Health care expenditure and environmental pollution: A cross-country comparison across different income groups

Nicholas Apergis

University of Derby, UK, n.apergis@derby.ac.uk

Mita Bhattacharya (Corresponding Author)

Monash University, Australia, Mita.Bhattacharya@monash.edu

Walid Hadhri

University of Tunis, Tunisia, walid.hadhri@isg.rnu.tn

Health care expenditure and environmental pollution: A cross-country comparison across different income groups

Abstract
This paper investigates the long-run dynamics between health care expenditure and environmental pollution across four global income regions. The analysis uses data from 178 countries, spanning the period 1995-2017. Panel estimations are employed with unobserved heterogeneity, temporal persistence, and cross-sectional dependence in the form of a common correlated effects model. The findings document that the health care expenditure is a necessity for all sub-regions. Carbon emissions escalate health care expenses and the effects are more prominent for both the upper-middle and high-income regions. A 1% increase in health care expenses increases energy intensity by 0.108 to 0.164 across these regions. The results are robust with significant policy implications for the health care sector. In this respect, a coordinated approach to the integration of the energy and health sectors across different income regions is recommended. The findings also recommend that low-carbon emissions and energy efficient health care services will significantly reduce future health care expenses.

Keywords: Health care expenditure; environmental pollution; CO_2 emissions; income regions; panel estimation

JEL Classification: C310, C330, H510

1. Introduction

In 2012, the World Health Organisation (WHO) estimated that the deaths of seven million people were attributable to environmental pollution, the largest single health risk worldwide. 144 of 197 parties have ratified the Paris Agreement on Climate Change (COP21).[1] Spearheaded by the United Nations Framework Convention on Climate Change (UNFCCC), the COP21 treaty is a historic global health treaty. Furthermore, the World Health Organisation (WHO, 2015) recommends certain actions that countries should take to reduce emissions at both the national and local levels. These attempts are expected to protect and promote global economic health and well-being. As outlined by

[1] http://www.cop21paris.org/

the WHO in a recent policy scoping report (WHO, 2015), investments in low-carbon development, as well as strengthening climate resilience, are also directly related to investments in health care.

The reduction of global carbon dioxide (CO_2) emissions may not have immediate effects on health care expenditure. However, maintaining conditions conducive to combating diseases related to environmental pollution and extreme weather conditions, as well as minimising the breakdown in food systems, can be helpful in the long run. The increase in atmospheric CO_2, quantitatively the most important anthropogenic greenhouse gas, has occurred primarily due to fossil-fuel consumption (Robert and Grimes, 1997). Reducing CO_2 driven industrial changes will reduce environmental justice, improve public health, reduce inequality and increase the resilience of individuals, communities and broader society (Watts *et al.*, 2015).

Comprehensive reviews of the published literature relevant to national income and national health care expenditure accounting can be found in the early literature in Hitiris and Posnett (1992) and Feldstein (1988). Increases in healthcare expenditure have become a common problem for developed countries due to the increase in demand for aged care services (Geue *et al.,* 2014; Zweifel *et al.,* 1999). In their seminal research, Zweifel *et al.* (1999) establish a positive association between age and health care expenditure with individuals aged 65 and older. Payne *et al.* (2007) review the literature, while de Meijer *et al.* (2013) consider the interaction between an aging population and other factors affecting health care expenditure. Other studies, such as those by Jönsson and Eckerlund (2003) and Baltagi and Moscone (2010), analyse the determinants of health care expenditure in panel studies. Acemoglu *et al.* (2013) investigate the health care expenditure and income relationship in the US using an instrument for the local area income with time series variation in oil prices interacting with local oil reserves. Income elasticity turns out to be approximately 0.7.

There are fewer cross-country studies available for non-OECD countries. Amongst these, Fazaeli *et al.* (2016) consider countries in the Organization of the Petroleum Exporting Countries (OPEC), Samadi and Homaie (2013) Economic Cooperation Organization (ECO) countries, and Khan and Mahumud (2015) South-East Asian countries. Conversely, a significant volume of literature exists in explaining the persistent increase in healthcare expenditure over time. In particular, Gbesemete and Gerdtham (1992), Murthy and Ukpolo (1995), Hansen and King (1996), Matteo and Matteo (1998), Murthy and Okunade (2000), and Herwartz and Theilen (2003) consider both economic and non-economic factors affecting healthcare expenditure, including ageing populations, income, the rate of females participation in the labour force, government health care finance, external aid, and urbanisation. The literature on the health care-income relationship is succinctly summarised in Baltagi *et al.*, (2016).

In this research we investigate the impact of air pollution (measured by CO_2 emissions) on per capita health care expenditure across four income regions (i.e., low, lower middle, upper middle and high income). From a policy perspective, it is important to explain the relationship between health care expenditure and environmental pollution across different income regions, as development and economic activities will become increasingly concentrated outside the OECD regions in the coming decades. In the absence of effective governmental policies, health care expenditure and the associated impoverishment of individuals are expected to escalate.

Why do we need a new study to explore the emissions-health expenditure relationship across different income regions? After reviewing the relevant literature, we realise that the empirical literature with international comparisons provides little guidance towards linking health expenditure and environmental pollution across different income regions. This study fills the gap in the literature in three ways. In the current era of globalisation, countries are engaging more and more in trading activities, which can be a source of environmental pollution. At the same time, health care expenditure has increased in recent decades, particularly in the case of developed countries. Large differences have existed more historically between developed countries, while this has been a recent phenomenon in developing countries (Kea *et al.*, 2011). In 2011, health care expenditure in certain countries was more than 12% of GDP, and less than 3% in others. Our first contribution is to analyse the relationship between health care expenditure and economic, as well as non-economic factors. Along with other drivers, we need to capture the dynamic effects of environmental pollution on health care expenditure across different income regions. To the best of our knowledge, there is no such study in the literature considering different income regions for this purpose. To this end, the analysis makes use of the World Bank classification of income regions, i.e., low income, lower-middle income, upper-middle income and high income. The analysis also makes use of the longest available time period covering all 178 countries of interest. During this period, significant reforms occurred in the health care sector in many of these countries. Social and political changes prompted some countries to adopt increasingly prominent governmental roles in the introduction of non-governmental insurance institutions, the establishment of government-funded insurance schemes, and the creation of healthcare services funded by public or private organisations. This transition in healthcare financing has been coupled with increases in trade and environmental pollution across countries, and with economic activities resulting in higher energy consumption and environmental pollution that cause problems in human health.

Changes in socioeconomic structures and increases in the demand for health care are linked to increases in health care expenditure. The financial burden due to outdoor environmental pollution in developing countries has been reported by the United Nations Environment Program as approximately 5% of their GDP (UNEP, 2016). The empirical models presented by the UNEP capture the interdependence between health and energy consumption during the process of production, trade and urbanisation. In this process, democracy plays a key role in balancing the negative effects of energy consumption and increases in health care expenditure.

The remainder of this paper is structured as follows. Section 2 presents a brief review of the literature as the backdrop to our empirical models presented and analysed in this research. Section 3 describes the empirical models used herein, along with the relevant data set and measures. Section 4 provides a detailed discussion of the empirical methodology, followed by discussing the findings. The final section summarises the results and offers certain recommendations for policy purposes.

2. Literature review

We explore the major determinants of both health care expenditure and CO_2 emissions to develop the empirical models in the following sub-sections.

2.1. Health care expenditure: Determinants

What are the main drivers of aggregate health care expenditure? There is no straightforward theory to explain this; however, certain general hypotheses can be formulated in terms of our empirical model. We posit that the demand for health care is reflected through the overall health care expenditure (HCE) of any economy. Expenditure in this sector increases with national income, aging population, environmental pollution and increase in energy intensity (an overall indicator of technology).

