Environment, Development and Sustainability
https://doi.org/10.1007/s10668-020-01066-5

The dynamic association between healthcare spending, CO_2 emissions, and human development index in OECD countries: evidence from panel VAR model

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Received: 18 June 2020 / Accepted: 23 October 2020

Abstract
The present research aims to inspect the bidirectional association among healthcare expenditures, carbon dioxide (CO_2) emissions, and human development index (HDI). For this purpose, we employ a balanced panel data set of 33 OECD countries for the period 2006–2016. A newly developed econometric approach known as panel vector autoregression based on the generalized method of moments estimations is employed to test this relationship. The key empirical findings reveal that (1) all of the three main variables namely healthcare expenditures, CO_2 emissions, and HDI exhibit a causal relationship, (2) there exists bidirectional causality between healthcare expenditures and CO_2 emissions which suggests that CO_2 emissions significantly escalate the healthcare expenditures in OECD countries. Likewise, healthcare investments also increase emissions due to higher use of energy, (3) positive bidirectional causation between healthcare expenditures and HDI entails that investments in health infrastructure lead to improvement in the overall quality of living in these countries. Moreover, a higher HDI reinforces the governments to increase their healthcare spending, and (4) there is a unidirectional negative causality between CO_2 emissions and HDI which implies that carbon emissions significantly deteriorate human health and wellness in these countries. Based on these empirical outcomes, the policy prescriptions are discussed for the relevant authorities to curtail emission and enhance the quality of living of the masses.

Keywords CO_2 emissions · Healthcare expenditures · Human development index · Panel VAR · OECD countries

1 Introduction

Over the past two decades, debate on the linkage between healthcare spending, CO_2 emissions, and HDI has emerged as a hot topic in the economic literature for both advanced and developing countries. In the current era, the governments, policymakers, researchers, and economists are looking for ways to ensure a healthy and sustainable environment for

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society (Chaabouni and Saidi 2017). Government spending, especially in the healthcare sector, is a vital part of the fiscal expenditures in all economies.

Several studies claimed that government spending, especially on healthcare activities, helps in promoting human well-being (Fadilah et al. 2018; Prasetyo and Zuhdi 2013; Qureshi 2009), though studies such as (Baltagi and Moscone 2010; Kurt 2015; Oni 2014; Wang 2011) have proposed two different hypotheses about healthcare spending. The first hypothesis claims that healthcare is a luxury item and is the same as other commodities, which reflect the market forces in the best way. On the contrary, to support government intervention in the healthcare sector, the second hypothesis argues that healthcare spending is not a luxury rather it is a basic necessity. Besides, Doryan (2001) contends that during the periods of high economic growth, governments escalate healthcare spending. This will not only help the public to spend a healthy life but also increase the consumption level in society.

Further to this, climate change is the biggest challenge of time and threat to natural life, security, and prosperity (Ahmed et al. 2019). In 2013, the Inter-Governmental Panel on Climate Change (IPCC) claimed that the main cause of global warming is CO_2 emissions. In 1997, more than 100 countries of the world signed the "Kyoto Protocol" and planned for achieving the target of reducing CO_2 emissions to save the developed economies from the adverse effects of global warming (Javaid et al. 2018). Initially, developing countries were not paying considerable attention to curtail CO_2 emissions; however, after the rapid economic growth, these countries also exhibit serious concern towards the reduction of CO_2 emissions (Pang 2015). Moreover, in the context of developing countries, Yang et al. (2020) proved that increase in economic growth, as well as energy consumption, is positively linked with CO_2 emissions which in turn is harmful to environment. However, the interaction between healthcare spending and CO_2 emissions has not got much attention in the literature as compared to other areas of research. In recent years, only a few studies found a positive linkage between healthcare spending and CO_2 emissions (Beatty et al. 2009; Mead and Brajer 2005; Yazdi et al. 2014). Given the adverse implications of CO_2 emissions on the lives of people, gauging the impact of CO_2 emissions on health expenditures has emerged as an interesting area of research. The USA, which is a member of the OECD region, is the second largest CO_2 emitter in the world behind the most growing country China (Apergis et al. 2018). Jacobson (2008) was the first to demonstrate the linkage between CO_2 emissions and the health implications. He employed the high-resolution model and found that CO_2 increases the death rate in the USA due to increased air pollution. In addition, the study also highlights that CO_2 emissions enhance the particulate matter (PM) and surface ozone, which leads to an increase in hospitalization and consequent death rate. Therefore, CO_2 emissions can increase the health expenditures necessary to ensure that people enjoy a healthier life. Further, Allen et al. (2016) examine indoor CO_2 exposure and mental health. The empirical findings suggest that the less CO_2 exposed office workers have better cognitive scores than their counterparts. Similarly, the work of Chaabouni and Saidi (2017) reveals that pollutant emissions, especially CO_2 emissions, negatively affect human health. In the case of Iran, Yazdi et al. (2014) used the data from 1967 to 2010 and employed co-integration and autoregressive distributed lag (ARDL) approach, and they found that both carbon dioxide and carbon monoxide have a positive association with health expenditures. In contrast, another study deploys the fully modified ordinary least squares (FMOLS) technique and concludes that CO_2 emissions have a negative association with healthcare expenditures in Ghana (Boachie et al. 2014). Moreover, Narayan and Narayan (2008) examined the association between environmental quality and per capita health expenditures. They used a sample of eight OECD countries and employ panel co-integration technique to check whether the variables have a long-run relationship. Interestingly, estimations of their study prove the existence of a long-run relationship between environmental quality and health expenditures in eight OECD member countries. The study also indicates that environmental quality has a significantly positive association with healthcare. This long-run association is also proved by Abdullah et al. (2016) in the context of Malaysia. They revealed that CO_2 emission, NO_2 emission, and economic growth have a long-run relationship with healthcare expenditures. In contrast, Assadzadeh et al. (2014) investigated the consequences of CO_2 emissions on health expenditures. They cover the eight oil exporter countries' data for the period of 2000–2010. Their results conjecture that elasticity of CO_2 emissions has a positive implication for healthcare expenditures only in the short-run. Based on the extant literature, studies about CO_2 emissions and healthcare confirm the conservation hypothesis (unidirectional causality). On the other side, the feedback hypothesis claims that both CO_2 emission and healthcare may have bidirectional causality (Chaabouni and Saidi 2017) which is ignored in the literature. Hence, this study endeavors to fill this gap by inspecting the perceived bidirectional relationship between these variables. Moreover, Suescún (2007) states that health spending also has a positive influence on the development of humans. This perceived association between healthcare, CO_2 emissions, and HDI motivates us to conduct this research.

