesis: Evidence from G7 Countries. Sustainability, 12(21), 9150. https://doi.org/10.3390/su12219150

Kaya, A. (2021). Real exchange rate and trade balance in Turkey: Evidence from heterogeneous panel data. Panoeconomicus, 68(5), 699–715. https://doi.org/10.2298/pan161208007k

Kong, S. (2021). Environmental cost of energy consumption and economic growth: can China shift some burden through financial development? An asymmetric analysis. Environmental Science and Pollution Research, 28(20), 25255–25264. https://doi.org/10.1007/s11356-021-12397-9

Kong, Y., & Khan, R. (2019). To examine environmental pollution by economic growth and their impact in an environmental Kuznets curve (EKC) among developed and developing countries. PLOS ONE, 14(3), e0209532. https://doi.org/10.1371/journal.pone.0209532

Li, F., Chang, T., Wang, M.-C., et al. (2022). The relationship between health expenditure, CO2 emissions, and economic growth in the BRICS countries—based on the Fourier ARDL model. Environmental Science and Pollution Research, 29(8), 10908–10927. https://doi.org/10.1007/s11356-021-17900-w

Liu, Y. H., Chang, W. S., & Chen, W. Y. (2019). Health progress and economic growth in the United States: the mixed frequency VAR analyses. Quality & Quantity, 53(4), 1895–1911. https://doi.org/10.1007/s11135-019-00847-z

Meirun, T., Mihardjo, L. W., Haseeb, M., et al. (2020). The dynamics effect of green technology innovation on economic growth and CO2 emission in Singapore: new evidence from bootstrap ARDL approach. Environmental Science and Pollution Research, 28(4), 4184–4194. https://doi.org/10.1007/s11356-020-10760-w

Modibbo, H. U., Saidu, A. M. (2020). Health expenditure and economic growth nexus: A generalised method of moment approach for the case of selected Africa countries. Lapai Journal of Economics, 4(1),12-21.

Oyelade, A. O., Tijani, O. D., Wakile, M. O., Kanimodo, A. L. (2020). Environmental Quality and Its Attendant Effect on Human

Health: New Evidence from Panel Quantile Regression for Anglophone Countries in West Africa. International Journal of Immunology, 8(4), 89. https://doi.org/10.11648/j.iji.20200804.14

Ozturk, S., Topcu, E. (2014). Health expenditures and economic growth: Evidence from G8 countries, International Journal of Economics and Empirical Research, 2, 256-261.

Pesaran, M. H. (2004). General Diagnostic Tests for Cross Section Dependence in Panels. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.572504

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of Applied Econometrics, 22(2), 265–312. Portico. https://doi.org/10.1002/jae.951

Pesaran, M. H., Yamagata, T. (2008). Testing slope homogeneity in large panels. Journal of Econometrics, 142(1), 50–93. https://doi.org/10.1016/j.jeconom.2007.05.010

Pesaran, M. H. (2020). General diagnostic tests for cross-sectional dependence in panels. Empirical Economics, 60(1), 13–50. https://doi.org/10.1007/s00181-020-01875-7

Persyn, D., & Westerlund, J. (2008). Error-Correction-Based Cointegration Tests for Panel Data. The Stata Journal: Promoting Communications on Statistics and Stata, 8(2), 232–241. https://doi.org/10.1177/1536867x0800800205

Phrakhruopatnontakitti, P., Watthanabut, B., & Jermsittiparsert, K. (2020). Energy consumption, economic growth and environmental degradation in 4 Asian countries: Malaysia, Myanmar, Vietnam and Thailand. International Journal of Energy Economics and Policy, 10(2), 529–539. https://doi.org/10.32479/ijeep.9229

Piabuo, S. M., & Tieguhong, J. C. (2017). Health expenditure and economic growth - a review of the literature and an analysis between the economic community for central African states (CEMAC) and selected African countries. Health Economics Review, 7(1). https://doi.org/10.1186/s13561-017-0159-1

Portney, K. E. (2013). Taking sustainable cities seriously: Economic development, the environment, and quality of life in American cities: MIT Press, 2013.

Qehaja, S. S., Qehaja, D., Hoti, A., et al. (2022). The Relationship between Government Health Expenditure and Economic Growth: Evidence from Western Balkan Countries. International Journal of Applied Economics, Finance and Accounting, 15(1), 10–20. https://doi.org/10.33094/ijaefa.v15i1.724

Seker, F., Ertugrul, H. M., & Cetin, M. (2015). The impact of foreign direct investment on environmental quality: A bounds testing and causality analysis for Turkey. Renewable and Sustainable Energy Reviews, 52, 347–356. https://doi.org/10.1016/j.rser.2015.07.118

Senturk, M., Ekrem, A. Y., Gokcen, O. (2014). Cross sectional dependence and cointegration analysis among the GDP foreign direct investment and aggregate credits: Evidence from selected developing countries, Asian Economic and Financial Review, 4(11), 1485-1501.

Swamy, P. A. V. B. (1970). Efficient Inference in a Random Coefficient Regression Model. Econometrica, 38(2), 311. https://doi.org/10.2307/1913012

United Nations. (2015). Department of Economic and Social Affairs. Available online: https://social.desa.un.org/issues/disability/envision-2030/17goals-pwds (accessed on 15 March 2023).

Wang, C.-M., Chang, C.-Y., Yuan, C.-C., et al. (2020). Examining CO_2 Emissions, Health Expenditure, and Economic Growth Nexus for China: A Co-integration Approach. IOP Conference Series: Earth and Environmental Science, 555(1), 012020. https://doi.org/10.1088/1755-1315/555/1/012020

Westerlund, J. (2007). Testing for Error Correction in Panel Data*. Oxford Bulletin of Economics and Statistics, 69(6), 709–748. https://doi.org/10.1111/j.1468-0084.2007.00477.x

Westerlund, J., & Edgerton, D. L. (2007). A panel bootstrap cointegration test. Economics Letters, 97(3), 185–190. https://doi.org/10.1016/j.econlet.2007.03.003