National income

According to the seminal research by Newhouse (1977), there is a vast empirical literature relating health care expenditure to income. Many researchers consider income as their primary explanatory variable (Hitiris and Posnett, 1992; Baltagi and Moscone, 2010; Mehrara, 2012; Samadi and Homaie, 2013; Chaabouni and Abednnadher, 2014; and Boachie and Ramu, 2016). A positive relationship is established in most cases; however, the size of income elasticity of health care expenditure varies across countries due to differences in the explanatory variables used, the estimation methodologies, and the period of development for the countries considered. For example, in the case of 30 African countries, income elasticity was found to be close to unity (Gbesemete and Gerdtham, 1992), while in the case of Mexico, Parker and Wong (1997) report measures of the elasticity of health care expenditure measures with respect to income and show that it is larger for the case of low-income uninsured groups. For Canada, the elasticity is below one (Bilgel and Tran, 2013), while Kea *et al.* (2011) use a panel of 143 countries to establish an income elasticity ranging from 0.75 to 0.95. With panel data from twenty OECD countries, Baltagi and Moscone (2010) establish health care expenditure as a necessity, with lower elasticities across heterogeneous panels with cross-sectional dependence. For the case of 14 OECD countries, Blazquez-Fernandez *et al*. (2014) document health care expenditure as a luxury item in the long-run.

There are also other studies establishing simultaneity between these two variables. Erdil and Yetkiner (2009) report bi-directional causality between GDP and health care expenditure with panel data from 75 low to high income countries. Hartwig (2008), however, could not establish one-way causality from health care expenditure to per-capita income growth for the case of 21 OECD countries, while Baltagi *et al*. (2016) summarise the literature over the last six decades. In general, they highlight that income elasticities are positive and greater than unity for the case of developed countries, while the values are less than unity for low to middle income countries. Overall, elasticity varies across countries, with cyclical movements over time, with the estimates being dependent on the data used, the estimation methodologies, the country's stage of development, as well as other non-economic factors.

Aging population

The impact of an ageing population on health and welfare systems are the focus of political agendas throughout the developed world. Decreasing birth rates and increasing life expectancy are the primary causes of the increasing trend in health care costs, with serious consequences for the social structure and long-term sustainability of public finances as the major source of health care expenditure. Zweifel *et al*. (1999) emphasise that population ageing acts as a barrier to the growth of health care expenditure. Based on a conceptual model, Pammolli *et al*. (2012) identify the indirect effect of ageing on the growth of health care expenditure through certain societal factors, such as medical technology. Meijer *et al*. (2013) critically review the effect of population ageing on health care expenditure. They focus on the interaction between factors, such as the growth of national income, medical technology, wages and prices, with an ageing population being shown to have the greatest effect on the future growth of health care expenditure.

Other studies in the literature that use the ageing population as a covariate include those by Matteo and Matteo (1998), Rahman (2008), Murthy and Okunade (2009), de Meijer *et al*. (2013), Samadi and Homaie (2013), Chaabouni and Abednnadher (2014) and Novignon *et al*. (2015). Bloom *et al*. (2015) suggest that an ageing population will lead to major macroeconomic difficulties, while the gap is getting wider in terms of population health, as measured by life expectancy, between the worst and best performing countries in their study, i.e. Sierra Leone and Japan, respectively. Therefore, 'healthy ageing' depends on demographic changes, while health care expenditure is different across different income regions.

CO_2 emissions

A large volume of the literature exists on the determinants of health care expenditure. Despite the significance of the related effects of environmental quality indicators on health, the literature on environmental quality indicators of HCE is still embryonic. Existing studies include those by Beatty and Shimshack (2014), Brunekreef and Holgate (2002), Janke *et al*. (2009), and Mead and Brajer (2005). Using a panel cointegration approach, Narayan and Narayan (2008) examine both the short- and long-run effects of environmental quality on health care expenditure for eight OECD countries. In the short-run, carbon emissions have a positive and statistically significant effect on health expenditure, while in the long-run, both carbon and sulphur oxide emissions have an inelastic and positive impact on health expenditure. Qureshi *et al*. (2015) document that environmental issues escalate health care expenditure in a panel of five selected Asian countries. In a panel study based on eight oil exporting countries, Assadzadeh *et al*. (2014) establish positive elasticities for carbon dioxide on health expenditure. Using quantile regressions, Apergis *et al*. (2018) report that the effect of CO_2 emissions is stronger at the upper end of the conditional distribution of health care expenditure. They establish that tangible health related benefits can be achieved with lower CO_2 emissions across U.S. states. CO_2 emissions are thus widely shown to increase health care expenditure, particularly in the case of low-income countries. The health effect of CO_2 emissions depends on certain advances in technology, as well as on the income of a particular country.

Energy intensity

Monitoring energy intensity is needed to check whether policies in reducing environmental pollutions have the desired effects. This has received growing attention for sustainable development, as well as for the reduction of poverty and health care expenditure. Chung and Meltzer (2009) estimate the carbon-footprint of the US health sector. Increases in overall energy efficiency can be due to improvements in technology, newer capital equipment, or to changes in the structural composition of the economy (Bhattacharya *et al.*, 2018). In the absence of any relevant literature, the analysis presumes that higher overall energy intensity will have detrimental effects on environmental pollution, while it will increase health care expenditure of any particular country. Technological developments, along with environmental mitigation efforts, may reduce health care expenditure, along with low carbon-footprint health care supply chains.[2]

2.2. CO_2 emissions: major drivers

Countries are constantly implementing strategies in place to reduce CO_2 emissions. Economic growth around the globe is increasing environmental pollution. Ignoring the composition and technology effects, economic growth has a carbon-enhancing effect. In the presence of technology and structural changes, the analysis includes health care expenditure (an indicator of health care demand) and energy intensity, capturing the

[2] Efficiency improvements in the use of energy alone could achieve 31% reduction necessary to halve emissions by 2050, compared to 2009 levels (IEA, 2012).

technological changes in reducing per capita emissions. Therefore, the CO_2 emissions function is defined with income, health care expenditure and energy intensity.

Income

The relationship between economic growth (measured as per capita income) and environmental pollution (measured as CO_2 per capita) has been a popular research area over the last three decades. However, the empirical evidence remains inconclusive to prescribe policies across countries. Sustainable increases in income may reduce CO_2 emissions as described by the environmental Kuznets curve (EKC) hypothesis. Acaravci and Ozturk (2010), Ahmed et al. (2017), Ozcan et al. (2018), among others, have examined the emissions-income nexus across countries over different time periods. Balsalobre-Lorente et al. (2017) and Stern (2017) provide excellent reviews on the EKC literature.

Health care expenditure

Health care providers are large consumers of energy. For example, intensive care units are operational twenty-four hours a day, while operating theatres are kept on standby should they be required at short notice. Specialist medical equipment, such as machines for magnetic resonance imaging, magnetic resonance tomography and computed tomography scans, all consume high volumes of energy. The characterisation of direct and indirect energy use in this sector is critical for the design of more efficient energy and CO_2 emissions reduction policies.

Reduced healthcare expenditure through dietary changes can also reduce CO_2 emissions. Healthy diets are associated with less non-communicable diseases and this has a positive impact on reducing per capita HCE (Hallström *et al.*, 2017). The food system is associated with health care expenditure and they establish a positive impact on reducing CO_2 emissions. In the absence of a rich literature, it is assumed that higher health care expenditure increases energy demand and indirectly can increase CO_2 emissions in the long-run.[3]

Energy intensity

Energy intensity depends on structural changes across countries and energy efficiency across sectors including the health sector. In the absence of energy data across different sectors for our selected panel of countries, the analysis makes use of this overall energy intensity to capture the effects on CO_2 emissions.[4] Linares and Labandeira (2010) identify specific policies in promoting energy conservation (which reduces energy intensity) based on economic instruments. Higher energy intensity will increase CO_2 emissions, therefore, the reduction in energy intensity across sectors is needed to combat CO_2 emissions.

3. Modelling and data

The analysis posits the empirical models considering the above discussions. In this respect, it follows a unified framework for the modelling purposes. Data and the measure of variables are described here.

3.1 Empirical models

Modelling heath care expenditure

The empirical model follows Newhouse (1977), where per capita health expenditure is a function of per capita income. In this work, the analysis extends this method as follows: per capita health care expenditure (HCE) is explained by GDP per capita (GDPC) and a selection of non-income variables. We select aging population, proxied by the proportion of the population over the age of 65 (POP65), CO_2 emissions (CO_2),

---

[3] We ignore here other sectors in an economy as our emphasis is on health care sector.

