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Does Carbon Emission Matter for Health Care Expenditure? Evidence from SAARC region using Panel Cointegration

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Abstract: *This study investigates the impact of increased carbon emissions on per capita health expenditure exploiting the panel data with Engle – Granger based cointegration test, Fully Modified Ordinary Least Square (FMOLS) and Dynamic Ordinary Least Square (DOLS) method. Data for the South Asian Association for Regional Cooperation (SAARC) countries from 1995 to 2014 have been collected from World Development Indicators (WDI). The confirmation of integration order of the variables has been made using two panel unit root tests suggested by Im – Pesaran – Shin, 2003 (IPS) and Levin, Lin & Chu, 2002 (LLC). Following the procedure suggested by Pedroni (1999, 2003) and Kao (1999), existence of long run relationship has been examined among the variables. Application of Fully Modified Ordinary Least Square (FMOLS) and Dynamic Ordinary Least Square (DOLS) further confirmed the presence of long run significant positive relationship between carbon emissions and per capita health expenditure. The coefficients of carbon emissions varied from 0.246 to 0.355 under the model estimated by FMOLS while the coefficients varied from 0.198 to 0.283 under the model estimated by DOLS. The findings can be generalized by saying that increased carbon emissions due to environmental degradation would increase the health expenditure as well as cost of the nations.*

Key Words: *Health Care Expenditure, Carbon Emission, Panel Cointegration, FMOLS, DOLS, SAARC*

JEL Classification: *Q54, H51, C33*

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1. Introduction

The traditional concept of growth and development has come to a new dimension in the present days. The world now opts for a sustainable economic development ensuring equal opportunity and prospect for all across the different cohorts. A mare economic growth resulting from an unbridled aggression and destruction towards the nature and environmental resources would be nothing but a curse for both the current and the future generation. Even after a long journey of human civilization for more than ten thousand years a significant part of the world is still suffering from hunger, illiteracy, malnutrition, deadly diseases and so on.

The deprivation of equal opportunity is not rare as well. In order to cope with all these the nations are continuously revising their goals and the policies towards achieving those. Their road to growth and development sometimes becomes a hindrance to the healthy coexistence of humans and the nature. The deterioration of environment not only has an abrupt impact on human health and productivity but a thousand fold negative influences on the economy in the long run as well. A persistent growth of carbon emission due to high industrialization and increased economic activity has been considered a peril of this modern era. This environmental degradation due to rapid industrialization as well as increased unfriendly economic activity has changed the world climate significantly over time.

Globally the SAARC region is considered to be a key economic zone. Although the countries of the region are experiencing attractive economic growth, these developing countries are still struggling in ensuring primary education, poverty alleviation, sanitation and birth control. Despite an approximate seven percent growth rate with a little fluctuation since 2009 (World Bank, 2017), poverty is still a widespread phenomenon in this part of the world. World Bank (2017) also shows that around 399 million people were still living below the poverty line till 2011.

The HDI (Human Development Index) which is a combined measurement of social and economic development shows very poor value, 0. 621, which is only higher than that of Sub-Saharan Africa, 0.523 (United Nations Development Program (UNDP), 2016). These countries are under tremendous pressure to achieve higher economic growth and competitiveness in order to upgrade their status from least developed or developing countries. This leads them towards a rapid expansion of industrialization and urbanization.

This transition is no doubt a panacea for them but inevitably this drags them to a threat of hazardous environmental degradation. Industrialization along with rapid urbanization has increased the demand in the economy in terms of materials and energy in this region. The change in the pattern of consumption and production, introduction of new technologies and development of infrastructures accelerated environmental degradation causing the change in climate. Since climate change indicates the long term significant statistical change of whether including temperature, rainfall, storm patterns and other measures of climate (Wu, Lub, & Chen, 2016), one of the main causes of climate change is believed to be the explosion of carbon dioxide, methane, nitrous oxide, fluorinated gases concentration in the atmosphere.

The health risks driven by climate change are of long term and difficult to reverse. Recent changes in climate in the south Asia region have had adverse impacts on health. These impacts are thought to be disproportionately greater for the vulnerable groups in terms of age and health condition i.e. the children, the elderly and the medically ill people or in terms of geography i.e. people living in the areas with high possibility of climate-sensitive diseases, living on islands, coastal areas or mega cities.

High population density has significantly worsen the scenario in south Asia. Carbon dioxide, one of the most harmful greenhouse gases is classed as the 'substance hazardous to health'. These health hazards would create a two dimensional burden for these low and middle income countries. Firstly, it would inflate the cost of healthy living by incurring more expenditure to tackle the health problems both at public and private level. Whereas these countries are already sunk in poverty, malnutrition, illiteracy and so on, these increased health expenditure would undoubtedly create extra pressure on the government and individuals. Secondly, despite taking necessary health facilities and medical interventions, sick leave would noticeably increase.

More alarming, this would cause the decline in labor productivity of the economy in the long run. As a result, this demands some empirical works in the field of health and environment. Despite the importance of environment on health care expenditure as well as on the economy, the number of studies that have been explicitly dedicated to find out the causal relationship between the health care expenditure and environment would be mare small. Against this backdrop the current study has given effort to contribute to the literature of the long run causal relationship between health care expenditure and carbon dioxide emission in the SAARC countries.