Human development (HD, hereafter) may be defined as the process of providing freedom and opportunities to people for their well-being. There are six major components of HDI (empowerment, sustainability, cooperation, security, productivity, and equity), all of these components support the development of humans (Javaid et al. 2018). Others claimed that lifestyle and the ecosystem play a more crucial role in human development (Badulescu et al. 2019; Tait et al. 2014).

Though, Razmi et al. (2012) and Iskandar (2017) claimed that the best source to evaluate the development of human resources and capabilities is the human development index (HDI). Furthermore, HDI is not only concerned about the rise and fall of economies, it also deals with the expansion and contraction in people's choices (Javaid et al. 2018). Moreover, Suescún (2007) asserts that by upgrading human capabilities, the countries can grow their economy as well as ensure that people are enjoying a healthy life. Healthcare is a key indicator that significantly contributes to the development of humans and improves the HDI through multiple channels such as decreasing the rate of mortalities and improving country's economic growth. Bhowmik (2020) contends that expenditures on health diminish the rate of infant mortality, which not only increases the GDP per capita and literacy rate but also leads the advancement in HDI of a country. Further, Fattah and Muji (2012) examined the impact of local government bodies' expenditures on improvement in human development indicators. They found that government expenditure on health and education has a positive influence on human development in Jeneponto regency. Government expenses on health and education are positively linked with all three components of HDI indicators (Fadilah et al. 2018). Moreover, the empirical findings of Qureshi (2009) revealed that higher government spending on human development undertakings not only improves the HDI indicators but also bolsters economic growth. Baldacci et al. (2003) stated that both education and health expenditures have a considerable positive influence on human development. Craigwell et al. (2012) found that spending on the healthcare sector has a positive association with HDI. In contrast, some studies also reveal that healthcare spending has no significant linkage with improvement in HDI, such as Rajkumar and Swaroop (2008) found that healthcare, education, and infrastructure spending often do not have a significant connection with HDI. Similarly, Prasetyo and Zuhdi (2013) examine the impact of government subsidies, transfers, education, and health expenses on HDI and reveal that all these variables do not always lead to the improvement in HDI.

Besides, few studies also claimed a two-way association between healthcare and HDI. Higher spending on HD along with the increase in health supplies may be attributed to the growth in population which requires more health facilities (Qureshi 2009). This indicates that both HDI and healthcare are interdependent and may exhibit a two-way association thus supporting the feedback hypothesis. Likewise, Alin and Marieta (2011) reveal the existence of a correlation between health expenditures and HDI in the case of Europe. Their results also confirm that healthcare expenditures promote HDI and HDI leads to an increase in health expenditures, which suggest a bidirectional causality between these two variables.

The next strand of study examines the relationship between CO_2 emissions and HDI, which has also been tested by a few studies in various economic settings. In the context of 44 sub-Saharan African countries, Asongu and Odhiambo (2019) examined the extent to which CO_2 emissions affect the inclusive development of humans. The empirical outcome suggests that an increase in CO_2 emissions has a negative impact on HD. Likewise, Asongu et al. (2017) assert that Information Communication Technologies (ICT) diminish the negative effects of CO_2 emissions on HD. Moreover, Boogaard et al. (2017) and Rich (2017) show that environmental degradation negatively affects life expectancy and human health. Using the data of ten top CO_2 emitting countries (USA, Russia, Saudi Arabia, Iran, Japan, South Korea, Germany, China, Canada, and India), Mohmmed et al. (2019) reveal that causality does exist between CO_2 emission and HDI. Also, Shah Shah (2016) found that CO_2 emissions, fertility rate, and inflation rate harm HDI. While literacy level and GDP per capita have a positive influence on HDI. By covering the time span from 1992 to 2011, Bedir and Yilmaz (2016) explore the unidirectional causality between CO_2 emissions and HDI in the context of nine OECD countries. They argue that if policymakers want to dampen the negative consequences of CO_2 emissions on HD, they must ensure the efficient use of energy. Further, Asongu (2018) investigated how CO_2 emissions affect inclusive HD. The study categorizes based on different fundamental characteristics such as religious denomination, resource endowments, legal origin, income level, proximity to the sea, and political stability. The empirical outcomes suggest that in all these scenarios CO_2 emissions negatively affect the inclusive HDI and are harmful to the health and wellness of humans.

The fundamental objective of this study is to investigate the bidirectional association among the HDI, CO_2 emissions, and healthcare expenditures in the OECD region by employing the PVAR technique based on GMM. Novelties of this study are manifold; first, the considerable prior literature only examines the unidirectional association between CO_2 emissions and healthcare expenditures (Apergis et al. 2016, 2018; Badulescu et al. 2019; Beatty and Shimshack 2014; Chaabouni and Abednnadher 2014; Chaabouni and Saidi 2017; Jacobson 2008; Ullah et al. 2019; Yazdi et al. 2014), while the feedback hypothesis states that CO_2 emission and healthcare can have a bidirectional causality (Chaabouni and Saidi 2017). Therefore, the present study endeavors to fill this gap by examining the bidirectional association between CO_2 emissions and healthcare expenditures. Second, the extant literature reflects that HDI has not received much attention from scholars concerning its relationship with healthcare spending and CO_2 emissions.

