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 CO₂ 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 CO₂ 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. CO₂ 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 CO₂ 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.

CO₂ emissions from OECD countries represent half of world CO₂ emissions. However, CO₂ emissions in OECD countries have reduced from 2001. CO₂ emissions per GDP unit reduced from 4.9 kg/USD in 2001 to 2.7 kg/USD in 2015. The share of CO₂ emissions on worldwide CO₂ emissions also reduced from 54% in 2001 to 38% in 2015 (Liu et al., 2019). The average per capita CO₂ 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 CO₂ emissions for EU for the cost of 1ton CO₂ on EU ETS from 2005 until 2016 (see Bayera and Aklin (2020, p. 8805)).
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 CO₂ emissions in 27 EU countries from 1800–2020 is presented.

From Figure 2 above we can see that there is a substantial decrease on per capita carbon dioxide emissions CO₂ 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 Hausman (1978), for the suitability between the fixed and random effects model.
- 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.
- 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. CO₂ emissions and economic growth

Many studies showed that in countries that use traditional energy sources, economic growth increases CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ 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 CO₂ emissions. The causality results through the error-correction model indicated a bidirectional long-term causal relationship between energy consumption and CO₂ emissions, as well as between energy consumption and economic growth. Additionally, the research showed a unidirectional short-term causal relationship from CO₂ 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. CO₂ emissions, health expenditure, and economic growth

The literature on the relationship between CO₂ 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 CO₂ 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, CO₂ 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, CO₂ 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$_2$O). 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>
<thead>
<tr>
<th>Variables</th>
<th>Description</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>HEC</td>
<td>Current health expenditure per capita (PPP current international $)</td>
<td>World Development Indicators database, World Bank</td>
</tr>
<tr>
<td>GDPC</td>
<td>GDP per capita, PPP (current international $)</td>
<td>World Development Indicators database, World Bank</td>
</tr>
<tr>
<td>GHGC</td>
<td>Greenhouse gas emissions per capita (in metric tons per capita)</td>
<td>World Development Indicators database, World Bank</td>
</tr>
</tbody>
</table>

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:

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

(1)

which follows the \(\chi^2\) 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 \(\chi^2\) 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:

\[
LHEC_{i,t} = \beta_0 + \beta_1 \text{LGDPC}_{i,t} + \beta_2 \text{LGHGC}_{i,t} + u_{i,t}
\]

(2)

where \(t\) indicates time period \(t = 1, ..., T\), \(i\) indicated the cross-sectional unit \(i = 1, ..., N\) and \(u_{i,t}\) 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) \(\beta_1\) coefficient is expected to be positive. \(\beta_1\) measures the effect of per capita GDP on the per capita health care expenditure. If \(\beta_1\) is between 0 and 1, \(0 \leq \frac{\partial \text{LHEC}_{i,t}}{\partial \text{LGDPC}_{i,t}} = \beta_1 \leq 1\) then per capita expenditure for health care is a necessity good. If \(\beta_1\) is greater than 1, \(\frac{\partial \text{LHEC}_{i,t}}{\partial \text{LGDPC}_{i,t}} = \beta_1 > 1\) 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:

\[
y_{i,t} = \alpha_i + \beta_{i,t} x_{i,t} + u_{i,t}
\]

(3)

The null hypothesis \(H_0\) for the equation above is: \(H_0: \hat{\rho}_{i,j} = corr(u_{i,t}, u_{j,t}) = 0\) 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:

\[
LM = T \sum_{i=1}^{N-1} \sum_{j=(i+1)}^{N} \hat{\rho}_{i,j}^2
\]

(4)

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

freedom.

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

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

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

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

$$CD_p = \frac{2}{N(N - 1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T_{ij} \hat{\rho}_{ij}^2)$$  \hspace{1cm} (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:

$$LM_{BC} = \frac{1}{N(N - 1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T_{ij} \hat{\rho}_{ij}^2 - 1) - \frac{N}{2(T - 1)}$$  \hspace{1cm} (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 $\Delta$ and $\Delta_{adj}$ as follows:

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

where: $N$ is the number of cross-section unit, $\hat{S}$ 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)).

$$\tilde{\Delta}_{adj} = \sqrt{N} \left( \frac{N^{-1} \hat{S} - E(\tilde{Z}_{IT})}{\sqrt{Var(\tilde{Z}_{IT})}} \right)$$  \hspace{1cm} (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:

\[
\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i \bar{y}_{t-1} + \sum_{j=0}^{p} \delta_{i,j} \Delta \bar{y}_{t-j} + \sum_{j=0}^{p} \lambda_{i,j} \Delta y_{i,j,t} + \epsilon_{i,t} \tag{10}
\]