This study has been organized in the following way: *Section one* describes the background and motivational aspects under introduction. *Section two* covers the discussion on existing literature in the field of health and environment. *Section three* comprises the discussion regarding methodological process and data. The estimation results and finding of the paper have been analyzed in *section four*. Finally, concluding remarks and policy suggestion have been explained in *section five*.

2. Literature Review

There are many literatures in the fields of Economics and Health Economics where researchers have devoted much effort to find out the determinants of health care expenditure for different countries and different regions of the world over the time. Most of them estimated the income elasticity of health care expenditure and many of those found it to be inelastic showing that health belongs to goods of necessity. Some of the recent studies reviewed here are Hansen & Selte (2000), Tekabe (2012) and Abdullah, et al. (2017). Since environment is considered as the most important determinants of health status, environmental degradation due to rapid climate change might affect the health status negatively.

Numerous diseases like respiratory and cardiovascular disease, injuries and premature deaths can be thought as the result of climate change which may necessarily accelerate the public health care expenditure. However, very few studies are found which were dedicated to explore the causal relationship between health care expenditure and climate change. A few empirical literatures on Middle East, some parts of Africa and Canada revealed quite expected results. Nevertheless, the effect of carbon dioxide emission (as a measure of climate change) on health care expenditure of this south Asian region is yet to discover.

Matteo & Matteo (1998) tried to find out the determinants of real per capita provincial government health care expenditure of Canada using the pooled time series and cross section data spanning from 1965 to 1991. They established the real provincial per capita income, proportion of provincial population over age 65 and real provincial per capita transfer revenues as the major catalysts. They found that established program financing had a negative and significant influence in Newfoundland and Quebec. It was found that the elasticity of real provincial per capita income of real per capita provincial government health care expenditure is 0.77. This implies that the real per capita provincial government health care expenditure is necessarily good. Applying Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS), a panel study based on 36 Asian countries found health care as necessary goods in nature for those countries (Abdullah, Siddiqua, & Huque, 2017).

A similar study using cross section data tried to find out the link of certain socioeconomic and demographic factors in determining health care expenditure in Africa (Gbesemete & Gerdtham, 1992). The explanatory variables of the study- GNP per capita, percentage of birth attending health staff and per capita foreign aid, explained about 78% of the variations of health care expenditure. Like Matteo & Matteo (1998), this study found health care expenditure is inelastic with respect to GNP per capita.

However, crude birth rate and percentage of population under 15 years of age were found not to be significant in case of Africa. Another study (Tekabe, 2012) based on low-income countries and sub-Saharan Africa found the existence of simultaneity between GDP per capita and health care expenditure. Although the study failed to find out any causal relationship between income and per capita health expenditure, it found an evidence of two way relationship between GDP per capita and mortality.

Gerdtham et al. (1992) has tried to explore the factors that determine and explain the variation of aggregate health care expenditure of OECD (Organization for Economic Cooperation and Development) countries. This study explained the importance of institutional factors that enhance the health system besides GDP (Gross Domestic Product). The main finding of this study (Gerdthama, Søgaard, Andersson, & Jönsson, 1992) is the significant contribution of institutional factors of health system in explaining the variation of health care expenditure among the countries. Another study on OECD countries during the period of 1960 to 1987 found a positive relationship between income and population aged over 65 with health care spending (Hitiris & Posnett, 1992).

An extensive study on 70 countries made a comparison between low and high income countries to figure out the importance of public health expenditure. They showed that public health expenditure in lower income countries provides a higher return compared to high income countries (Gupta, Verhoeven, & Tiongson, 2001). This higher return might come by increasing labor productivity because a good health can make a worker more productive by working efficiently in lower income countries. A non-linear panel analysis for the period 1960 to 1990 has examined the impact of health care expenditure on labor productivity (Bloom, Canning, & Sevilla, 2001). It found a significant positive impact of health care expenditure on economic growth. More precisely, a one year increment of life expectancy of the population led a 4% increment in the production.

Although a number of studies have attempted to find out the determinants of health care expenditure as mentioned earlier, very few studies attempted to outline the causal relationship between health care expenditure and climate change. The relationship between environmental quality and economic growth based on the Middle East and North African region (MENA) countries for the period 1995 to 2014 has been examined by Yazdi & Khanalizadeh (2017). By using Autoregressive Distributed Lag (ARDL) method, they found cointegrating relationship among health expenditure, income, CO_2 and PM_{10} emission. As the measures of climate change, CO_2 and PM_{10} emission were found to have statistically significant positive relationship with health care expenditure (Khoshnevis Yazdi, 2017). Yazdi & Khanalizadeh (2017) also found health care as necessary goods like the other studies (Abdullah, Siddiqua, & Huque, 2017), (Matteo & Matteo, 1998).