Third, this study also contributes from a methodological standpoint as for the first time, we have used a recently developed technique panel VAR to inspect the bidirectional association among healthcare, CO_2 emissions, and HDI. We observed that a wide range of studies on CO_2, healthcare, and HDI have employed different statistical techniques, such as OLS (He et al. 2017; Narayan and Narayan 2008; Qureshi et al. 2015) dynamic ordinary least square (DOLS) and FMOLS (Apergis et al. 2018; Bouchoucha 2020), and Panel ARDL (Badulescu et al. 2019; Khoshnevis Yazdi and Khanalizadeh 2017; Wang et al. 2019; Zaidi and Saidi 2018). However, Nickell (1981) stated that in dynamic panels OLS cannot be employed because in these panels, individual effect term could be correlated with the error term, which leads to biased estimations. Further to this, the core objective of the present study is to check the bidirectional association among the proposed variables, while the aforementioned techniques are only suitable to examine the unidirectional relationship. Therefore, the present study has made full use of a concrete econometric technique panel VAR based on the GMM model, which is developed by (Arellano and Bond 1991) and then extended by (Arellano and Bover 1995). The choice of this methodology is inspired by several reasons, (1) this technique not only measures the future results based on past data but also shows the $t-1$ estimations by deploying years "t" data. (2) PVAR uses an auto time lag system, which is the best way to cope up with reverse causality and endogeneity problems. (3) By considering all the variables as endogenous, this technique controls the inherited longitudinal data issue that is unobserved individual heterogeneity by combining the panel data with the VAR method. (4) This technique also shows the extent of the overall effect through the analysis of variance decomposition, which reflects the change in one variable caused by the shocks in other variables.

This empirical results of this research entail some interesting findings which can help the relevant government bodies to devise appropriate strategies to curb the pollutant emissions and enhance human development. First, a causal nexus between healthcare expenditures, CO_2 emissions, and HDI juxtaposes that governments must understand the interaction of these variables to put forward an effective policy response to preserve the environment and ensure better and well-being of society. Second, the bidirectional association between CO_2 emissions and healthcare expenditures suggests that though expanding health facilities contribute towards CO_2 emissions, however, the adverse impact of pollutant emissions to escalate health expenditure is more profound. Likewise, a positive bidirectional relationship between healthcare expenditures and HDI proposes that the optimization of health facilities positively contributes towards human development. Though negative unidirectional causation between CO_2 emissions and HDI asserts that pollutant emissions adversely affect the overall health and wellness of the people. Hence, these OECD countries should take concrete steps for pollution abatement to ensure the development of healthy and sustainable societies.

The rest of the paper is structured as follows: Sect. 2 critically evaluates the literature about healthcare, HDI, and CO_2 emissions. Section 2 describes data and methodology, including the empirical model, sample period, and analysis techniques. The results are shown in Sect. 3. Section 4 concludes the study and provides implications for the policymakers.

2 Materials and methods

2.1 Data

In this research, we use country-level annual data for healthcare spending (HC_Exp), human development index (HDI), carbon dioxide emissions per capita (CO_2_PC), research and development expenditures (RD_Exp), and population growth rate (POP_GR). Initially, we have collected the data of all the 36 OECD countries, but eliminated three countries (Australia, New Zealand, and Spain) from the final sample due to the unavailability of sufficient observations. Our final sample constitutes a panel of 33 countries covering the time span from 2006 to 2016. The data are collected from the World Development Indicators (WDI) of the World Bank online database. This data set is strongly balanced which consists of 33 countries having 363 observations. Description of variables:

The variable description is provided in the table below (Table 1).

2.2 Empirical models

Three models were employed for empirical analysis; the first model exhibits the relationship between healthcare expenditures and CO_2 emissions along with other control variables, the second model represents the association between health expenditures and HDI, and our third model depicts the linkage between HDI and CO_2.

2.2.1 Model 1 healthcare expenditures and CO_2 emissions

Equations 1 and 2 show the models for causality between health expenditures and CO_2 emissions. In the first equation, healthcare expenditure for year t is the dependent variable, while CO_2 emissions in the year $t-1$ is independent variables. The second equation shows that CO_2 emissions at year t is the dependent variable, while HC_EXP in the year $t-1$ is the independent variable.

$$\mathrm{HC}_{\mathrm{EXP}it} = \alpha + \beta_1 \mathrm{CO}_{2\,\mathrm{PC}\;it-1} + \mu_i + e_{it,i=1,2,\ldots,N;\;t=1,2,\ldots,T} \tag{1}$$

$$\mathrm{CO}_2\_\mathrm{PC}_{it} = \alpha + \beta_1 \mathrm{HC\_EXP}_{it-1} + \mu_{\mathrm{i}} + e_{it,i=1,2,\ldots,N;t=1,2,\ldots,T} \tag{2}$$

The β_1 holds a positive expected sign in both equations, which implies that CO_2_PCt-1 is assumed to have a positive relationship with HC_EXPt. Likewise, HC_EXPt-1 is expected to have a positive association with CO_2_PCt. The unidirectional association between CO_2 emissions and HC_EXP is tested by various studies including (Chaabouni and Saidi 2017; Chaabouni et al. 2016; Ghorashi and Rad 2017; Sasana et al. 2019; Ullah et al. 2019) and found positive relationship between CO_2 emissions and health expenditures.

