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# Impact of Environmental Quality Variables and Socio-Economic Factors on Human Health: Empirical Evidence from China

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**ABSTRACT:** Carbon dioxide ($CO_2$) is the foremost gas, emanated from human activities, and the best-known greenhouse gas, contributing to global warming, thus its negative effect on human health cannot be disregarded. The current paper investigates the relation between environmental quality variables, socio-economic factors, and human health from 1960 to 2014 in China, using Auto Regressive Distribution Lag (ARDL) Model. It selects three main environmental quality indicators (carbon emissions from coal, natural gas, and petrol) along with two representative socio-economic factors variables (per capita income and urban population) to explain the interaction mechanism. The results validate the long-term negative equilibrium impact of carbon emissions from the consumption of natural gas, coal, and petroleum on human health. The findings also reveal that migration from the countryside to cities and increase in per capita income improve quality of health. It is suggested that lowering emission of Carbon dioxide ($CO_2$), which is the principal cause of greenhouse gas emissions, should be important in setting up the high quality of life for citizens.

**Keywords:** $CO_2$ emissions, per capita income, Urban population, ARDL.

## INTRODUCTION

Air pollution is the foremost ecological issue in China. Around one third of China's land is affected by acid rain, which can slow down the growth of forests, putting in danger not only aquatic life but also human health. China's main contributing element to global warming is its rising energy demand as well as its dependence on coal, both of which pose difficult challenges for air quality enhancement, reduction of acid deposition, along with its strive to trim down carbon dioxide emissions (A World Bank country study, 2001). Thus, the increasing worsening situation of environmental quality in China is causing major challenges to human health, simultaneously rising the threat of its contribution to global warming. Given the latest discussion on environmental problems, global warming, the nexus between the environment and human health outcomes, is

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currently receiving more attention from environmental policymakers. Changes in the environment in the shape of greenhouse gas emissions and global warming lead to an upsurge of concerns for the usage of fossil fuels. (Sinha and Mehta, 2014; Zhao and Wang, 2015; Balan, 2016). Policymakers from all over the world are concerned about air pollution particularly, for air pollution from fast expansion of industrialization and the utilization of energy has been accepted to be the main reason for serious health diseases. Especially, emission of Carbon Dioxide ($CO_2$) and Sulphur Dioxide (SO2) from the burning of fossil fuels is the foremost contributing factor to pollution substantially (Roberts & Grimes, (1997). As matter of fact, the release of carbon dioxide is considered to be the main contributor to global warming. It has become a tropical problem among policymakers and quite a few numbers of researchers across various fields of study, (Odusanya et al., 2014).

Contrariwise, the urban population is a central element in shaping the quality of life, especially in urban areas, not to mention the influence of the urban areas on the broader environment. Various urban environmental issues are comprised of insufficient sanitation and water, industrial polution, and deficiency of rubbish disposal (Kolsrud and Torrey, 1992). Health-related consequences of these environmental issues include respiratory infections, parasitic diseases, etc. Population growth has both advantages and disadvantages for developing countries. The main advantage is its positive effects on economic growth (Mankiw et al., 1992), whereas its chief disadvantages involve pressure on the government to provide basic health facilities to its citizens along with human capital inequality (Castello and Domenech, 2002). Additionally, capital expenditure for construction of better-quality environmental infrastructures, like money spent on a cleaner public transportation system, specifically the subway, as well as building new clinics and hospitals goes higher in big cities, where the earnings are greater than rural areas. Due to the competition for space, urban land prices are comparatively greater. On the other hand, not all urban areas have the identical type of health problems. Various studies advocated that indicators of health conditions, such as mortality rate, are higher in cities that keep expanding briskly, than those wherein the growth is much slower (Martin & Ellen, 1998). Meanwhile, migration from villages to big cities leads to greater $CO_2$ emissions levels (Kolsrud and Boyle, 1992; Zhou et al., 2018). Moreover, some studies concluded that along with an increase in urban population, life expectancy or human health also improve (Bayati et al., 2013; Eckert & Kohler, 2014; Monsef & Mehrjardi, 2015), while several others argued that different socio-economic factors have both positive and negative impacts on the health (Lilliard and Weiss, 1997; Berger and Messer, 2002; Yavari and Mehrnoosh, 2006; Bergh and Nilsson, 2009; Balan and Jaba, 2011; Hazan, 2012).