Using data of 49 regions, counties and districts of Ontario, Canada, a study tried to find out the relationship between health care expenditure and environmental variables (Jerrett, Eyles, Dufournaud, & Birch, 2003). They aimed to chalk out the complex system that determines the health expenditure in a two stage regression model by controlling for the endogenous relation between past health care expenditures, mortality and the influence of mortality on current health expenditure. Besides, they controlled the other influences on health care expenditure to avoid any muddy relation between health care expenditure and environmental variables. Their result showed strong relation between toxic pollution and municipal defensive expenditure with current health expenditure. Almost 67% of the variation in current health expenditure was from four significant variables that they had used. It revealed that counties suffering from higher pollution tend to have higher per capita health care expenditure whereas those that are imprudent to spend for environmental quality have lower expenditures on health care.

Unlike the cross section and panel data analysis, a time series study for Iran has been done for the time period 1967-2010 to find out cointegrating relationship (Yazdi, Tamhmasebi & Mastorakis, 2014). They used ARDL model of cointegration to estimate the short run and long run impacts of environmental quality on health care expenditure. They found that different kinds of emission, income and health expenditure were cointegrated series. Both the long run and short run elasticity showed that income and different kinds of emissions had a significant positive impact on health expenditure in Iran for the period of time they studied.

Pollution can cause different types of illness and health hazard which might hamper the productivity of workers (Hansen & Selte, 2000). They focused on the channel that air pollution would lead to a bad health condition and that would induce workers taking more sick leaves and as a result labor productivity would be hampered. They actually found the evidence that yearly increase of small particulate matter induced more sick leaves and negatively impacted the trade and industry. This implies that it might necessarily increase the health expenditure.

3. Data and Methodology

Data, Variables and Model

For investigating the long run causal relationship between carbon emission and health expenditure, heterogenous panel data model has been adopted. To exploit the objective, this study wielded the annual data spanning from 1995 to 2014 of the South Asian Association for Regional Cooperation (SAARC) countries from World Development Indicators (WDI) of World Bank (World Bank, 2017). Due to unavailability of the data, the current study used the data of seven countries, namely Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan and Sri Lanka, excluding Afghanistan.

Together with several other factors it is well accepted that environment is one of the most vital determinants of health status. Environmental degradation in any form would have worse implication for health leading to increase in expenditure in the long run. As the prime objective of the current research work is to explore the effect of environmental pollution measured by carbon emission on health measured on the other hand by expenditure on health care, we tried to model the health care expenditure with carbon emission alongside its other potential determinants. More specifically, the model that we are concerned with can be presented in the following implicit manner:

$$PHE = f(PGDP, DP, CO_2)$$

In the above expression PHE stands for per capita health care expenditure, PGDP and DP indicates per capita Gross Domestic Product and dependent population respectively. Where dependent population is defined as the sum of two individual dependent age groups (sum of total population ages 0-14 and total population ages 65 and above). Lastly, Co_2 stands for carbon emission. As a priori it is expected that all the three independent variables would carry positive coefficients. Consciousness regarding health among people is positively influenced with the stimulation of their income. Increase in per capita income hence would lead to more allocation for health both in personal and public level resulting in higher per capita health expenditure.

There is no denying the fact that dependent populations are the most vulnerable to health hazards in any area. The health care sector would require more fund to ensure the health security whenever the size of this dependent population rises resulting in higher health care expenditure. Besides these factors as environment is considered as an important component in determining the health status, the model has been augmented with the Co_2 variable. It is evident that increase in Co_2 emission worsens respiratory and cardiovascular illnesses, emphysema and asthma which may lead to higher mortality rate. Hence with the increase in Co_2 emission reducing health risk and fighting with diseases would require more health care expenditure.

For the ease of explanation and receiving the elasticity measurement we have performed logarithmic transformation of all the variables and have estimated the following regression model:

$$lnPHE_{it} = \alpha_0 + \alpha_1 lnPGDP_{it} + \alpha_2 lnDP_{it} + \alpha_3 lnCO_{2it} + \varepsilon_{it}$$

Here, i denotes the cross sectional dimension that varies from 1 to 7 (SAARC countries) and t denotes the time series dimension that varies from 1 to 20 (1995 to 2014).

Testing Variable Characteristics

Since the constructed panel is long in nature and the time dimension is considerably large, the stationarity property of the variables would be essential. Regression with non-stationary variables would be spurious and provide misleading results even though the data is panel. The stationarity characteristics has been diagnosed statistically following the testing procedure developed by Im, Pesaran and Shin (2003) and Levin, Lin and Chu, (2002). Both of these tests (Im, Pesaran, & Shin, 2003), (Levin, Lin, & Chu, 2002) are considered as first generation test of stationarity as they require cross sectional independence. The null hypothesis that would be tested here in two tests is quite different. While IPS considers the presence of unit root (non stationarity) of the variables in each cross section, LLC considers the non stationarity of the variables assuming they have common unit root for the panel as a whole. In terms of alternative hypothesis IPS argues that at least in one of the cross section the series is stationary, in contrast LLC requires all has to be stationary.