Table 1 Variables definitions

Notation	Variable name and definitions	Time span	Source
HC_Exp	Healthcare spending % share of GDP at constant 2010	2006–2016	WDI
HDI	Human development index	2006–2016	WDI
CO_2_PC	Carbon dioxide emissions per capita	2006–2016	WDI
RD_Exp	Research and development expenditure % share of GDP at constant 2010	2006–2016	WDI
POP_GR	Population growth rate	2006–2016	WDI

2.2.2 Model 2 health expenditures and HDI

The association between health expenditures and HDI is expressed in Eqs. (3) and (4).

$$\mathrm{HDI}_{it} = \alpha + \beta_1 \mathrm{HC\_EXP}_{it-1} + \mu_{\mathrm{i}} + e_{it,i=1,2,\ldots,N;\ t=1,2,\ldots,T} \quad (3)$$

$$\mathrm{HC\_EXP}_{it} = \alpha + \beta_1 \mathrm{HDI}_{it-1} + \mu_{\mathrm{i}} + e_{it,i=1,2,\ldots,N;\ t=1,2,\ldots,T} \quad (4)$$

Here, again β_1 is expected to have a positive coefficient in both Eqs. (3) and (4). It implies that by following the feedback hypothesis, an increase in healthcare expenditures at time $t-1$ will increase HDI at time t and vice versa. A unidirectional positive relationship is reported between health expenditures and HDI by various studies (Assadzadeh et al. 2014; Craigwell et al. 2012; Fattah and Muji 2012; Qureshi 2009).

2.2.3 Model 3 HDI and CO_2 emissions

Equations (5) and (6) indicate the relationship between HDI and CO_2 emissions;

$$\mathrm{HDI}_{it} = \alpha + \beta_1 \mathrm{CO}_{2\,it-1} + \mu_i + e_{it,i=1,2,\ldots,N;\ t=1,2,\ldots,T} \quad (5)$$

$$\mathrm{CO}_{2it} = \alpha + \beta_1 \mathrm{HDI}_{it-1} + \mu_i + e_{it,i=1,2,\ldots,N;\ t=1,2,\ldots,T} \quad (6)$$

The coefficient of β_1 is expected to have a negative sign in Eqs. (5) and (6). This means that increase in CO_2 emissions will lead to a decrease in HDI and vice versa. A negative relationship is also expected between HDI and CO_2 emissions in the past literature including (Allen et al. 2016; Asongu and Odhiambo 2019; Bedir and Yilmaz 2016; Jacobson 2008). The e_i is the error term of the model in Eqs. (1)–(6) which assume no variations among the information framework for the cross-sectional measurement of N (Asteriou and Hall 2015).

2.3 Econometric technique

In this paper, we use an advanced econometric technique known as the panel VAR using the generalized method of moments (GMM) estimations developed by Abrigo and Love (2016) to cope up with the modeling deficiencies encountered by the previous studies. To examine the bidirectional association among multiple variables is a challenging task. Hence, we employ the panel VAR technique, as it is used to create empirical differentiation in the transformation mechanism of economic activity (Lin et al. 2019). Abrigo and Love (2016) argue that equation-by-equation GMM estimations produce predictable estimates of panel VAR. Additionally, Jouida (2018) states that panel VAR allows to generate efficient estimations of coefficients in the system with endogenous variables. It is a much powerful technique for analysis because panel VAR adds the structural-time disparity and cross-sectional dimensions in the standard VAR model (Canova and Ciccarelli 2013).

This study selects the OECD countries as the context of research, because the characteristics of OECD countries are very well adapted to the goals of this investigation. The OECD economies not only enjoy the energy-led-growth hypothesis, they also stay at the largest energy consumption economies with 41% of world energy consumption (Duffour 2012). The large portion of this energy is coming from the traditional resources such as, coal, oil, and natural gas, which are the main cause of $CO_{2\ \mathrm{emissions}}$ that leads the environmental degradation (Saidi and Omri 2020). Further, although the population of OECD countries is less than 20% of the world population, they are accounted for over 85% of world health spending (Linden and Ray 2017). Linden and Ray (2017) and WHO (2014) both claimed that OECD countries spend a greater amount on health per capita as compared to the rest of the world. These hallmarks indicate that OECD countries are very interesting for this title.

Table 2 reports the average statistics of the study variables of 33 selected OECD countries. This table illustrates that Luxembourg (22.35), Norway (22.05), Canada (20.81), Portugal (18.34), and Estonia (15.14) have the highest average values of CO2 emissions in the OECD region which is mainly attributed to the large size of these countries, while Mexico (5.86) Netherlands (5.74), Chile (5.72), and Latvia (5.57) have the lowest average values of CO2 emissions. Moreover, Norway (15,539.80), Japan (5804.28), Germany (3511.09), France (2694.75), and Canada (1669.21) have the highest average values of gross domestic product, whereas Estonia (21.97) and Iceland (14.71) depict the lowest average GDP values in OECD countries. Growth rates about the population indicate that Norway (311.23), Japan (127.67), Mexico (115.59), Germany (81.53), and France (65.32) are the top five highly populated OECD countries. However, Iceland (0.32) and Luxembourg (0.52) have the lowest annual population in selected sample, though the top five energy from fossil fuel production average values was observed in Israel (99.13), Slovenia (92.07), Poland (84.56), Luxembourg (84.19), and Mexico (81.34), whereas the fossil fuel consumption of these countries is (96.22), (92.54), (92.37), (86.48), and (90.16), respectively (see Table 2). The countries such as Norway (16.10), France (11.10), USA (10.97), Germany (10.72), and Poland (10.23) have the highest average percentage of healthcare expenditures, whereas Estonia (5.96), Latvia (5.75), Mexico (5.64), and Netherlands (4.79) had the lowest average healthcare expenditure during the study period. Table 2 also indicates that all selected OECD countries achieve the positive average value of HDI between the period from 2006 to 2016. Nevertheless, Japan (83.05), and USA (82.49) have the highest life expectancy (at birth), whereas Lithuania (73.16) and Latvia (73.22) have lowest average life expectancy (at birth) in selected OECD countries (see Table 2).