Based on simple measurements, most recent models try to find a relation between per capita health expenses, environmental quality, and health effects, e.g. Jerrett et al. (2003) investigated the association between healthcare expenditure and environmental quality in Canada, having used cross-sectional data from 49 districts, counties, and regions. Their findings showed that regions with higher pollution had greater the per capita health expenditures, while districts with a higher environmental budget spent much less on health expenditures. Correspondingly, Narayan & Narayan (2008) showed that there exists a positive nexus between $CO_2$ emissions on health expenditures in eight OECD (Organization for Economic Co-operation and Development) countries; findings by Assadzadeh et al. (2014) revealed that the rise in $CO_2$ emissions increased health-related expenses, while an upsurge in life expectancy at birth trimmed healthcare expenditure in the short run. Moreover, Odusanya at el. (2014) concluded that increased $CO_2$ emissions led to a rise in health-related expenditure in both short and long run in Nigeria and Sinha (2014) found a bidirectional causal association between $CO_2$ emissions and infant mortality rate. On the other hand, a few studies have been carried out on the relation between environment and health, e.g. Obrizan et al. (2012) and Kim & Lane (2013) employed life expectancy, infant motility rate, and health expenditure to find the connection between public health expenditure and national life expectancy with respect to developing and developed countries, finding that the money was not effectively allocated towards health-related expenditure in developing countries, though in developed countries, it was vice versa.

The economic approach utilizes carbon dioxide release as logical results of industrial production, which --regardless of their causing pollution in our environment-- are generating value added, thus guaranteeing strong economic growth. That is why most researches have focused on the connection between $CO_2$ emissions and economic growth, whereas few studies have been dedicated to the possible impacts of environmental quality on total human health outcomes with respect to socio-economic factors and loss of life quality. Additionally, previous studies just took total carbon emissions as a proxy of environmental quality. Thus, to fill this gap, emissions of carbon from three different sources have been used as a proxy for environmental quality in order to individually investigate their relations with human health. Besides, the study is carried out for an extension period of time from 1960 to 2014, never tested by other researchers previously.

## MATERIAL AND METHODS

The long-term nexus between life expectancy, $CO_2$ emissions from the consumption of natural gases, $CO_2$ emissions from burning coal, $CO_2$ emissions through petroleum consumption, per capita income, and urban population of China have been tested by applying the following linear logarithmic form:

$$\begin{aligned} lnLE_t &= \gamma_0 + \gamma_1 lnCO2\_Gas_t + \gamma_2 lnCO2 \\ &\quad \_Coal_t + \gamma_3 lnCO2\_Patrol_t \\ &\quad + \gamma_4 lnPCI_t + \gamma_5 lnUP_t + \varepsilon_t \end{aligned} \tag{1}$$

whereas, $LE$ signifies life expectancy in total years, $CO2\_Gas$ denotes the emissions of carbon dioxide from consumption of natural gases in kiloton (kt), CO2_Coal shows the emissions of carbon dioxide from burning coal in kiloton (kt), $CO_2$_Patrol indicates emissions of carbon dioxide from consumption of petroleum in total percentage, $PCI$ is per capita income in current US dollar, and $UP$ stands for total urban population. This study takes life expectancy as proxy of life quality, while $CO_2$_Gas, $CO_2$_Coal, and $CO_2$_Patrol represent environmental quality variables. All of the variables have been selected carefully from several studies.

The current study has utilized time series data from 1960 to 2014; with its data, comprised of life expectancy rate, emission of carbon dioxide from consumption of gas, coal, and patrol, per capita income, and urban population. All the data have been compiled from World Bank database.