[4] Changes in the energy intensity may occur due to a greater number of other factors which may or may not be carbon related.

and energy intensity (EINT) as the major control variables in explaining health care expenditure:

$$HCE_{it} = a_{1i} + a_2\ GDPC_{it} + a_3\ POP65_{it} + a_4\ CO_{2it} + a_5\ EINT_{it} + e_{1it} \tag{1}$$

where i = 1, …, n represents each country in the panel and t = 1995, …, 2017 is the time period. a_{1i} allows for country fixed effects, while e_{1it} indicates the residuals factor.

Modelling carbon emissions

We also consider carbon emissions to depend on GDP per capita (GDPC), health care expenditure per capita (HCE), and energy intensity (EINT):

$$CO_{2it} = b_{1i} + b_2\ GDPC_{it} + b_3\ HCE_{it} + b_4\ EINT_{it} + e_{2it} \tag{2}$$

CO_2 captures carbon emissions (in per capita); GDPC is income per capita; HCE represents health care expenditures; and, EINT proxies for energy intensity. The parameter b_{1i} also allows for country fixed effects, while e_{2it} denotes the error term.

3.2. Data

In model (1), health care expenditure (HCE) is measured as real per capita health expenditure; real GDP is also in per capita terms (GDP). Both HCE and GDPC are measured in US dollars at constant 2005 prices, based on purchasing power parity (PPP). Population age structure is captured by using the population over the age of 65, expressed as the percentage of total population (POP65). Carbon dioxide emissions (CO_2) are measured as metric tons per capita and are used as a proxy for environmental pollution. This measure includes carbon dioxide produced during the consumption of solid, liquid and gaseous fuels, and gas flaring (WDI, 2017). EINT captures energy intensity of well-being per capita. The data are obtained from the World Development Indicators (WDI) series published by World Bank (WDI, 2017).

We consider annual data, spanning the period 1995 to 2017 for 178 countries (as described in the Appendix). Following Bhattacharya *et al.* (2016), the analysis uses logarithmic versions of the modelling approach, which allows us to interpret the coefficients as elasticities. The selection of time span and countries are determined by data availability. The analysis is undertaken using the full sample of countries, along with sub-samples based on the World Bank income classifications, i.e., low income, lower-middle income, upper-middle income, and high income. Out of 178 countries, we have 58 high income countries, 49 upper middle-income countries, 45 lower middle-income countries, and 26 low income countries. The heterogeneous nature of health care expenditure will minimise any bias regressions when considering groups of countries with similar income levels. Descriptive statistics, as well as a correlation matrix across the modelling variables, are presented in the Appendix (Tables A1 and A2, respectively).

4. Empirical findings

Following Matteo and Matteo (1998) and Costa-Font (2007), cross-country studies of healthcare expenditure may impose some restrictions due to country-specific heterogeneity causing differences in healthcare. Given the heterogeneous nature of our panel for this study, we consider cross-sectional dependence across panels in establishing long-run dynamics. Cross-sectional dependence may arise due to changes in health care and energy policies across countries or due to other external shocks, which may directly or indirectly affect policies on health care expenditure and carbon emissions.

Cross-sectional dependence tests

Second-generation panel unit root tests are implemented when the presence of cross-sectional dependence has been established. Therefore, it is first crucial to determine the presence of cross-sectional dependence. The cross-sectional dependence (CD) statistic by Pesaran (2004) is employed to explore the presence of cross-sectional dependence. The CD statistic is described as:

$$\mathrm{CD} = \frac{\sqrt{2\mathrm{T}}}{[\mathrm{N}(\mathrm{N}-1)]} \sum_{\mathrm{i}=1}^{\mathrm{N}-1} \sum_{\mathrm{j}=\mathrm{i}+1}^{\mathrm{N}} \rho_{\mathrm{ij}} \qquad (3)$$

where N is the number of countries; T is the time dimension of the panel; ρ_{ij} denotes the pair-wise correlation coefficients. Under the null hypothesis of cross-sectional independence, the statistic asymptotically follows a two-tailed standard normal distribution. The results, both for the full sample and sub-samples, are reported in Table 1; they reject the null hypothesis of cross-sectional independence, across all lags (one to four) included in the ADF regressions.

[Insert Table 1 about here]

Panel unit root tests

Two second-generation panel unit root tests determine the degree of integration in the variables under consideration. The Pesaran (2007) panel unit root test makes use of a statistic based on the average of the individual cross-sectional ADF statistics (CADF), which is denoted as a cross-sectional augmented Im et al. (2007) test (CIPS):

$$\mathrm{CIPS} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{t_i}(\mathrm{N},\mathrm{T}) \qquad (4)$$

where $\mathrm{t_i}(\mathrm{N},\mathrm{T})$ is the t-statistic of the OLS estimate for b_i in:

$$\Delta \mathrm{y_{it}} = \alpha_{\mathrm{i}} + \mathrm{b_i y_{i,t-1}} + \mathrm{c_i t} + \sum_{\mathrm{j}=1}^{\mathrm{p}} \mathrm{d_{ij}}\, \Delta \mathrm{y_{i,t-j}} + \mathrm{v_{it}} \qquad (5)$$

CIPS* is the truncated version of the CIPS test defined as:

$$CIPS^{*} = \frac{1}{N} \sum_{i=1}^{N} t_i^{*}(N,T) \qquad (6)$$

$$\begin{cases} \mathrm{t_i} \text{ if } -\mathrm{K_1} < \mathrm{t_i}(\mathrm{N},\mathrm{T}) < \mathrm{K_2} \\ \end{cases}$$

where $t_i^* = \quad -K_1 \text{ if } t_i(N,T) \leq -K_1$

$\qquad\qquad K_2 \text{ if } t_i(N,T) \geq K_2$

Where the truncation points K_1 and K_2 are chosen through a normal approximation for $t_i(N,T)$. Both statistics are under the null hypothesis of a unit root. In addition, the bootstrap panel unit root tests by Smith et al. (2004) is also used and they are identified as t-bar, Lagrange Multiplier (LM)-bar, max-bar, and min-bar version of the test. All four tests consider the presence of a unit root in the null hypothesis. The t-bar test is the bootstrap version of the well-known panel unit root test of Im et al. (2003):

$$t - \text{bar} = \frac{1}{N}\sum_{i=1}^{N} t_{iT} \tag{7}$$

where t_{iT} are the time-series (countries') ADF t-statistics. The LM-bar test is the mean of the individual Lagrange Multiplier (LM_i) test statistics (Solo, 1984) as follows:

$$LM - \text{bar} = \frac{1}{N}\sum_{i=1}^{N} LM_i \tag{8}$$

and the LM statistics are:

$$LM_i = (\rho_n - 1)\sum_{t=2}^{n} \frac{y_{t-1}^2}{\sigma_n^2} \tag{9}$$

where σ_n^2 is the restricted maximum likelihood estimator defined as:

$\frac{1}{(n-1)}\sum_{t=2}^{n}(y_t - y_{t-1})^2$; ρ_n is the maximum likelihood estimation of the autoregressive parameter. The max-bar test is the max Dickey-Fuller (DF) test of Leybourne (1995), which requires the joint application of forward and reverse regressions. Given a series of interest $\{y_t\}_{t=0}^{T}$, the DF test is applied to both $\{y_t\}$ and $\{y_t^*\}$, where $z_t = y_{T-t}^*$ for t = 0, . . . , T; thus, z_t denotes the deterministic terms employed in the DF regressions. The maximum DF test is the maximum (less negative) of the two test statistics obtained. Finally, the min-bar test is a more powerful variant of the individual Lagrange Multiplier (LM_i):

$$\min - \text{bar} = \frac{1}{N}\sum_{i=1}^{N} \min_i \tag{10}$$

with $\min_i = \min(LM_{fi}, LM_{ri})$ where LM_{fi} and LM_{ri} are based on forward and reverse regressions.

The results of the panel unit root tests are reported in Table 2 and support the presence of a unit root in levels across all variables under consideration, not only for the case of the full sample, but also across all the country panels. As a result, first differences are recommended for the remaining parts of the empirical analysis.