Technically the test regression for both IPS and LLC tests are quite similar, nevertheless they differ in terms of formulating null using the autoregressive coefficient. For convenience consider the following autoregressive of order one, AR(1) process for panel:

$$y_{it} = \rho_i y_{it-1} + z_{it}\gamma_t + \varepsilon_{it}$$

Where, i = 1, 2, —-, N cross section units observed over time, t = 1, 2, —-, T. Any fixed or random effect is included in z_{it} and ε_{it} is the error term. The coefficient of interest here is ρ_i which if found to be less than unit in absolute value would imply the weakly stationarity of the variable,γ_{it}. The IPS procedure formulates the null saying "ρ_i may vary across all cross section units", in contrast the null for LLC procedure argues "ρ_i is identical across all cross section units". For performing the test the following Augmented Dickey Fuller (ADF) test regression has been estimated:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j=1}^{p_i} \theta_{ij}\Delta y_{it-j} + z_{it}'\gamma + \varepsilon_{it}$$

The appropriate null and alternative hypothesis under LLC would be $Ho : \alpha = o$ and $Ho : \alpha < o$ respectively. Under the null we assume a common unit root for the variable γ_{it} over all cross sections i.e. $\alpha = \rho - 1$. On the other hand the null hypothesis under IPS would be $Ho : \alpha_i = o$ for all cross sectional units, therefore the autoregressive coefficient might differ section to section.

Testing the Presence of Cointegration

In pure time series framework whenever a group of variables are found to be difference stationary then perhaps there might be some linear combination of those variables which is expected to be stationary. This idea is referred to as cointegration which is also very common in macro panel i.e. a panel structure where time dimension (T) is sufficiently larger than cross section (N) one. As in the current study the time period is larger than cross section assuming that the variables would be difference stationary we performed panel cointegration test. In particular two procedures developed by Pedroni (1999, 2004) and Kao (1999) have been followed. All these three tests (See (Pedroni P., 1999); (Pedroni P., 2004) and (Kao C., 1999) formulate the null arguing that there would be no correlation among the variables. Construction of the test statistic for these tests requires the residuals of panel statistic regression. The idea is that if the variables form cointgration then the residuals of the panel regression would be stationary i.e. I(0).

Allowing for short run dynamics as well as the long run slope coefficients to be heterogeneous across sections, the residuals have been estimated following Pedroni (1999, 2004) from the regression written below:

$$lnPHE_{it} = \alpha_i + \beta_i t + \gamma_{1i} lnPGDP_{it} + \gamma_{2i} lnDR_{it} + \gamma_{3i} lnCO_{2it} + \varepsilon_{it}$$

Here, $i = 1, 2, \ldots, 7$ and $t = 1, 2, \ldots, 20$. All the variables are expected to be I(1), α_i and β_i are respectively standing for section specific fixed effect and linear trend and γ's are the cointegrating slopes. Under the null of "no cointegration" it is expected that ε_{it} would be I(1). Thus the test regression involving ε_{it} would be as follows:

$$\varepsilon_{it} = \theta_i \varepsilon_{it-1} + \sum_{j=1}^{p_i} \phi_{ij} \Delta\varepsilon_{it-1} + v_{it}$$

The null is tested on the significance of autoregressive coefficient θ_{it} against two alternatives; one is within dimension, $H_1^W: \theta_i = \theta < 1 \; \forall i$ other is between dimension, $H_1^B: \theta_i < 1 \; \forall i$.

The test elucidated by Kao (1990) follows the similar procedure we observed in Pedroni (1999, 2004). However, unlike the later one, the former one does not allow heterogeneity under alternative hypothesis and assumes cointegration vectors are homogeneous across sections. Thus, we would estimate the regression model of Pedroni (1999, 2004) subject to the fact that α_i would be heterogeneous, β_i the trend coefficient would be zero and γ's would be homogeneous across sections. Similar residual based regression has been then estimated and ADF t – statistic employed to perform the test.

Estimation Problem

With an expectation that the variables under consideration would be cointegrated we would be estimating the cointegrating relationship employing the Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) method. The FMOLS estimates are unbiased asymptotically while DOLS results in asymptotically efficient estimators because of its control over serial correlation and endogeneity. Following Phillips and Moon (1999), Kao and Chiang (2000) and Pedroni (2000, 2001), three different FMOLS estimators namely, Pooled, Weighted and Group Mean would be estimated. The first one removes the deterministic components from the variables and applies the FMOLS method on the pooled sample. The weighted version differs from the pooled one as it weights the data ahead of the estimation by the country specific long run covariance. This helps the weighted method over standard pooled method to capture the heterogeneity. Finally, the group mean uses individual country FMOLS estimates to calculate the cross sectional averages. To explain the estimators consider the model written below:

$$lnPHE_{it} = \alpha_i + X_{it}^{t}\beta + u_{it}$$

Here α_i are the country specific intercepts, β is the vector of slope coefficients, is the error term with I(0) feature and ε_{it} is vector of independent variables consists of *lnPGDP*, *lnDP* and $lnCO_2$. Besides the entire number of variable in, χ_{it} lnPHE is assumed to be I(1). Following the notation of EViews technical details, here the FMOLS estimators could be written as follows:

$$\hat{\beta}_{Polled} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{X}_{it}\tilde{X}_{it}'\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{X}_{it}\widehat{lnPHE}_{it}^{+} - \hat{\lambda}_{12}^{+\prime})$$