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 \( \epsilon_{i,t} \) 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:

\[
CIPS = \frac{1}{N} \sum_{i=1}^{N} \frac{CADF_i}{CADF}
\]

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)).

\[
\Delta y_{i,t} = \delta_i \Delta d_t + \alpha_i (y_{i,t-1} + \beta_i x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,j,t} + \sum_{j=0}^{p_i} \vartheta_{ij} \Delta x_{i,j,t} + \epsilon_{i,t} \tag{12}
\]

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, \( \alpha_i \) is the adjustment coefficient (error correction parameter), \( d_t \) shows the deterministic factors, \( \delta_i \) are the vector parameters, and \( \epsilon_{i,t} \) are the residuals of white noise.

The above function can be written as follows:

\[
\Delta y_{i,t} = \delta_i \Delta d_t + \alpha_i (y_{i,t-1} + \beta_i x_{i,t-1}) + \sum_{j=1}^{p_i} \alpha_{ij} \Delta y_{i,j,t} + \sum_{j=0}^{p_i} \vartheta_{ij} \Delta x_{i,j,t} + \epsilon_{i,t} \tag{13}
\]

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

The parameter \( \alpha_i \) denotes the speed adjustment. If \( \alpha_i < 0 \) then there is error correction, meaning that the variables of the model are cointegrated. If \( \alpha_i = 0 \) 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 \( G_{\alpha} \), based on weighted amounts of \( \alpha_i \) and estimated for individual countries, belong to the first category. In the second category, panel tests
$P_t$ and $P_a$, are based on estimation of $a_t$ for the total of panel data. The four test statistics of Westerlund (2007) are the following:

$$G_i = \frac{1}{N} \sum_{t=1}^{N} \frac{\hat{a}_i}{s_{e}(\hat{a}_i)}, \quad G_a = \frac{1}{N} \sum_{t=1}^{N} \frac{T\hat{a}_i}{s_{e}(\hat{a}_i)}, \quad P_t = \frac{\hat{a}}{s_{e}(\hat{a})}, \quad P_a = T\hat{a}$$

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:

$$y_{it} = \alpha_t + x_{it}' \beta_i + z_{it}$$

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 $v_{it} = \sum_{j=1}^{N} n_{ij}$, where $n_{ij}$ is (i.i.d) and $Var(n_{ij}) = \sigma^2_{v_i}$.

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

$$w_{it} = \sum_{j=0}^{\infty} a_{ij} e_{it-j}$$

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:

$H_0: \sigma^2_{v_i} = 0$ for all $i$.

$H_1: \sigma^2_{v_i} > 0$ 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)).

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

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

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)):

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

The first stage on bootstrap method is the $\phi_{ij}$ estimation from the above equation using $\hat{\omega}_{it} = (\hat{z}_{it}, \Delta x_{it}')$ instead $w_{it}$ and $p_t$ lags. The residuals can be calculated as follows: (Senturk et al., 2014).

$$\hat{e}_{it} = \sum_{j=0}^{\infty} \hat{\phi}_{ij} w_{it-j}$$
On the second stage, the $e_t^*$ 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 $w_{it}$ and $\hat{e}_t$ on Equation (18), we used $e_t^*$ 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 formed with the following procedure: (Senturk et al., 2014).

$$y_{it}^* = \tilde{\alpha}_i + x_{it}^*\tilde{\beta}_i + z_{it}^*$$ and $x_{it}^* = \sum_{j=1}^{T} \Delta x_{ij}^*$

(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:

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

(20)

where,

$$u_{it} = \alpha_{1i} + \lambda_i f_t + e_{it}$$

(21)

and

$$x_{it} = \alpha_{2i} + \lambda_i f_t + y_{it} + e_{it}$$

(22)

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

The unobservable series on Equation (21) consist of a group of fixed effects $\alpha_{1i}$ which capture the timely fixed heterogeneity in all groups, as well as an observable common factor $f_t$, with heterogeneous factor loadings $\lambda_i$, 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:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} y_{ik} y_{i,t-k} + \sum_{k=1}^{K} \beta_{ik} x_{i,t-k} + \epsilon_{it}$$

(23)