[Insert Table 2 about here]

GMM estimates

The GMM estimation considers reverse causality issues and, thus, avoids potential endogeneity (Arrelano and Bover, 1995; Blundell and Bond, 1998). The Hansen test for overidentification checks the validity of instruments. The GMM modeling process yields:

$$\Delta logHCE_{i,t} = b_0 + \sum_{i=1}^{q_1} bi1\Delta logHCE_{i,t-i} + \sum_{i=0}^{q_2} b2i\Delta logGDPC_{i,t-i} + \sum_{i=0}^{q_3} b_{3i}\Delta logPOP65_{i,t-i} +$$

$$\sum_{i=0}^{q_4} b_{3i}\Delta logCO2_{i,t-i} + \sum_{i=0}^{q_5} b_{3i}\Delta logEINT_{i,t-i} + \Delta\varepsilon 1_{i,t} \qquad (11)$$

and

$$\Delta logCO2_{i,t} = b_0 + \sum_{i=1}^{q_6} bi1\Delta logCO2_{i,t-i} + \sum_{i=0}^{q_{27}} b2i\Delta logGDPC_{i,t-i} + \sum_{i=0}^{q_8} b_{3i}\Delta logHCE_{i,t-i} +$$

$$\sum_{i=0}^{q_9} b_{3i}\Delta \log EINT_{i,t-i} + \Delta\varepsilon 2_{i,t} \quad (12)$$

where Δ is the first difference operator, $HCE_{i,t}$ stands for health expenditure of country i at time t, $GDPC_{i,t}$ denotes the GDP per capita, $POP65_{i,t}$ represents the population up to the age of 65, $CO2_{i,t}$ is carbon emissions, $EINT_{i,t}$ denotes energy intensity, the bs are parameters to estimate, and $\varepsilon 1_{i,t}$ and $\varepsilon 2_{i,t}$ are the error terms.

The results are reported in Table 3. The dynamic presentation of the model is described through the inclusion of certain lags with respect to a number of the variables involved. The number of lags has been determined through the Akaike criterion. Panel A reports the estimates of the health care expenditure equation (11). HCE is income inelastic, with a positive sign for the full sample, as well as across all four different income regions. An 1% increase in national income increases health expenditure by 7.2% in the full sample, and 9.3%, 8.6%, 6.8% and 2.9% for low, low-middle, upper-middle, and high-income regions, respectively. Moreover, an 1% increase in CO_2 emissions increases health care expenditure by 2.5% in the overall sample and by 2.9%, 1.2%, 2.3% and 2.6% for the corresponding income groups. The results between health care expenses and carbon emissions are in line with those provided in other studies in the literature, such as in Mehrara *et al.* (2014) and Zhang (2011). Aging population has similar effects across the various income regions, as well as for the full sample. In economic terms, the estimates indicate that an increase in carbon emissions of one metric tonne increases the health expenditure to GDP ratio of the low-income region countries by 1.4. The corresponding figures for the low-middle income region, the upper-middle income region and the high-income region are 1.56, 2.07 and 3.32, respectively, highlighting the extra burden on health expenditure from environmental pollution in the case of high-income or developed countries. The estimations reflect heterogeneity across the income regions. Countries with similar income and pollution per capita should therefore act together to reduce health care expenditure and implement necessary policy actions to mitigate escalating future health care expenses. Moreover, energy intensity is illustrated to be a significant driver for health care expenditure. The relative coefficients are positive and statistically significant across all income groups, as well as for the full sample. The overall results are similar to those documented by Matteo and Matteo (2005) and Narayan and Narayan (2008). All the relevant diagnostics are reported in the bottom part of Panel A in Table 3. For the validity of the instruments, the results need to reject the test for second-order autocorrelation, AR(2) in disturbances. It is evident that the test for AR(2) of disturbances fails to reject the respective null. Thus, this test supports the validity of the instruments used. The diagnostics also report the Hansen test for over-identifying restrictions. In the estimation process, a range from 18 to 22 instruments has been used across all income groups. Reported Hansen test results fail to detect any problem in the validity of the instruments used in the estimation approach.

In terms of the estimates with respect to carbon emissions, the findings, reported in Table B, indicate that income per capita exerts a positive and statistically significant impact on carbon emissions across all country sample cases, while there exists a reverse effect running from health care expenditure on carbon emissions, where in the case of the full sample, an 1% increase in these expenditure exerts a 2.8% increase in carbon emissions, with the impact getting higher with the income classification group. Finally, energy intensity also has a positive and statistically significant effect on carbon emissions, with this effect remaining robust across all income regions. The empirical evidence in relevance to Equation (12) is consistent with the results reported by Hossain

(2011) and Sebri and Ben-Salha (2014). Once again, the relevant diagnostics, reported in the bottom part of Panel B in Table 3 indicate the acceptance of the second-order autocorrelation, as well as that the reported Hansen test results fail again to detect any problem in the validity of the instruments used in the estimation of equation (12).

[Insert Table 3 about here]

In order to study the robustness of the results presented in Table 3, a different methodological approach is followed. In particular, this sub-section makes use of the dynamic simultaneous equations method (DSEM) recommended by Miltze (2011). This method carefully accounts for the trade-off between the likely increase in estimation efficiency based on a full information system approach and the additional complexity brought into the system, which may translate into increasingly biased results if the estimation error of one equation is transmitted to all other equations. The use of simultaneous equations models with panel data is not that common. However, Baltagi and Chang (2000), Park (2005), and Baltagi (2008), among others, discuss both fixed effects and random effects panel data estimators in a system manner where right-hand side endogeneity matters. The approach makes use of instrumental variables (IV) estimation, thereby, building on the Hausman-Taylor (1981) (HT) model. This model may be seen as a hybrid version of the Fixed Effects (FEM) and Random Effects (REM) model. The idea of the obtained estimator is to derive consistent instruments from internal data transformations to cope with endogeneity, but still to avoid the strong all-or-nothing assumptions of the FEM and REM in terms of any residual correlation of the right-hand side regressors, respectively. The model splits both the vectors of time-varying and time-fixed variables into two sub-vectors. To the empirical ends of our work, the robust analysis uses the HT setup for estimating a 3SLS-GMM estimator, which has the advantage over standard 3SLS estimations, because it allows the use of different instruments in subsequent equations of the system, while standard 3SLS assumes that the same IV-set applies to every equation in the system.

The new results in terms of the overall sample are plotted in Table 4. They clearly document the presence of similar estimates vis-à-vis those reported in Table 3. In terms of diagnostics, both equations pass the weak identification test in terms of the Staiger and Stock (1997) rule of thumb ($F \geqslant 10$). Moreover, the Sargan/Hansen test for overidentification of moment conditions shows that both equations have law test statistics, implying the validity of the instruments. To assess the appropriateness of the chosen full information system approach, the Hausman (1978) test (m-stat) is also reported. Under the assumption that the 3SLS estimator is generally highly efficient, the test results indicate that under the null hypothesis, the estimates are consistent and efficient. The results of the Hausman test clearly show that the full information method passes the test for convenient confidence intervals across both equations. In other words, these results point to favourable evidence for our specified full information method.

[Insert Table 4 about here]

5. Conclusion and policy implications

In 2015, the Lancet Commission on Heath and Climate Change was established with a mission to improve the potential health co-benefits of climate change at local and national levels. This has been a challenging task in our time. Our contribution to this research was to explain some of these aspects. We analysed the dynamics of the CO_2 emissions-health care nexus in a cross-sectional panel with 178 countries from low, lower-middle, upper-middle and high-income regions. We established the dynamics of this relationship, as well as the differences between short- and long-term elasticities across the full sample, along with the four defined income regions across the globe. We examined the effects of other major determinants of health care expenditure, such as income, aging population and most importantly CO_2 emissions on health care expenditure. We established that a 1% increase in national income increased health expenditure by 7.2% in the full sample, and 9.3%, 8.6%, 6.8% and 2.9% for low, low-middle, upper-middle and high-income regions, respectively.

The empirical results indicated that CO_2 emissions, our primary research interest variable, had a significant positive effect on health care expenditure, while their impact increased for higher income countries. Moreover, we found that a 1% increase in CO_2 emissions increased health care expenditure by 2.5% in the overall sample and by 2.9%, 1.2%, 2.3% and 2.6% for low, low-middle, upper-middle and high-income regions, respectively. The key recommendations out of this research are as follows:

- A coordinated approach to energy and health services integration across the different income regions seems to be a necessity.
- Low carbon emissions, along with energy efficient health care services, are expected to reduce health care expenses significantly. In particular, green technologies, improved infrastructures, and reducing regulatory barriers in low- and middle-income countries are expected to substantially assist help in this integration process.
- High-income countries should take a lead role along with international organisations, such as the WHO, in combating escalated health care expenditure. This leadership, along with a low carbon economy, and healthy ageing

population, are expected to play a vital role in reducing the expenses in this sector.