3 Results and discussion

Table 3 reports the descriptive statistics for healthcare, human development index, CO_2 emissions, R&D expenditures, and population growth rate in OECD countries. On average, sample countries spend 8.47% of their GDP on the healthcare sector. In contrast, only 1.85% of GDP spending is allocated to innovation or R&D related activities. The mean value of the population growth rate is quite low (0.0077), while average CO_2 emissions per capita is (10.76) which still needs to be curtailed to the lowest level.

Table 4 presents the correlation matrix to understand the level of association among variables. Values suggest that HDI exhibits a significant correlation with healthcare as an increase in healthcare expenditure improves the quality of human well-being. Likewise, CO_2 emissions and healthcare and HDI and CO_2 emissions also exhibit moderate correlations with each other. These associations suggest a nexus between the aforementioned variables which has been explored further in the empirical analysis.

In Table 5, we use Andrews and Lu's (2001) methodology based on Bayesian information criteria (MBIC), Akaike information criteria (MAIC), and Hannan–Quinn information criteria (MHQIC) to check consistency and asymptotic normality of the data. We employ

Table 2 Average statistics of selected OECD countries

Countries	CO_2_PC	GDP (in billions)	Pop (in millions)	Fossil fuel production	Fossil fuel consumption	HDI	HCGDP	Life expectancy
Austria	9.78	400.90	8.44	27.37	69.22	0.89	10.08	80.80
Belgium	11.52	488.38	10.97	37.36	72.62	0.90	9.79	80.39
Canada	20.81	1669.21	34.34	22.42	74.44	0.90	10.05	81.32
Chile	5.72	232.09	17.24	56.71	73.96	0.82	7.16	78.92
Czech Republic	12.93	211.57	10.45	59.27	79.44	0.87	6.97	77.75
Denmark	10.40	332.02	5.57	58.87	75.52	0.92	10.03	79.53
Estonia	15.14	21.97	1.33	6.00	21.51	0.85	5.96	75.59
Finland	12.52	252.23	5.39	26.94	46.16	0.91	8.92	80.35
France	7.68	2694.75	65.32	8.42	49.41	0.88	11.10	81.82
Germany	11.50	3511.09	81.53	59.49	80.35	0.92	10.72	80.22
Greece	10.39	282.14	11.00	82.94	89.91	0.86	8.86	80.53
Hungary	6.44	137.23	9.95	47.76	73.77	0.83	7.34	74.63
Iceland	14.82	14.71	0.32	0.02	12.59	0.91	8.61	82.07
Ireland	13.51	244.05	4.56	73.95	88.20	0.91	9.25	80.63
Israel	10.11	243.92	7.78	99.13	96.22	0.89	7.10	81.55
Italy	8.23	2124.23	59.55	71.04	83.89	0.87	8.80	82.17
Japan	10.52	5804.28	127.67	71.49	87.67	0.89	9.72	83.05
Korea	13.00	1175.52	24.68	34.04	72.38	0.88	6.30	80.55
Latvia	5.57	27.14	2.08	42.54	62.06	0.83	5.75	73.22
Lithuania	7.01	41.09	3.06	45.62	66.31	0.84	6.39	73.16
Luxembourg	22.35	55.44	0.52	84.19	86.48	0.89	6.53	81.08
Mexico	5.86	1114.08	115.59	81.34	90.16	0.75	5.64	75.05
Netherlands	5.74	876.61	73.82	75.74	89.30	0.75	4.79	74.91
Norway	22.05	15,539.80	311.23	69.41	84.01	0.91	16.10	78.44

Table 2 (continued)

Countries	CO_{2}_PC	GDP (in billions)	Pop (in millions)	Fossil fuel production	Fossil fuel consumption	HDI	HCGDP	Life expectancy
Poland	12.04	855.85	16.67	84.56	92.37	0.92	10.23	80.88
Portugal	18.34	153.81	4.40	27.81	62.97	0.90	9.25	80.90
Slovak Republic	11.06	441.99	4.95	2.02	59.26	0.94	8.93	81.31
Slovenia	10.61	493.25	38.07	92.07	92.54	0.84	6.27	76.47
Spain	6.68	232.15	10.49	54.95	76.66	0.83	9.30	79.81
Sweden	8.38	92.33	5.40	24.61	68.22	0.83	7.30	75.65
Turkey	7.97	1414.15	46.19	50.88	77.18	0.87	8.75	82.12
UK	6.25	508.94	9.46	2.14	31.55	0.91	9.80	81.62
USA	6.51	595.58	7.92	1.32	51.50	0.93	10.97	82.49

Description of Variables: CO_{2}_PC (carbon dioxide emission per capita in metric tones), GDP (gross domestic product at constant 2010 in billions), Pop (total population in millions), Fossil fuel production (Electricity produced from gas, coal, and oil sources), Fossil fuel consumption (Fossil fuel energy consumption), HDI (human development index), HCGDP (healthcare expenditures as a share of GDP), Life expectancy (life expectancy rate at birth)

Table 3 Descriptive statistics

Variable	Obs	Mean	Std.	Min.	Max.
HC_Exp	363	8.4713	2.2176	4.1385	17.0734
CO_2_PC	363	10.7667	4.4814	5.2090	27.1931
HDI	363	0.8721	0.0468	0.7020	0.9510
RD_Exp	363	1.8458	1.0175	0.3096	4.4286
POP_GR	363	0.0077	0.0512	−0.0223	0.9689