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

where $y_{it}$ and $x_{it}$ are observations of two stationary variables for individual $i$ on period $t$. The coefficients $y_{ik}$ and $\beta_{ik}$ can differ between individual units. $\epsilon_{it}$ 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:

$$H_0: \beta_{t1} = \cdots = \beta_{tk} = 0 \ \forall i = 1, \ldots, N_1.$$  
$$H_1: \beta_{t1} \neq 0 \ or \ ... \ or \ \beta_{tk} \neq 0 \ \forall i = N_1 + 1, N_1 + 2, \ldots, N.$$

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 $\beta_{t1} = \cdots = \beta_{tk} = 0$ to retrieve the individual Wald statistic $W_i$ and to calculate the average Wald statistic $\bar{W}$ as below:

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

4. Research results

The Hausman 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 Hausman test (1978) we use the $\chi^2$ distribution. The results of this test are presented on Table 2.

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

<table>
<thead>
<tr>
<th>Test summary</th>
<th>$\chi^2$ statistic</th>
<th>$\chi^2$ d.f.</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cross-section random</td>
<td>12.983473</td>
<td>2</td>
<td>0.0015</td>
</tr>
</tbody>
</table>

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).

<table>
<thead>
<tr>
<th>Cross-sectional dependence test ($H_0$: No cross-sectional dependence)</th>
<th>Test Statistic</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breusch-Pagan $LM$</td>
<td>1497.451</td>
<td>0.000</td>
</tr>
<tr>
<td>Pesaran scaled $LM_s$</td>
<td>43.27001</td>
<td>0.000</td>
</tr>
<tr>
<td>Bias-corrected scaled $LM_p$</td>
<td>42.52001</td>
<td>0.000</td>
</tr>
<tr>
<td>Pesaran $CD_{BC}$</td>
<td>23.97770</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Homogeneity test ($H_0$: Slope coefficients are homogeneous)

<table>
<thead>
<tr>
<th>Test Statistic</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta\bar{\hat{\alpha}}$</td>
<td>12.436</td>
</tr>
<tr>
<td>$\hat{\Delta}_{adj}$</td>
<td>15.893</td>
</tr>
</tbody>
</table>

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

Table 4. Panel unit root test.

<table>
<thead>
<tr>
<th>Pesaran-CADF</th>
<th>Constant</th>
<th>Constant and trend</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
<td>$t$-bar</td>
<td>Prob.</td>
</tr>
<tr>
<td>LHEC</td>
<td>−1.495</td>
<td>&gt;0.01</td>
</tr>
<tr>
<td>LGDP</td>
<td>−1.931</td>
<td>&gt;0.10</td>
</tr>
<tr>
<td>LGHGC</td>
<td>−1.735</td>
<td>&gt;0.10</td>
</tr>
<tr>
<td>$\Delta$LHEC</td>
<td>−15.194*</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\Delta$LGDP</td>
<td>−2.635*</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>$\Delta$LGHGC</td>
<td>−7.031*</td>
<td>&lt;0.01</td>
</tr>
</tbody>
</table>

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, $\Delta$ 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.

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).

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
<th>$Z$-value</th>
<th>$P$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_t$</td>
<td>−2.221</td>
<td>−3.324</td>
<td>0.028**</td>
</tr>
<tr>
<td>$G_a$</td>
<td>−8.964</td>
<td>−4.174</td>
<td>0.047**</td>
</tr>
<tr>
<td>$P_t$</td>
<td>−8.221</td>
<td>−4.253</td>
<td>0.004*</td>
</tr>
<tr>
<td>$P_a$</td>
<td>−7.729</td>
<td>−5.023</td>
<td>0.001*</td>
</tr>
</tbody>
</table>

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).

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th></th>
<th></th>
<th>Constant and trend</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LM statistic</td>
<td>Asymptotic p-value</td>
<td>Bootstrap p-value</td>
<td>LM statistic</td>
<td>Asymptotic p-value</td>
<td>Bootstrap p-value</td>
</tr>
<tr>
<td>LM bootstrap</td>
<td>1.426</td>
<td>0.227</td>
<td>0.569</td>
<td>0.735</td>
<td>0.253</td>
<td>0.678</td>
</tr>
</tbody>
</table>

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’.

\[ \Delta y_{it} = \alpha_t + \beta_i \Delta x_{it} + \sum_{t=2}^{T} c_t \Delta D_t + \epsilon_{it} \]  \hspace{1cm} (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”.

\[ y_{it} = \alpha_t d_t + \beta_i x_{it} + \lambda_i \hat{c}_t + \epsilon_{it} \]  \hspace{1cm} (26)

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

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

\[ \hat{\beta}_{AMG} = \frac{1}{N} \sum_{i=1}^{N} \beta_i \]  \hspace{1cm} (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.