Here $\tilde{X}_{it}$ and $\widehat{lnPHE}_{it}$ and are the demeaned variables, $\widehat{lnPHE}_{it}^{+}$ and $\hat{\lambda}_{12}^{+}$ while and are the modified version of dependent variable and serial correlation term.

$$\hat{\beta}_{Weighted} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\tilde{X}_{it}^{*}\tilde{X}_{it}^{*\prime}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(\tilde{X}_{it}^{*}\widehat{lnPHE}_{it}^{*} - \hat{\lambda}_{12i}^{*\prime})$$

Here $\widehat{lnPHE}_{it}^{+}$ and $\hat{\lambda}_{12}^{+}$ and are the weighted versions variables and serial correlation term, where estimates of country specific long run covariances has been used as weights.

$$\hat{\beta}_{Grouped\ Mean} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\sum_{t=1}^{T}\tilde{X}_{it}\tilde{X}_{it}'\right)^{-1}\sum_{t=1}^{T}(\tilde{X}_{it}\widehat{lnPHE}_{it}) - \hat{\lambda}_{12i}'\right\}$$

Thus group mean estimator is the cross sectional average of individual country specific FMOLS estimates.

Following Kao and Chiang (2000), Mark and Sul (1999) and Pedroni (2001), the model has been augmented with the optimum number of lags and leads of differenced regressors as well as differenced regressend. The model which would be estimated can be written as follows:

$$\begin{aligned} lnPHE_{it} = {} & \alpha_i + \beta_1 lnPGDP_{it} + \beta_2 lnDP_{it} + \beta_3 CO_{2it} + \sum_{k=-p_i}^{m_i}\delta_k \Delta PHE_{it-k} + \sum_{k=-q_i}^{r_i}\lambda_k \Delta lnPGDP_{it-k} \\ & + \sum_{k=-w_i}^{z_i}\gamma_k \Delta lnDP_{it-k} + \sum_{k=-g_i}^{h_i}\eta_k \Delta lnCO_{2it-k} + u_{it} \end{aligned}$$

Similar as FMOLS, the above model when estimated using DOLS would result in three group of estimators. Pooled version would adjust all the variables from the deterministic components, weighted version would adjust for heterogeneity and group mean version completes the estimation using the average of country specific DOLS estimates.

4. Estimation Results and Findings

Summary Statistics

Table 1 and Table A1 (Appendix) provide summary statistics of the variables included in the model. We have explained the summary statistics in two categories. Table 1 describes pooled summary statistics and Table A1 of appendix indicates the summary statistics of SAARC countries separately. During the study period, the average per capita health expenditure (current US $) of seven countries has been measured to be approximately 88 US $ while average per capita Gross Domestic Product (GDP) has been observed to be approximately 1461 US $. The economies of seven countries studied here have carried approximately 220 thousands CO_2 emissions measured in kiloton (kt) on average during this time. Summary table (pooled) also consists of the size of average population of seven countries against two specific age groups needed to estimate size of dependent population.

Table 1: Summary Statistics (Pooled)

Variables	Mean	Std. Dev.
Health expenditure per capita (current US$)	88.158	165.454
CO2 emissions (kt)	220211.100	493114.300
Population ages 0-14, total (‘000)	70581.220	125261.900
Population ages 65 and above, total (‘000)	9880.3410	18685.940
Dependent population (sum of ages 0-14 and above 65, in 000)	80461.560	143681.000
GDP per capita (current US$)	1460.931	1709.619

Source: Prepared by authors

Average population of ages below 14, above 65 and the sum of both ages group (defined as dependent population) are approximately 71 million, 10 million and 80 million respectively. Table A1 shows that Maldives experienced the highest average per capita health expenditure with a value of 388 US $ followed by Bhutan with 73 US $. In contrast Bangladesh spent the lowest amount with an average value of around 16 US $. For the purpose of health. In case of carbon emissions as expected, India as a large country geographically produced the largest amount of carbon emissions, approximately 1.4 million (kt) followed by Pakistan 0.13 million (kt). On the other hand, Bhutan as an environment friendly country produced the lowest amount of emissions, approximately 0.0005 million (kt).

Graph A1 (Appendix) contains the trends of per capita health care expenditure and carbon emission of the seven countries chosen for this particular study. For being consistent, we take natural logarithm of per capita health expenditure (current

US$) and carbon emissions (kt). It is clear from the graph that both the variables have been consistently trending upward implying a positive relationship between health care expenditure per capita and carbon emissions.

Testing variable behavior

Considering the relative time length in relation to the number of units (i.e. countries), the data current study exploited can be thought to be as "long panel" in nature. If the concerned variables in the regression model where time length is large, move together then there might arise the problem of spurious results. Therefore behavior of all the variables has been diagnosed as a first step. More specifically, to confirm the presence of well behavior of the variables (measured in terms of presence of stationarity property) two panel unit root tests have been applied; namely Im, Pesaran, & Shin (2003) and Levin, Lin & Chu (2002). Both of these tests are characterized as the first generation because of their reliance on the assumption of "cross sectional independence". It implies that all the variables here are assumed to be independently distributed over the sample countries.