Table 4 Correlation matrix

	HC_Exp	CO_2_PC	HDI	RD_Exp	POP_GR
HC_Exp	1.0000	–	–	–	–
CO_2_PC	0.335	1.0000	–	–	–
HDI	0.6135	0.4707	1.0000	–	–
RD_Exp	0.4237	0.2726	0.6372	1.0000	–
POP_GR	0.1507	0.2068	0.0513	0.0696	1.0000

Table 5 Panel VAR's optimal moment and model selection criteria

Lag	CD	*J*	J *p*-value	MBIC	MAIC	MQIC
1	1	73.2232	0.53652	−323.4	−76.777	−176.6
2	1	40.616	0.82554	−223.8	−59.384	−125.93
3	1	11.4661	0.99037	−120.74	−38.534	−71.808

first-to-third-order PVAR sets by using the initial three lags of all the variables. The findings of Table 5 report that the first-order PVAR model is more consistent subject to the criteria developed by (Abrigo and Love 2016; Andrews and Lu 2001). First-order lag is selected because it presents the lowest values for MBIC, MAIC, and MQIC. Furthermore, Hansen's J-statistics also satisfies the stability condition as the moment condition value is greater than other associated values of the endogenous variable. Hence, these findings validate that first-order panel VAR model is more stable using the GMM estimations.

Generally, in a panel VAR setting, modulus values against the eigenvalues are considered as the standardized condition for stability. Further, if the modulus values are < than 1, then it proves the stability of the underlying model (Brüggemann and Lütkepohl 2006; Hamilton 1994). The stability of panel VAR not only implies the invertible interpretations but also implies the interpretations of infinite order-vector moving averages. The estimations shown in Table 6 verify the stability conditions as each modulus value in the table is lower than 1. This assessment satisfies the condition of the stability of eigenvalues. Besides, Fig. 1 also indicates the determination of the eigenvalues chart, the *x*-axis contains the genuine segment and *y*-axis encompasses the components that are complex in nature. Figure 1 highlights that all the eigenvalues are placed within circle, which satisfies the stability through panel VAR for the selected variables.

Table 7 presents the coefficients of panel VAR analysis using GMM estimations. Findings show that the response of CO_2 emissions to healthcare expenditures is positive and significant ($p < 0.01$). This result implies that a one percent change in CO_2 emissions leads

Table 6 Eigenvalue stability condition

Eigenvalue		
Real	Imaginary	Modulus
0.979246	0.005757	0.979263
0.979246	−0.005757	0.979263
0.027825	0	0.601553
0.409545	0	0.409545
0.027825	0	0.027825

Remark: all eigenvalues lie under the unit of circle, which confirms the stability of the model

Fig. 1 Companion Matrix's Eigenvalues

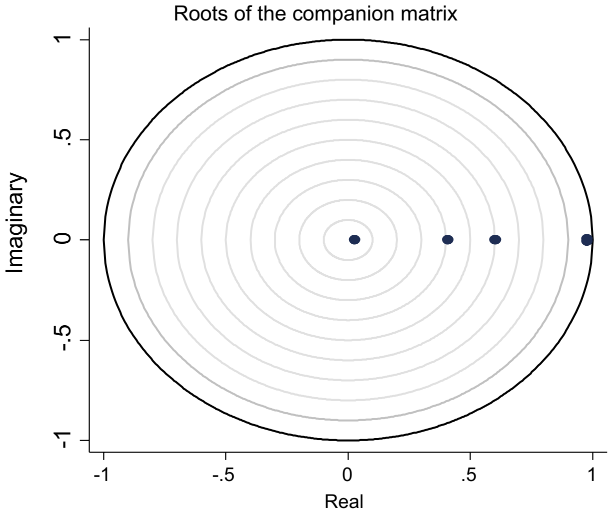

Table 7 Main results of five-variable panel VAR model

Response to	Response of				
	HC_Exp t-1	CO_2_PC t-1	HDI t-1	RD_Exp t-1	POP_GR t-1
HC_Exp	0.4993151 ***	0.1630373**	0.0018576 ***	0.0171814	−0.0001464
	(0.0567213)	(0.0835183)	(0.0005155)	(0.0144361)	(0.0004596)
CO_2_PC	0.0931602 ***	0.924843 ***	−0.0014086 ***	0.0236927 ***	0.0009731 ***
	(0.0335417)	(0.0372467)	(0.0002793)	(0.0069947)	(0.0002416)
HDI	10.60878 ***	−3.310947	0.8831152 ***	0.5329929	0.1539039 ***
	(2.345776)	(3.784141)	(0.0221913)	(0.5874779)	(0.0219144)
RD_Exp	−0.2438559	0.9183683 ***	−0.0004437	0.6967315 ***	−0.0157055***
	(0.158234)	(0.3140483)	(0.0019719)	(0.0488228)	(0.0017218)
POP_GR	3.992315	−3.889709	−0.0231553	0.6300317	−0.0065893
	(7.298858)	(7.709756)	(0.0430954)	(1.001937)	(0.0089438)
Observations	297	297	297	297	297
No. of Id	33	33	33	33	33

Standard error is in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

to a 0.0932% increase in healthcare expenditures. The results are in line with Chaabouni and Saidi (2017) and Apergis et al. (2018), who contend that an increase in environmental degradation (CO_2 emissions) causes an increase in health expenditures. Interestingly, our study also confirms the positive response of health expenditures to CO_2 emissions ($p < 0.05$) suggesting that healthcare activities may also amplify the pollutant emissions due to an escalated use of energy. Therefore, these two outcomes prove the bidirectional association between CO_2 emissions and healthcare expenditures. Likewise, the results also prove a two-way positive nexus between healthcare expenditures and HDI ($p < 0.01$). These findings are consistent with the earlier studies of Qureshi (2009) and Alin and Marieta (2011) and support the notion that both healthcare expenditures and HDI are interdependent and thus reinforce each other.