Table 1: Cross-sectional dependence tests

		Lags		
Panel A: Full sample				
Variable	1	2	3	4
HCE	45.62	47.89	50.31	55.59
	[0.00]	[0.00]	[0.00]	[0.00]
GDPC	48.93	50.84	53.17	56.83
	[0.00]	[0.00]	[0.00]	[0.00]
POP65	43.29	46.18	49.88	52.74
	[0.00]	[0.00]	[0.00]	[0.00]
CO_2	49.26	53.48	57.92	62.18
	[0.00]	[0.00]	[0.00]	[0.00]
EINT	47.62	50.38	54.16	58.93
	[0.00]	[0.00]	[0.00]	[0.00]
Panel B: Low income countries				
HCE	42.18	46.93	49.25	51.08
	[0.00]	[0.00]	[0.00]	[0.00]
GDPC	45.32	48.11	50.09	54.36
	[0.00]	[0.00]	[0.00]	[0.00]
POP65	42.84	45.25	48.16	51.29
	[0.00]	[0.00]	[0.00]	[0.00]
CO_2	45.24	47.26	50.06	52.37
	[0.00]	[0.00]	[0.00]	[0.00]
EINT	44.21	46.37	49.62	52.39
	[0.00]	[0.00]	[0.00]	[0.00]
Panel C: Lower middle-income countries				
HCE	44.73	47.35	50.56	53.51
	[0.00]	[0.00]	[0.00]	[0.00]
GDPC	46.41	49.38	51.46	55.18
	[0.00]	[0.00]	[0.00]	[0.00]
POP65	44.50	47.31	49.62	52.84
	[0.00]	[0.00]	[0.00]	[0.00]
CO_2	47.41	49.82	52.65	55.14
	[0.00]	[0.00]	[0.00]	[0.00]
EINT	46.25	48.74	51.09	54.53
	[0.00]	[0.00]	[0.00]	[0.00]
Panel D: Upper middle-income countries				
HCE	48.32	50.14	53.28	56.14
	[0.00]	[0.00]	[0.00]	[0.00]
GDPC	47.29	51.85	53.73	58.79
	[0.00]	[0.00]	[0.00]	[0.00]
POP65	46.19	49.10	52.24	55.58
	[0.00]	[0.00]	[0.00]	[0.00]
CO_2	49.15	50.27	54.88	57.05

	[0.00]	[0.00]	[0.00]	[0.00]
EINT	48.16	50.47	54.36	57.33
	[0.00]	[0.00]	[0.00]	[0.00]
Panel E: High income countries				
HCE	53.61	57.42	60.19	66.05
	[0.00]	[0.00]	[0.00]	[0.00]
GDPC	50.46	55.29	59.14	64.01
	[0.00]	[0.00]	[0.00]	[0.00]
POP65	49.93	53.58	57.12	60.06
	[0.00]	[0.00]	[0.00]	[0.00]
CO_2	53.26	57.72	60.15	65.48
	[0.00]	[0.00]	[0.00]	[0.00]
EINT	52.64	56.13	59.64	63.47
	[0.00]	[0.00]	[0.00]	[0.00]

Under the null hypothesis of cross-sectional independence the CD statistic is distributed as a two-tailed standard normal. Figures in brackets denote p-values.

Table 2: Panel unit root tests

Panel A: Full sample

Variable	Pesaran CIPS	Pesaran CIPS*	Smith et al. t-test	Smith et al. LM-test	Smith et al. max-test	Smith et al. min-test
HCE	-1.16	-1.23	-1.32	3.35	-1.34	1.38
ΔHCE	-5.50***	-5.81***	-5.67***	22.46***	-7.29***	6.90***
GDPC	-1.20	-1.34	-1.31	3.18	-1.35	1.37
ΔGDPC	-5.58***	-5.92***	-6.69***	23.19***	-7.54***	6.95***
POP65	-1.36	-1.25	-1.36	3.14	-1.35	1.30
ΔPOP65	-5.79***	-5.48***	-6.49***	24.81***	-7.44***	7.08***
CO_2	-1.45	-1.58	-1.33	3.28	-1.51	1.46
ΔCO_2	-5.43***	-5.92***	-6.64***	22.91***	-7.69***	7.92***
EINT	-1.36	-1.52	-1.30	3.24	-1.46	1.40
ΔEINT	-5.36***	-5.65***	-6.58***	22.52***	-7.85***	7.38***

Panel B: Low income countries

Variable	Pesaran CIPS	Pesaran CIPS*	Smith et al. t-test	Smith et al. LM-test	Smith et al. max-test	Smith et al. min-test
HCE	-1.24	-1.35	-1.34	3.35	-1.33	1.49
ΔHCE	-5.18***	-5.39***	-5.47***	20.24***	-7.68***	7.48***
GDPC	-1.36	-1.34	-1.32	3.34	-1.56	1.43
ΔGDPC	-5.39***	-5.29***	-6.58***	22.52***	-7.69***	7.27***
POP65	-1.38	-1.46	-1.43	3.27	-1.46	1.42
ΔPOP65	-5.29***	-5.62***	-6.78***	22.92***	-7.92***	7.28***
CO_2	-1.40	-1.52	-1.31	3.22	-1.36	1.35
ΔCO_2	-5.63***	-5.47***	-6.49***	22.15***	-7.90***	7.51***
EINT	-1.32	-1.27	-1.34	3.21	-1.40	1.42
ΔEINT	-5.30***	-5.54***	-6.82***	22.93***	-7.54***	7.19***

Panel C: Lower middle-income countries

Variable	Pesaran CIPS	Pesaran CIPS*	Smith et al. t-test	Smith et al. LM-test	Smith et al. max-test	Smith et al. min-test
HCE	-1.25	-1.34	-1.32	3.44	-1.36	1.42
ΔHCE	-5.15[a]	-5.58***	-5.59***	22.98***	-7.49***	7.67***
GDPC	-1.35	-1.45	-1.36	3.42	-1.45	1.52
ΔGDPC	-5.29***	-5.58***	-6.88***	22.64***	-7.40***	7.61***
POP65	-1.45	-1.44	-1.41	3.31	-1.41	1.52
ΔPOP65	-5.79***	-5.86***	-6.82***	23.24***	-7.57***	7.92***
CO_2	-1.53	-1.48	-1.30	3.15	-1.46	1.26
ΔCO_2	-5.38***	-5.63***	-6.45***	23.18***	-7.94***	7.53***
EINT	-1.25	-1.30	-1.34	3.20	-1.43	1.42
ΔEINT	-5.61***	-5.52***	-6.72***	21.98***	-7.65***	7.58***

Panel D: Upper middle-income countries

Variable	Pesaran CIPS	Pesaran CIPS*	Smith et al. t-test	Smith et al. LM-test	Smith et al. max-test	Smith et al. min-test
HCE	-1.25	-1.34	-1.41	3.40	-1.47	1.56
ΔHCE	-5.18***	-5.48***	-5.66***	22.35***	-7.68***	7.88***
GDPC	-1.41	-1.52	-1.35	3.62	-1.55	1.54
ΔGDPC	-5.49***	-5.82***	-6.76***	22.79***	-7.61***	7.49[a]
POP65	-1.41	-1.62	-1.29	3.22	-1.42	1.36
ΔPOP65	-5.63***	-5.95***	-6.75***	23.14***	-7.98***	7.82***

CO_2	-1.39	-1.50	-1.36	3.25	-1.39	1.37
ΔCO_2	-5.61***	-5.65***	-6.49***	23.08***	-7.85***	7.30***
EINT	-1.29	-1.54	-1.32	3.28	-1.38	1.46
ΔEINT	-5.64***	-5.39***	-6.89***	23.26***	-7.50***	7.42***