Table 2 contains the IPS panel unit root test results. The null hypothesis which is tested here can be stated as "panels contain unit roots (individual)". The test has

Table 2: Panel Unit Root Test Results of the Variables

Variables	Im – Pesaran – Shin (IPS) Test for Panel Unit Root *Null: Panels Contain Unit Roots (Individual)*				Comments
	Intercept		Intercept and Trend		
	IPS W - Stat	Prob.	IPS W - Stat	Prob.	
lnPHCE (Current US $)	4.107	1.000	-1.962**	0.024	lnPHCE is difference stationary under intercept specification and thus treated as I(1)
D(lnPHCE)	-6.865*	0.000	-5.548*	0.000	
lnPGDP (Current US $)	5.460	1.000	1.100	0.864	lnPGDP is difference stationary under both specification and thus treated as I(1)
D(lnPGDP)	-6.591*	0.000	-5.960*	0.000	
lnDP	-1.200	0.115	0.083	0.533	lnDP is non stationary
D(lnDP)	0.234	0.592	-0.977	0.164	
lnCO2 (KT)	2.439	0.992	-1.362***	0.086	lnCO2 is difference stationary under intercept

Note: * Indicates 1 per cent level of significance, ** Indicates 5 per cent level of significance, *** Indicates 10 per cent level of significance been performed with two regression specifications; one with drift term and the other with both drift and trend term. It can be observed from the results that the stated null can be rejected at one per cent level of significance in both regression specifications for the per capita GDP at first difference. Hence it can be considered as integrated of order one, I(1) in nature. Both the per capita health expenditure and carbon emission become stationary at the difference when test regression considered the intercept term. Thus, these two variables has also been treated as I(1). Nevertheless, the null arguing presence of unit root in panel from individual perspective did not have enough evidence against it in case of dependent population. Hence this variable is detected to be non-stationary irrespective of test regression following IPS procedure.

One potential weakness which can be argued for IPS test procedure is that it tests the non stationarity nature of the panel variable considering its unit root property for each cross sectional unit that the particular panel contains. Improvement of the credibility of findings is further possible to be made by following a procedure that can test the unit root property of the panel variable considering the panel as a whole. As LLC test procedure formulates the null hypothesis arguing presence of common unit root in the panel, it has been applied as a further option.

The results have been presented in table 3. It can be stated here that per capita GDP and carbon emission both behaves expectedly in the difference form regardless of the specification of test regression. Therefore, they can be treated as I (1). Similar as before here the null hypothesis of presence of common unit root in the panel can be rejected for per capita health expenditure at its difference form when the test regression contains intercept. So, this variable can also be considered as I(1). Finally, the dependent population which was characterized as non-stationary under IPS test procedure has been found to be difference stationary when the null changed from individual unit root to common unit root following LLC procedure both in intercept specification and intercept and trend specification. Hence the variable would be I(1)

Testing for Cointegration

Since all the variables considered in the panel construction has been observed to become stationary at a common level suggesting a common integration order, there might present cointegration among the variables formulating long run relationship among them. The existence of such relationship among the concerned variables has been diagnosed applying two Engle Granger based cointegration tests suggested by Pedroni (1999, 2004) and Kao (1999) While testing for

Table 3: Panel Unit Root Test Results of the Variables

Variables	*Null: Panels Contain Unit Roots (Common)* None		Intercept		Intercept and Trend		Comments
	LLC t–Stat	Prob.	LLC t – Stat	Prob.	LLC t – Stat	Prob.	
lnPHCE (Current US $)	8.782	1.000	2.433	0.992	-3.143*	0.000	lnPHCE is difference stationary under none and intercept specification and thus treated as I(1)
D(lnPHCE)	-4.483*	0.000	-8.602*	0.000	-7.681*	0.000	
lnPGDP (Current US $)	10.075	1.000	2.338	0.990	0.020	0.508	lnPGDP is difference stationary under all specifications and thus treated as I(1)
D(lnPGDP)	-4.457*	0.000	-7.931*	0.000	-7.987*	0.000	
lnDP	0.693	0.244	0.025	0.510	-1.247	0.106	lnDP is difference stationary under none and intercept and trend specification and thus treated as I(1)
D(lnDP)	-4.808*	0.000	-1.125	0.130	-1.467***	0.071	
lnCO2 (KT)	9.860	1.000	-0.508	0.307	-0.966	0.167	$LnCO_2$ is difference stationary under all

Note: * Indicates 1 per cent level of significance, ** Indicates 5 per cent level of significance, *** Indicates 10 per cent level of significance

cointegration, Kao (1999), allows heterogeneity in terms of intercepts only (slope coefficients are assumed to be homogeneous), Pedroni (1999, 2004) permits heterogeneity both in terms of intercepts and trend. The test results are presented in table 4 and table 5.