In contrast, our results indicate a negative impact of CO_2 emissions on HDI ($p < 0.01$) with a coefficient (−0.0014). As we know, life expectancy is a significant indicator of the composition of HDI. Hence, these results support the evidence that CO_2 emissions escalate the particulate matter and surface ozone, which leads to an increase in death rates (decrease life expectancy) and hospitalization (Jacobson 2008). Consequently, this increased mortality rate adversely impact human development index, though Table 7 shows that HDI does not significantly affect CO_2 emissions. Based on these two outcomes, we confirm a unidirectional association between CO_2 emissions and HDI. Up till now, we discuss the results of the main variable (HC_Exp, CO_2_PC, and HDI) of the study. Concerning the control variables, we observe that the response of R&D expenditures to CO_2 emissions is significant and positive in the estimated model. This result could be attributed to the fact that an increase in industrial research and development activities can contribute to an increase in carbon emissions. However, findings of the population growth rate (POP_GR) reflect an insignificant association with all other variables of the model.

To check the robustness of the results reported in Table 7, we conduct the multivariate Granger causality estimations. The findings of the Granger causality test are presented in Table 8, which reveals similar results as reported in Table 7. To further elaborate the results in Table 8, we provide Fig. 2 which demonstrates the form of causality (unidirectional or bidirectional) among three main variables namely CO_2 emissions, healthcare expenditures, and HDI.

Besides, we also run forecast error variance decomposition (FEVD) based on 2000 Monte Carlo simulations and impulse response function (IRF) introduced by Abrigo and Love (2016). The estimations of FEVD analysis are reported in Table 9. We observe that as much as 5% and 9% variation in healthcare spending are explained by CO_2 emissions and HDI, respectively (10 periods ahead). This outcome confirms that CO_2 emissions and HDI are reasonable predictors of healthcare spending in the OECD countries. The results also reveal that the ratio of variation in CO_2 emissions explained by healthcare expenditures will decrease from 6 to 2% as we move from 5 to 10 periods ahead. Furthermore, as much as 5% future variation in HDI is explained by healthcare expenditures, but 38% of the variation is explained by CO_2 emissions. Besides, 9%, 1%, and 21% future change in research and development expenditures is explained by the healthcare expenditures, HDI, and CO_2 emissions, respectively.

The results of the IRF are presented in Fig. 3. IRF depicts that when a single standard deviation is added in one variable, the IRF estimations generate an interesting effect in the other variables. In Fig. 3, plots depict that CO_2 emissions' response to shocks in healthcare is positive, while the impact of healthcare expenditures shock on CO_2 emissions is decreasing over time. In contrast, plots highlight that the response magnitude of HDI on healthcare expenditure and CO_2 emissions is positive over time. The IRF graph also demonstrates that

Table 8 Multivariate Granger causality test

		chi2	Df	*P*-Value
HC_Exp	HDI	20.453	1	0.000
	CO_2_PC	7.714	1	0.005
	RD_Exp	2.375	1	0.123
	POP_GR	0.299	1	0.584
	ALL	25.476	4	0.000
CO_2_PC	HC_Exp	3.811	1	0.051
	HDI	0.766	1	0.382
	RD_Exp	8.551	1	0.003
	POP_GR	0.255	1	0.614
	ALL	24.136	4	0.000
HDI	HC_Exp	12.985	1	0.000
	CO_2_PC	25.426	1	0.000
	RD_Exp	0.051	1	0.822
	POP_GR	0.289	1	0.591
	ALL	225.311	4	0.000
RD_Exp	HC_Exp	1.416	1	0.234
	HDI	0.823	1	0.364
	CO_2_PC	11.473	1	0.001
	POP_GR	0.395	1	0.529
	ALL	32.255	4	0.000

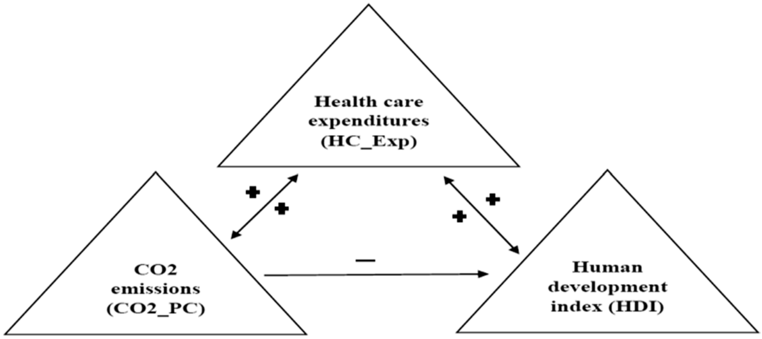

Fig. 2 Causality nexus between healthcare- CO_2- HDI. *Note* In Fig. 2 ↔ represents the bidirectional causal relation while → shows the unidirectional causality

Table 9 Forecast error variance decomposition

Response variable		Impulse variable				
	Periods-ahead	HC_Exp	CO_2_PC	HDI	RD_Exp	POP_GR
HC_Exp	5	0.8917	0.0457	0.0548	0.0068	0.0010
	10	0.8392	0.0539	0.0994	0.0066	0.0010
CO_2_PC	5	0.0622	0.8537	0.0008	0.0830	0.0003
	10	0.0299	0.8252	0.0014	0.1433	0.0001
HDI	5	0.0522	0.1422	0.7936	0.0119	0.0001
	10	0.0291	0.3898	0.5096	0.0714	0.0001
RD_Exp	5	0.0875	0.0725	0.0046	0.8350	0.0004
	10	0.0686	0.2108	0.0130	0.7073	0.0003
POP_GR	5	0.0694	0.0248	0.0508	0.1833	0.6717
	10	0.0649	0.0610	0.0582	0.1899	0.6260