Panel E: High income countries

Variable	Pesaran CIPS	Pesaran CIPS*	Smith et al. t-test	Smith et al. LM-test	Smith et al. max-test	Smith et al. min-test
HCE	-1.34	-1.40	-1.35	3.22	-1.45	1.42
ΔHCE	-5.59***	-5.98***	-5.49***	22.79***	-7.79***	7.96***
GDPC	-1.52	-1.52	-1.34	3.50	-1.41	1.43
ΔGDPC	-5.93***	-5.97***	-6.93***	22.35***	-7.56***	7.56***
POP65	-1.55	-1.65	-1.43	3.40	-1.45	1.32
ΔPOP65	-5.78***	-5.94***	-6.72***	22.53***	-7.49***	7.48***
CO_2	-1.39	-1.28	-1.29	3.21	-1.36	1.42
ΔCO_2	-5.36***	-5.95***	-6.38***	22.16***	-7.75***	7.97***
EINT	-1.28	-1.32	-1.37	3.21	-1.49	1.37
ΔEINT	-5.39***	-5.36***	-6.71***	22.94***	-7.55***	7.34***

Δ denotes first differences. A constant is included in the Pesaran (2007) tests. Rejection of the null hypothesis indicates stationarity in at least one country. CIPS* = truncated CIPS test. Critical values for the Pesaran (2007) test are -2.57 at 1%, -2.33 at 5%, and -2.21 at 10%, respectively. Both a constant and a time trend are included in the Smith et al. (2004) tests. Rejection of the null hypothesis indicates stationarity in at least one country. For both tests the results are reported at lag = 4. The null hypothesis is that of a unit root. Critical values for the Smith et al. (2004) test are: t-test = -3.43 at 1%, -2.86 at 5%, -2.57 at 10%, LM-test = 3.94 at 1%, 3.66 at 5%, 3.57 at 10%, max-test = -3.96 at 1%, -3.41 at 5%, -3.12 at 10%, min-test = 2.21 at 1, 2.15 at 5%, 2.12 at 10%. ***: $p \leq 0.01$.

Table 3: Panel GMM estimates

	Full sample	Low income countries	Lower middle income countries	Upper middle income countries	High income countries
Panel A: Heath care expenditure equation (11)					
Constant	-0.048*	1.596**	1.392**	0.846**	-0.369*
	[0.08]	[0.02]	[0.03]	[0.05]	[0.06]
HEC(-1)	0.094***	0.136***	0.115***	0.081***	0.049***
	[0.01]	[0.00]	[0.00]	[0.00]	[0.01]
GDPC	0.072***	0.093***	0.086***	0.068***	0.029***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
GDPC(-1)	0.043***	0.036***	0.051***	0.039***	0.017***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
POP65	0.034***	0.058***	0.045***	0.025**	0.018**
	[0.01]	[0.00]	[0.01]	[0.02]	[0.03]
CO_2	0.025***	0.029***	0.012***	0.023***	0.026***
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]
CO_2(-1)	0.014***	0.003**	0.019***	0.022***	0.008**
	[0.01]	[0.03]	[0.01]	[0.01]	[0.02]

EINT	0.089***	0.118***	0.125***	0.093***	0.054***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
EINT(-1)	0.051***	0.079***	0.062***	0.044***`	0.025**
	[0.01]	[0.00]	[0.00]	[0.01]	[0.03]
Countries	178	26	45	49	58
R^2-adjusted	0.63	0.39	0.45	0.48	0.74
Instruments used	21	19	18	20	22
Hansen p-value	0.98	0.98	0.99	0.99	0.98
AR1 p-value	0.02	0.02	0.03	0.02	0.01
AR2 p-value	0.48	0.54	0.49	0.52	0.55

Panel B: Carbon emissions equation (12)

Constant	-1.127**	-0.746**	-0.895**	-1.056**	-1.384**
	[0.04]	[0.05]	[0.05]	[0.04]	[0.03]
CO_2(-1)	0.784***	0.805***	0.652***	0.739***	0.996***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
GDPC	0.026***	0.043***	0.014***	0.038***	0.059***
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
GDPC(-1)	0.057***	0.064***	0.048***	0.054***	0.068***
	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]

HCE	0.065***	0.029**	0.038**	0.054**	0.083***
	[0.00]	[0.04]	[0.03]	[0.02]	[0.00]
HCE(-1)	0.028**	0.005*	0.013*	0.031**	0.045**
	[0.02]	[0.08]	[0.06]	[0.05]	[0.03]
EINT	0.135***	0.061***	0.084***	0.109***	0.149***
	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]
EINT(-1)	0.068***	0.037**	0.052**	0.059**	0.073***
	[0.00]	[0.03]	[0.02]	[0.02]	[0.01]
Countries	178	26	45	49	58
R^2-adjusted	0.59	0.34	0.39	0.46	0.70
Instruments used	18	17	18	21	20
Hansen p-value	0.99	0.99	0.99	0.99	0.98
AR1 p-value	0.01	0.01	0.02	0.02	0.00
AR2 p-value	0.46	0.48	0.52	0.54	0.58

Lagged values have been selected through the Akaike criterion. For the validity of the instruments, the results reject the test for second-order autocorrelation, AR(2) in disturbances. The AR2 test is the Arellano–Bond test for the existence of the second-order autocorrelation in first differences. It is evident that the test fails to reject the respective nulls and supports the validity of the instruments used. The diagnostics also report the Hansen test for overidentifying restrictions. Reported Hansen test results fail to detect any problem in the validity of the instruments used in the estimation approach. Figures in brackets denote p-values. ***: $p \leq 0.01$; **: $p \leq 0.05$, *: $p \leq 0.10$.

Table 4: Panel 3SLS-GMM estimates (full sample)

	Equation (1)	Equation (2)
Constant	-0.039*	-0.908**
	[0.10]	[0.05]
GDPC	0.067***	0.029***
	[0.00]	[0.00]
POP65	0.038***	
	[0.00]	
CO_2	0.029***	
	[0.00]	
EINT	0.096***	0.129***
	[0.00]	[0.00]
HCE		0.063***
		[0.00]
Countries	178	178
R^2-adjusted	0.67	0.62
Staiger-Stock Rule (F⩾10)	Passed	Passed
Hansen/Sargan test	[0.46]	[0.38]
|m|-stat. 3SLS/2SLS	[0.21]	[0.18]

Staiger-Stock test is the weak identification test (Staiger and Stock, 1997) rule of thumb (F⩾10). The Sargan/Hansen test is the test for the overidentification of moment conditions, testing for the validity of the instruments. |m|-stat assesses the appropriateness of the chosen full information system approach, where the null hypothesis is that the estimates are consistent and efficient. The diagnostics also report the Hansen test for overidentifying restrictions. Reported Hansen test results fail to detect any problem in the validity of the instruments used in the estimation approach. Figures in brackets denote p-values. ***: $p \leq 0.01$; **: $p \leq 0.05$, *: $p \leq 0.10$.

Appendix

Country Coverage

Full Sample: 178 countries

Low income countries: 26 countries
Benin, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, Comoros, Congo Democratic, Congo Republic, Ethiopia, Gambia, Guinea, Haiti, Liberia, Madagascar, Malawi, Mali, Mozambique, Nepal, Niger, Rwanda, Sierra Leone, Somalia, Tanzania, Togo, Uganda.

Lower middle-income countries: 45 countries
Armenia, Bangladesh, Bhutan, Bolivia, Cameroon, Cape Verde, Cote d'Ivoire, Djibouti, Egypt, El Salvador, Georgia, Ghana, Guatemala, Guyana, Honduras, India, Indonesia, Kenya, Kiribati, Kyrgyz Republic, Laos, Mauritania, Moldova, Morocco, Myanmar, Nicaragua, Nigeria, Pakistan, Papua New Guinea, Philippines, Samoa, Sao Tome & Principe, Senegal, Solomon Islands, Sri Lanka, Sudan, Swaziland, Syrian Arab Republic, Tajikistan, Ukraine, Uzbekistan, Vanuatu, Vietnam, Yemen, Zambia.

Upper middle-income countries: 49 countries
Albania, Algeria, Angola, Azerbaijan, Belarus, Belize, Bosnia-Herzegovina, Botswana, Brazil, Bulgaria, China, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, Fiji, FYROM, Gabon, Grenada, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Lebanon, Libya, Malaysia, Maldives, Marshall Islands, Mauritius, Mexico, Mongolia, Montenegro, Namibia, Panama, Paraguay, Peru, Romania, Serbia, South Africa, St. Lucia, St. Vincent & Grenadines, Suriname, Thailand, Tonga, Tunisia, Turkey, Turkmenistan.