Following Pedroni (1999, 2004), the null of “no cointegration” has been tested using a total of eleven statistics under three different specifications. Among which eight statistics namely “panel statistic” are within dimension and evaluate the null against homogeneous alternative. The rest three are “group statistics” based on between dimensions and evaluate null against heterogeneous alternatives. When the test regression is considered to be free of intercept and trend five out of eight within dimension statistics and two out of three between dimensions statistics has been found to be statistically significant arguing for the possible presence of cointegration among the variables.

Similar number of statistics has been observed to be significant rejecting the null of no cointegration when the test regression was augmented with intercept term only. Considering both intercept and trend term in the test regression, PP and ADF

Table 4: Panel Cointegration, Pedroni (1999, 2004)

Pedroni (1999, 2004) Engle – Granger Based Cointegration Test

H_0: No Cointegration

	Panel Statistic						Group Statistic		
	Intercept		Intercept & Trend		No Intercept & Trend		Intercept	Intercept & Trend	No Intercept & Trend
	Stat.	*W*-Stat	Stat.	*W*-Stat	Stat.	*W*-Stat	Stat.	Stat.	Stat.
V-Stat	1.707**	-0.607	1.127	-1.905	2.219**	-0.151	-	-	-
Prob.	0.043	0.728	0.129	0.971	0.013	0.560	-	-	-
Rho-Stat	-0.534	0.495	0.561	1.788	-1.082	-0.155	0.685	1.859	0.175
Prob.	0.296	0.689	0.712	0.963	0.139	0.438	0.753	0.968	0.569
PP-Stat	-2.598*	-2.519*	-3.508*	-4.026*	-3.194*	-2.478*	-7.049*	-7.507*	-5.931*
Prob.	0.004	0.005	0.000	0.000	0.000	0.006	0.000	0.000	0.000
ADF-Stat	-2.912*	-5.250*	-4.011*	-6.879*	-3.461*	-4.275*	-6.253*	-5.966*	-6.790*
Prob.	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: * Indicates 1 per cent level of significance and
** Indicates 5 per cent level of significance.

statistic has been detected to be statistically significant in within as well as between dimensions. Thus, it can be argued with evidence that the long run relationship among the variables exists. Alongside the cointegration test procedure suggested by Pedroni (1999, 2004), the procedure developed by Kao (1999) has also been applied. The ADF test statistic for Kao has been observed to be statistically significant at one per cent level rejecting the null of no cointegration.

Estimation of long run coefficients

As majority of the test statistics suggested by Pedroni (1999, 2004) and the statistic suggested by Kao (1999) turned out to be significant, the long run relationship among the variables would remain present. Also, since all the variables have been found to have common integration order the estimation techniques such as FMOLS (see (Phillips & Hansen, 1990) and DOLS ((Saikkonen, 1992) and (Stock & Watson, 1993)) can be applied to receive the long run coefficients. These estimation techniques have been extended further for panel during later time. Specifically, Pooled FMOLS, Weighted FMOLS and Grouped Mean FMOLS proposed by noteworthy works mentioned in the methodology parts (Phillips & Moon, 1999), (Pedroni P., 2000) and (Kao &

Table 5: Panel Cointegration, Kao (1999)

Kao (1999) Engle – Granger Based Cointegration Test	
H_0: No Cointegration, Deterministic Specification: Intercept Only	
ADF t - Statistic	Prob.
-3.250*	0.000

Note: * Indicates 1 per cent level of significance.

Chiang, 2000) and (Pedroni P. , 2000, 2001). Likewise Pooled DOLS, Weighted DOLS and Grouped Mean DOLS contributed respectively by Kao and Chiang (2000), Mark and Sul (1999) and Pedroni (2001). Both the estimation techniques have been applied with all three extensions for the panel.

Table 6 contains the estimation results of long run relationship among per capita health expenditure, per capita GDP, dependent population and carbon emission. As all the variables involved in the regression has been considered after logarithmic transformation, the resulting coefficients will actually be the measurement of long run elasticities. The elasticity of per capita health expenditure with respect to per capita income was found to be positive and statistically significant under all three FMOLS estimates. Specifically the responsiveness varied between 0.820 to 0.851. Thus increase in per capita income leads to increase in per capita health expenditure suggesting health care to be a normal service in nature. When the estimation technique has been altered to DOLS, again all three coefficients of per capita GDP observed to be positive and significant, however with different magnitudes. Here, it varied between 0.871 to 0.991. The elasticity coefficient of dependent population was measured to be negative in all cases. This contradicts our expectation.

Although under the methods of DOLS it has been found to be significant, under FMOLS (Pooled and Grouped methods) it turned out to be insignificant. This implies a mixed result. Finally, the variable which measures the effect of environment on health in current study is carbon emission defined by CO_2 emission. The elasticity of per capita health expenditure with respect to CO_2 emission has been measured to be positive and statistically significant. Under FMOLS the coefficient varied between 0.246 to 0.355 while under DOLS it varied between 0.198 to 0.283. Therefore, increase in carbon emission in the long run would necessarily lead to increase in per capita health expenditure. The current findings reemphasize the fact that environment is an important determinant of health as well as health care expenditure. Degradation in environment measured by increasing carbon emission would generate uncountable health care problems gradually. Fighting with which would require more and more fund allocation for health care both from private and public perspective. This would imply a higher health care expenditure than earlier.