In Table 9 estimations are based on 2000 Monte Carlo simulations, and only reports 5th and 10th period for brevity

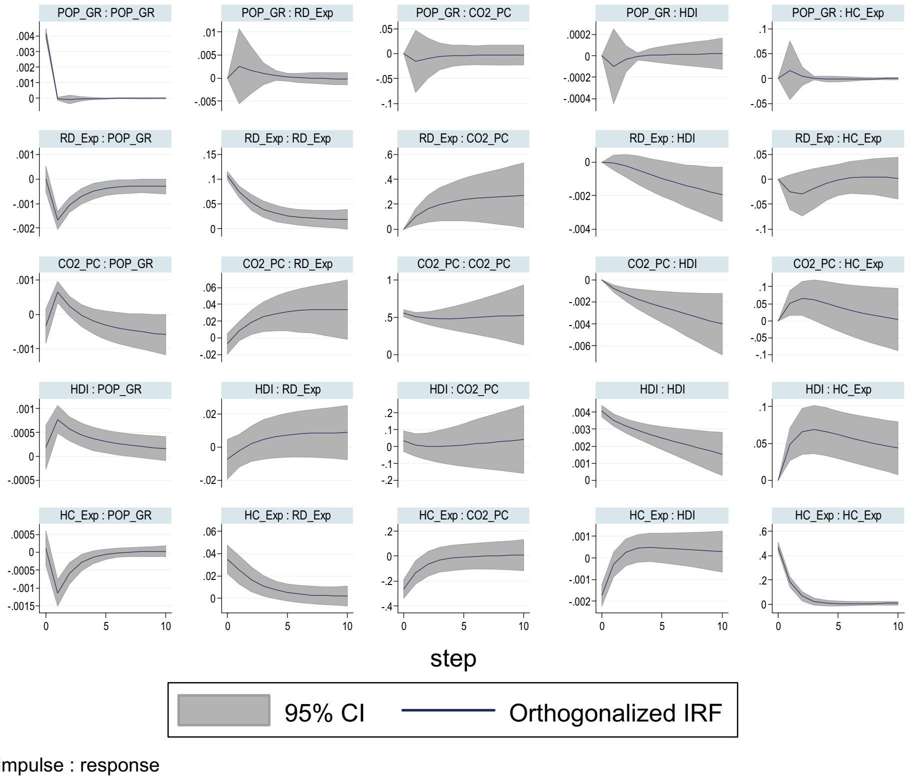

Fig. 3 Results of impulse response function (IRF)

the response propensity of healthcare expenditures on CO_2 emissions and HDI approximately becomes flat after the 5th period.

4 Conclusions and policy implications

The present research aims to explore the relationship between healthcare spending, CO_2 emissions, and HDI. We employ a strongly balanced panel of 33 OECD countries which consists of 363 country-year observations and cover a time span of 2006–2016. A newly developed econometric technique, PVAR via GMM technique, is employed for econometric analysis. The results of optimal moment and model selection criteria validate first-order panel VAR for our empirical models. Findings of PVAR reveal that all three main variables namely healthcare expenditures, CO_2 emissions, and HDI have a causal relationship. More specifically, we find a bidirectional causality between healthcare expenditures and CO_2 emissions which suggest that CO_2 emissions significantly escalate healthcare expenditures for OECD economies. Similarly, extensive healthcare spending also contributes to CO_2 emissions due to the higher use of energy. Moreover, healthcare expenditures and HDI also show a positive bidirectional relationship as these two variables reinforce each other, though a negative unidirectional causality between CO_2 emissions and HDI supports the notion that CO_2 emissions significantly harm the human development endeavors of sample OECD countries. Concerning control variables namely research and development expenditures (RD_EXP) and population growth rate (POP_GR), R&D expenditures have a positive influence on CO_2 emissions ($p<0.01$). These results are consistent with Fernández et al. (2018), as countries are still using highly pollutant energy resources and technologies to fuel higher economic growth. The implications of this research implore the concerned administrators in respective countries to undertake measures and devise policies to lower the CO_2 emissions of their respective countries in line with the sustainable development goals established by the United Nations. Consequently, these countries will not only be able to lower their healthcare burden but it will also lead to improved quality of living of their citizens as reflected by the HDI. Furthermore, it is also imperative to introduce cleaner technologies in the manufacturing processes to lower pollutant emissions to ensure a healthy environment for the people. Besides, it is equally essential for these OECD economies to drastically cut the use of carbon sources of energy and increase the share of renewable sources in their energy mix to preserve the ecosystem and enhance the quality of life of the masses.

This research also has some limitations which are worth noting: first, owing to the difficulty of collecting the data on the proposed variables for longer periods, the study only covers 11-year time span. Second, we do not segregate healthcare expenditures into public and private sector health expenses. Third, though CO_2 emissions are a major contributor to pollution emissions, yet it is useful to observe the adverse impact of other GHG emissions such as methane, SO_2, and nitrous oxide on human health and resulting health expenditures. Hence, these are the open research questions for researchers for further exploration.

Acknowledgement We acknowledge the thoughtful comments of 2 anonymous reviewers on the earlier version of this article.

Funding This research received no external funding.

Availability of data and material Data is available upon request.

Code availability Analysis files and codes are available upon reques.

Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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