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

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.**

<table>
<thead>
<tr>
<th>Country</th>
<th>ΔLGDP, ΔLHEC</th>
<th>ΔLHEC, ΔLGHC</th>
<th>ΔLGHC, ΔLGDP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria (AUT)</td>
<td><strong>⇔</strong>*</td>
<td>≠</td>
<td>⇐***</td>
</tr>
<tr>
<td>Belgium (BEL)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Bulgaria (BGR)</td>
<td>⇐***</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Cyprus (CYP)</td>
<td>⇒**</td>
<td>⇐***</td>
<td>≠</td>
</tr>
<tr>
<td>Czech Republic (CZE)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Germany (DEU)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Denmark (DNK)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Spain (ESP)</td>
<td>⇒***</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Estonia (EST)</td>
<td>⇒***</td>
<td>≠</td>
<td>⇒**</td>
</tr>
<tr>
<td>Finland (FIN)</td>
<td>⇒**</td>
<td>≠</td>
<td>⇐***</td>
</tr>
<tr>
<td>France (FRA)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Greece (GRC)</td>
<td>⇒**</td>
<td>⇐***</td>
<td>≠</td>
</tr>
<tr>
<td>Croatia (HRV)</td>
<td>⇒***</td>
<td>⇐***</td>
<td>⇒***</td>
</tr>
<tr>
<td>Hungary (HUN)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Ireland (IRL)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Italy (ITA)</td>
<td>≠</td>
<td>⇐***</td>
<td>≠</td>
</tr>
<tr>
<td>Lithuania (LTU)</td>
<td>≠</td>
<td>⇐***</td>
<td>≠</td>
</tr>
<tr>
<td>Luxembourg (LUX)</td>
<td>≠</td>
<td>≠</td>
<td><strong>⇔</strong>*</td>
</tr>
<tr>
<td>Latvia (LVA)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Malta (MLT)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Netherlands (NLD)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Poland (POL)</td>
<td>≠</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Portugal (PRT)</td>
<td>≠</td>
<td>≠</td>
<td>⇒**</td>
</tr>
<tr>
<td>Romania (ROU)</td>
<td>≠</td>
<td>⇐***</td>
<td>≠</td>
</tr>
<tr>
<td>Slovak Republic (SVK)</td>
<td>⇐***</td>
<td>≠</td>
<td>≠</td>
</tr>
<tr>
<td>Slovenia (SVN)</td>
<td><em>⇔</em></td>
<td><em>⇔</em></td>
<td>≠</td>
</tr>
<tr>
<td>Sweden (SWE)</td>
<td>⇒***</td>
<td>≠</td>
<td>≠</td>
</tr>
</tbody>
</table>

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 ($\bar{W}$) the standardized statistic ($\bar{Z}$) and the corresponding $p$-value.

Table 9. Dumitrescu and Hurlin test results.

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>$\bar{W}$</th>
<th>$\bar{Z}$</th>
<th>$p$-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>DLGDPC does not homogeneously cause DLHEC</td>
<td>4.02997</td>
<td>2.68861</td>
<td>0.0072*</td>
</tr>
<tr>
<td>DLHEC does not homogeneously cause DLGDPC</td>
<td>2.91015</td>
<td>0.78971</td>
<td>0.4297</td>
</tr>
<tr>
<td>DLGHGC does not homogeneously cause DLHEC</td>
<td>4.67570</td>
<td>3.78359</td>
<td>0.0002*</td>
</tr>
<tr>
<td>DLHEC does not homogeneously cause DLGHGC</td>
<td>2.22475</td>
<td>-0.37254</td>
<td>0.7095</td>
</tr>
<tr>
<td>DLGHGC does not homogeneously cause DLGDPC</td>
<td>2.92095</td>
<td>0.80802</td>
<td>0.4191</td>
</tr>
<tr>
<td>DLGDPC does not homogeneously cause DLGHGC</td>
<td>3.08323</td>
<td>1.08320</td>
<td>0.2787</td>
</tr>
</tbody>
</table>

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\textsubscript{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\textsubscript{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-Pagan $LM$ (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\textsubscript{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
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


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


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


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