Table 6: Panel Cointegration, FMOLS and DOLS

	Cointegrating Regression					
Variables	FMOLS			DOLS		
	Pooled	Weighted	Grouped	Pooled	Weighted	Grouped
lnPGDP	0.841*	0.851*	0.820*	0.871*	0.873*	0.995*
	0.000	0.000	0.000	0.000	0.000	0.000
lnDP	-0.697	-0.596*	-0.199	-0.256*	-0.315*	-0.390*
	0.107	0.000	0.732	0.000	0.000	0.000
lnCO2	0.270**	0.246*	0.355*	0.198*	0.283*	0.206***
	0.012	0.000	0.000	0.000	0.000	0.058

Note: * Indicates 1 per cent level of significance, ** Indicates 5 per cent level of significance, *** Indicates 10 per cent level of significance.

5. Conclusion

A wide range of pioneering research works has been done in the field of health economics worldwide to explore the determinants of health expenditure employing different types of econometric models. Some of them wielded micro level data while others used macro level data (see (Hansen & King, 1996); (Abdullah, Siddiqua & Huque, 2017). However, very few studies have been devoted to explore the causal relationship between health care expenditure and environmental degradation.

Because of unplanned industrialization, environmental degradation has been resulting by causing rapid change in climate. Environmental degradation has become the major concern of the policymakers because it is distorting their anticipation and increasing the cost of the economy. Due to rapid climate change, health condition is deteriorating over time leading to the uncountable health care problems. As a result various types of diseases are spreading out worldwide which causes acceleration in the health expenditure. The present study tries to explore the causal relationship between health care expenditure and carbon emissions from a long run perspective. As mentioned earlier, it takes SAARC countries excluding Afghanistan data spanning from 1995 to 2014.

The findings of the study showed that the coefficients representing long run the elasticity of per capita health care expenditure with respect to carbon emissions vary from 0.198 to 0.355 under different method of estimation following FMOLS and DOLS. Since all the coefficients of carbon emissions from different models are statistically significant, this leads to the conclusion that increased carbon emissions will increase health care expenditure in the long run. The findings hence reemphasize on environment as a crucial and important determinant of health care expenditure for SAARC countries. Like the coefficients of carbon emissions, the coefficients of per capita GDP representing the elasticity of health care expenditure with respect to per capita GDP are positive and statistically significant confirming the prior expectation.

The main contribution of this paper is that it can be thought of as one of the very few works that empirically investigated the causal relationship between health care expenditure and environmental degradation of SAARC countries using standard econometric methodology. This study has some strong recommendations for the policymakers. Firstly, since all the countries of South Asia region are at the stage of growing phase of the business cycle, they should adopt the environment friendly production technology. Secondly, as urbanization is considered as one of the major indicators that is responsible for carbon emission as well as climate change, policymakers should reemphasize on planned and decentralized urbanization. Lastly, a common fund could be generated to support the most victimized people of this region. On the other hand, since climate change is an integrated concept, the developed countries are also producing carbon emissions and deteriorating the world climate, the SAARC countries might claim contribution to this common fund.

The current exercise is not free from flaws. To begin with it embraces only SAARC countries. Although, Afghanistan is a member of SAARC, it is excluded due to unavailability of data. Secondly, the study could incorporate all the developing countries to provide better and strong implication of climate change. This could also be done by segmenting the countries based on income groups. Also, variation in the developed model would be possible to make changing the variables which would lead to expectedly different results. Nevertheless all these might generate and open the opportunities for further studies and research.

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Appendix

Table A1 : Summary Statistics (Based on individual countries)

Variables	Bangladesh		Bhutan		India		Maldives		Nepal		Pakistan		Sri Lanka	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Health expenditure per capita (current US$)	15.56	7.29	72.87	28.89	36.84	20.34	387.89	291.06	22.56	11.84	23.56	8.51	57.83	31.89
CO2 emissions (kt)	42650.51	16812.65	477.26	211.46	1350938.00	440168.40	680.05	311.48	3719.07	1646.51	131399.40	29297.77	11613.57	3214.36
Population ages 0-14, total (000)	48697.12	642.97	228.16	6.014	371311.00	9000.69	105.26	10.07	9764.50	373.14	58883.42	3545.024	5079.09	113.18
Population ages 65 and above, total (000)	6003.72	1253.16	24.90	6.08	54154.95	9893.71	13.08	3.23	1099.88	233.58	6521.22	1081.73	1344.64	218.34
Dependent population (sum of ages 0-14 and above 65, in 000)	54700.84	1502.37	253.05	3.60	425466.00	18424.17	118.33	6.92	10864.38	518.66	65404.64	4615.19	6423.73	250.84
GDP per capita (current US$)	564.47	221.40	1384.76	699.63	820.88	434.95	4582.96	2461.66	385.14	189.41	793.59	316.54	1694.71	1082.19

Graph A1: Trends of (ln) Health Care Expenditure and (ln) Carbone Emission (co2 in kt)