High income countries: 58 countries
Andorra, Argentina, Australia, Austria, Bahamas, Bahrain, Barbados, Belgium, Brunei, Canada, Chile, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Kuwait, Latvia, Liechtenstein, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Oman, Poland, Portugal, Qatar, Russia, San Marino, Saudi Arabia, Seychelles, Singapore, Slovakia, Slovenia, South Korea, Spain, St. Kitts & Nevis, Sweden, Switzerland, Taiwan, Trinidad & Tobago, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela.

Table A1: Descriptive statistics of variables: 1960-2013

		Low Income	Lower middle income	Upper middle income	High Income
Dependent Variables					
HCE	Mean	22.67994	73.82116	263.0419	1981.971
	Std. dev	14.27070	65.04361	193.0327	1860.908
	Min	4.034908	1.798487	6.702595	17.27888
	Max	95.83287	411.3768	1153.720	9714.786
CO_2	Mean	0.185568	0.741914	2.890086	9.922524
	Std. dev	0.377799	0.942501	2.756862	10.50674
	Min	0.000580	0.010134	0.018135	0.018067
	Max	3.527648	12.30446	17.55388	99.84044
Independent Variables					
GDPC	Mean	308.5553	901.5935	2768.961	17171.58
	Std. dev	208.5328	810.7197	2489.322	20172.77
	Min	37.51817	40.61487	58.03385	35.36773
	Max	1696.146	4257.061	14231.60	193648.1
POP65	Mean	3.051433	4.135767	5.479366	9.623768
	Std. dev	0.745377	2.053770	2.785427	4.727976
	Min	1.128442	1.739457	2.121566	0.696889
	Max	9.554625	16.13981	19.72911	25.70542
EINT	Mean	2.541025	2.696893	3.087482	3.601792
	Std. dev	0.243933	0.290165	0.273715	0.282813
	Min	1.755339	0.981587	0.981587	2.398029
	Max	3.002429	3.481899	3.689619	4.341621

Table A2: Correlations

	HCE	GDPC	POP65	CO_2	EINT
HCE	1	0.377	0.004	0.490	0.511
GDPC		1	0.011	0.426	0.446
POP65			1	0.061	0.082
CO_2				1	0.416
EINT					1

References

Acaravci, A., Ozturk, I. (2010). On the relationship between energy consumption, CO2 emissions and economic growth in Europe. *Energy*, *35*(12), 5412-5420.

Acemoglu D, Finkelstein A, Notowidigdo MJ., (2013). Income and health spending: evidence from oil price shocks. *Review of Economics and Statistics* 95 (4), 1079-1095.

Ahmed, K., Bhattacharya, M., Shaikh, Z., Ramzan, M., & Ozturk, I. (2017). Emission intensive growth and trade in the era of the Association of Southeast Asian Nations (ASEAN) integration: An empirical investigation from ASEAN-8. *Journal of Cleaner Production*, *154*, 530-540.

Apergis, N., Gupta, R., Lau, C. K. M., & Mukherjee, Z. (2018). US state-level carbon dioxide emissions: Does it affect health care expenditure?. *Renewable and Sustainable Energy Reviews, 91*, 521-530.

Arrelano, M., Bover, O. (1995). Another look at the instrumental variables estimation of error components models. *Journal of Econometrics,* 68, 29-51.

Assadzadeh A., Bastan F., Shahverdi A., (2014). The impact of environmental quality and pollution on health expenditures: A case study of petroleum exporting countries, Proceedings of 29th International Business Research Conference 24 - 25 November, Sydney, Australia, ISBN: 978-1-922069-64-1.

Balsalobre-Lorente, D., Shahbaz, M., Ponz-Tienda, J. L., & Cantos-Cantos, J. M. (2017). Energy innovation in the environmental Kuznets curve (EKC): A theoretical Approach. In *Carbon Footprint and the Industrial Life Cycle* (pp. 243-268). Springer, Cham.

Baltagi, B. (2008). Econometric Analysis of Panel Data, 4th Edition. Chichester: John Wiley & Sons.

Baltagi B. H., & Moscone F., 2010. Health care expenditure and income in the OECD reconsidered: Evidence from panel data. *Economic Modelling*, 27(4), pp.804-811.

Baltagi, B., & Chang, Y. (2000). Simultaneous equations with incomplete panels. Econometric Theory, 16, 269-279.

Baltagi, B. H., Lagravinese, R., Moscone, F., and Tosetti, E. (2017). Health care expenditure and income: A global perspective. *Health Economics*, *26*(7), 863-874.

Beatty T. K. M, Shimshack J. P, 2014. Air pollution and children's respiratory health: A cohort analysis. *Journal of Environmental Economics and Management* 67, 39-57.

Bhattacharya, M., Paramati, S. R., Ozturk, I., & Bhattacharya, S. (2016). The effect of renewable energy consumption on economic growth: Evidence from top 38 countries. *Applied Energy*, *162*, 733-741.

Bhattacharya, M., Inekwe, J. N., Sadorsky, P., and Saha, A. (2018). Convergence of energy productivity across Indian states and territories. *Energy Economics*, *74*, 427-440.

Bilgel F., Tran K. C., 2013. The determinants of Canadian provincial health expenditures: Evidence from a dynamic panel. *Applied Economics* ,45(2), 201-212.

Blazquez-Fernandez C., Cantarero D., Perez P., (2014). Disentangling the heterogeneous income elasticity and dynamics of health expenditure. *Applied Economics*, 46, 1839-1854.

Bloom D.E., Chatterji S., Kowal P., Lloyd-Sherlock P., McKee M., Rechel B., Smith J. P., (2015). Macroeconomic implications of population ageing and selected policy responses. *The Lancet*, 385 (9968), 649-657.

Blundell, R., Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87, 115-143.

Boachie M. K., Ramu K., (2016). Effect of public health expenditure on health status in Ghana. *International Journal of Health*, 4(1), 6-11.

Brunekreef B., Holgate S. T., (2002). Air pollution and health. *The Lancet*, 360, 1233-1242. http://dx.doi.org/10.1016/S0140-6736(02)11274-8

Chaabouni S., Abednnadher C., (2014). The determinants of health expenditures in Tunisia: An ARDL bounds testing approach. *International Journal of Information Systems in the Service Sector* (IJISSS) 6(4), 60-72.

Chung, J. W., and Meltzer, D. O. (2009). Estimate of the carbon footprint of the US health care sector. *Jama*, *302*(18), 1970-1972.

COPS21 at http://www.cop21paris.org/ (accessed January 30, 2018)

Costa-Font J., Pons-Novell J., (2007). Public health expenditure and spatial interactions in a decentralized National Health System. *Health Economics*, 16, 291-306.

de Meijer C., Wouterse B., Polder J., Koopmanschap M.,(2013). The effect of population aging on health expenditure growth: a critical review. *European Journal of Ageing*, 10(4), 353-361.

Di Matteo, L., Di Matteo, R., (2005). Does testing for prostate-specific antigen contribute to declining prostate cancer mortality? *The European Journal of Health Economics*, 6(4), 298-308.

Di Matteo L., Di Matteo R., (1998). Evidence on the determinants of Canadian provincial government health expenditures: 1965–1991. *Journal of Health Economics*, 17(2), 211-228.

Erdil E., Yetkiner I. H., (2009). The Granger-causality between health care expenditure and output: a panel data approach. *Applied Economics*, 41(4), 511-518.

Fazaeli A. A., Ghaderi H., Salehi M., Fazaeli A. R., (2016). Health care expenditure and GDP in oil exporting countries: Evidence from OPEC Data, 1995-2012. Global *Journal of Health Science,* 8(2), 93.

Feldstein M., (1988). The effects of fiscal policies when incomes are uncertain: A contradiction to Ricardian equivalence. *American Economic Review*, American Economic Association 78(1), 14-23.

Gbesemete K. P., Gerdtham U. G., (1992). Determinants of health care expenditure in Africa: a cross-sectional study. *World Development,* 20(2), 303-308.

Geue C., Briggs A., Lewsey J., Lorgelly P., (2014). Population ageing and healthcare expenditure projections: new evidence from a time to death approach. *The European Journal of Health Economics*, 15(8), 885-896.

Hallström E., Gee Q., Scarborough P., Cleveland D. A., (2017). A healthier US diet could reduce greenhouse gas emissions from both the food and health care systems. *Climatic Change*, 1-14.

Hansen P., King A., (1996). The determinants of health care expenditure: a cointegration approach. *Journal of Health Economics*, 15(1), 127-137.

Hartwig J., 2008. What drives health care expenditure? Baumol's model of 'unbalanced growth' revisited. *Journal of Health Economics,* 27(3), 603-623.

Hausman, J. (1978). Specification tests in econometrics. Econometrica 46, 1251-1271.

Hausman, J., & Taylor, W. (1981). Panel data and unobservable individual effects. Econometrica 49, 1377-1399.

Herwartz H., Theilen B., 2003. The determinants of health care expenditure: testing pooling restrictions in small samples. *Health Economics* ,12(2), 113-124.

Hitiris T., Posnett J., 1992. The determinants and effects of health expenditure in developed countries. *Journal of Health Economics*, 11(2), 173-181.

Hossain, M.S., (2011). Panel estimation for CO_2 emissions, energy consumption, economic growth, trade openness and urbanization of newly industrialized countries. *Energy Policy*, 39, 6991-6999.

IEA, 2012. World Energy Outlook,(2012). International Energy Agency, Paris.

Im K.S., Pesaran M. H., Shin Y., (2003). Testing for unit roots in heterogeneous panels, *Journal of Econometrics*, 115, 53-74.

Janke K., Propper C., Henderson J., (2009). Do current levels of air pollution kill? The impact of air pollution on population mortality in England. *Health Economics*,. 18, 1031-1055.

Jönsson B., Eckerlund I., (2003). Why do different countries spend different amounts on health care ?. in OCDE.

Kea X., Saksena P., Holly A., (2011). The determinants of health expenditure: a country-level panel data analysis. Geneva: World Health Organization.

Khan J. A., Mahumud R. A.,(2015). Is healthcare a `necessity' or `luxury'? an empirical evidence from public and private sector analyses of South-East Asian countries?. *Health Economics Review*, 5(1), 1-9.

Leybourne S., (1995). Testing for unit roots using forward and reverse Dickey–Fuller regressions. *Oxford Bulletin of Economics and Statistics*, 57, 559-571.

Linares, P., & Labandeira, X. (2010). Energy efficiency: Economics and policy. *Journal of Economic Surveys*, *24*(3), 573-592.

Mead R.W., Brajer V., (2005). Protecting China's children: valuing the health impacts of reduced air pollution in Chinese cities. *Environment and Development Economics*, 10, 745-769.

Mehrara, M., Sharzei, G., Mohaghegh, M., (2014). The relationship between health expenditure and environmental quality in developing countries. *Journal of Health Administration*, 14(46), 79.

Mehrara M., Musai M., Nasibparast S., (2012). The causality between non-oil exports and GDP in petroleum exporting countries. *International Journal of Advanced Research in Management and Social Sciences,* 1(5), 22-34.

Meijer A. J., Grimmelikhuijsen S., Fictorie D., Thaens M., Siep P., (2013). Politie & Sociale Media. Van hype naar onderbouwde keuzen [Police and Social Media: From Hype to Solid Choices]. Amsterdam: Reed.

Mitze, T. (2011). Dynamic simultaneous equations with panel data: small sample properties and application to regional econometric modelling. Chapter 7 in Mitze, T. Empirical Modelling in Regional Science. Towards a Global Time-Space-Structural Analysis, Berlin, 219-272.

Murthy N. R. V., Okunade A. A., (2000). Managed care, deficit financing, and aggregate health care expenditure in the United States: A cointegration analysis. *Health Care Management Science,* 3(4), 279-285.

Murthy, V.N., Okunade, A. A., 2009. The core determinants of health expenditure in the African context: Some econometric evidence for policy. Health policy 91(1), 57-62.

Murthy N. R., Ukpolo V., (1995). Aggregate health care expenditure in the United States: New results. *Applied Economics Letters*, 2(11), 419-421.

Narayan P. K., Narayan S., (2008). Does environmental quality influence health expenditures? Empirical evidence from a panel of selected OECD countries. *Ecological Economics*, 65(2), 367-374.

Newhouse J. P., (1977). Medical Care Expenditure: A Cross-National Survey. Journal of Human Resources. *Economic Journal*, 12(1), 115–25.

Novignon J., Nonvignon J., Arthur E., (2015). Health Status and Labour Force Participation in Sub-Saharan Africa: A Dynamic Panel Data Analysis. *African Development Review*, 27(1), 14-26.

Ozcan, B., Apergis, N., Shahbaz, M. (2018). A revisit of the environmental Kuznets curve hypothesis for Turkey: new evidence from bootstrap rolling window causality. *Environmental Science and Pollution Research*, 1-14.

Pammolli F., Riccaboni M., Magazzini L., (2012). The sustainability of European health care systems: beyond income and aging. *The European Journal of Health Economics*, 13(5), 623-634.

Park, S. (2005). Estimating a linear simultaneous equation model with panel data. Working Paper, Carleton University.

Parker S., Wong R., (1997). Household income and health care expenditures in Mexico. *Health Polic*y ,40, 237–255.

Payne G., Laporte A., Deber R., Coyte P. C., (2007). Counting backward to health care's future: using time-to-death modeling to identify changes in end-of-life morbidity and the impact of aging on health care expenditures. Milbank Q 85(2), 213–257.

Pesaran M. H., (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers in Economics, No. 435 and CESifo Working Paper, No. 1229.

Pesaran M. H., (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, 22, 265-312.

Qureshi M. I., Khan N. U., Rasli A. M., Zaman K., (2015). The battle of health with environmental evils of Asian countries: promises to keep. *Environmental Science and Pollution Research*, 22(15), 11708-11715.

Rahman T., 2008. Determinants of public health expenditure: some evidence from Indian states. *Applied Economics Letters,* 15(11), 853-857.

Roberts J. T., Grimes, P. E., (1997). Carbon intensity and economic development 1962–1991: a brief exploration of the environmental Kuznets curve. *World Development* ,25(2), 191-198.

Samadi A. H., Homaie Rad E., (2013). Determinants of healthcare expenditure in Economic Cooperation Organization (ECO) countries: evidence from panel cointegration tests. *International Journal of Health Policy and Management*, 1(1), 73-79.

Sebri, M., Ben-Salha, O., (2014). On the causal dynamics between economic growth, renewable energy consumption, CO_2 emissions and trade openness: fresh evidence from BRICS countries. *Renewable and Sustainable Energy Reviews*, 39, 14-23.

Smith V., Leybourne S., Kim T. H., (2004). More powerful panel unit root tests with an application to the mean reversion in real exchange rates. *Journal of Applied Econometrics*, 19, 147-170.

Solo V., (1984). The order of differencing in ARIMA models. *Journal of the American Statistical Association,* 79, 916-921.

Staiger, D., & Stock, J. (1997). Instrumental variables with weak instruments. Econometrica 65, 557-586.

Stern, D. (2017). The Environmental Kuznets Curve after 25 years. *Journal of Bioeconomics*, 19(1), 7-28.

United Nations Environment Program, (2016). UNEP Environment for development, urban environment unit. http://www.unep.org/urban_environment/Issues/urban_air.asp4/3/2016

Watts, N.; Adger, W.N.; Agnolucci, P.; Blackstock, J.; Byass, P.; Cai, W.; Chaytor, S.; Colbourn, T.; Collins, M.; Cooper, A.; (2015). Health and climate change: Policy responses to protect public health. *The Lancet*, 386, 1861–1914.

Wei Y. M., Liu L. C., Fan Y., Wu G., (2007). The impact of lifestyle on energy use and CO_2 emission: an empirical analysis of China's residents. *Energy Policy*, 35 (1), 247–257.

World Bank (2017), World Development Indicators, Washington D.C., U.S.A.

World Health Organisation, (2015). Reducing global health risks through the mitigation of short-lived climate pollutants: Scoping Report for Policymakers'. *World Health Organisation*; 2015.

Zhang, Y.J., (2011). The impact of financial growth on carbon emissions: an empirical analysis in China. *Energy Policy*, 39, 2197-2203.

Zweifel P., Felder S., Meiers M., (1999). Ageing of population and health care expenditure: a red herring? *Health Economics*, 8(6), 485-496.