The data of the time series are comprised of either stationary or non-stationary series. If non-stationary data are employed in a regression model, the outcomes may spuriously imply significant associations even when there are no relations. In this situation, the Ordinary Least Square (OLS) is biased and the t-statistics, inconsistent (Lutkepohl & Kratzig, 2004). This study has employed Augmented Dickey-Fuller test to look at the null hypothesis of non-stationary against stationary data. Another important part of ADF test is to find an appropriate number of lag, which is based on Schwarz Criteria (SC) as well as Akaike Information (AIC) in a simple autoregressive model.

The testing technique of Auto Regressive Distribution Model (ARDL) bounds was first introduced and later extended by Pesaran & Shin (1999) and Pesaran et al. (2001). It has had several applications over other co-integration procedures, e.g. Johansen & Juselius (1990) and Engle & Granger (1987). Such co-integration methods are based on an assumption, which states that the variables in a model should be integrated in one order. Hence, this assumption is biased when estimating co-integration test bound, while the variables' order of integration relies on the selection of lag length along with unit root test. The testing technique, called Auto Regressive Distributive Lag (ARDL) bound, does not allow the restriction that all variables must be integrated in the same order come into effect, implying that ARDL technique is appropriate regardless whether the order of integration is zero, one, or mixed. In addition, the ARDL bound testing technique is also applicable if the sample size is either relatively small (normally below 30) or quite limited. Even in the existence of endogeneity, the procedure of ARDL not only estimates in the long run but also yields a valid t-statistics (Sollis & Harris, 2003). Furthermore, Error Correction Model (ECM) gives short-run coefficients in line with long-term equilibrium.

The Bound testing approach involves computing the unrestricted ECM for Equation (1) follow as:

$$\begin{aligned}\Delta \ln LE_t = {} & \xi_0 + \sum_{i=1}^{d} \xi_{1i} \Delta LE_{t-i} + \sum_{i=0}^{e} \xi_{2i} \Delta lnCO2\_Gas_{t-i} + \sum_{i=0}^{e} \xi_{3i} \Delta lnCO2\_Coal_{t-i} + \\ & \sum_{i=0}^{e} \xi_{4i} \Delta lnCO2\_Patrol_{t-i} + \sum_{i=0}^{e} \xi_{5i} \Delta lnPCT_{t-i} + \sum_{i=0}^{e} \xi_{6i} \Delta lnUP_{t-i} + \\ & \xi_{7i} lnLE_{t-i} + \xi_{8i} lnCO2\_Gas_{t-i} + \xi_{9i} lnCO2\_Coal_{t-i} + \xi_{10i} lnCO2\_ \\ & Patrol_{t-i} + \xi_{11i} lnPCT_{t-i} + \xi_{12i} lnRP_{t-i} + \upsilon_t\end{aligned} \tag{2}$$

where, $\xi_0$ signifies the drift and $\upsilon_t$ stands for the error term, while $\xi_7, \xi_8, \xi_9, \xi_{10}, \xi_{11}$, and $\xi_{12}$ show the long-term coefficients, $\Delta$ indicates the first difference operator, and $d$ and $e$ are optimal lag lengths. Selection of optimal lag in unrestricted ARDL model is based on Schwarz Criteria (SC) and Akaike Information (AIC) criterion.

The ARDL bounds testing technique also involves the joint F-statistics of the coefficients of different variable levels. For this reason, the unrestricted ARDL model of Equation (2) is firstly estimated by means of OLS technique in order to test the null hypothesis $\xi_7 = \xi_8 = \xi_9 = \xi_{10} = \xi_{11} = \xi_{12} = 0$ against the alternative hypothesis $\xi_7 = \xi_8 \neq \xi_9 \neq \xi_{10} \neq \xi_{11} \neq \xi_{12} \neq 0$. The present study used critical values, generated by Narayan (2005). The null hypothesis of no co-integration is rejected if estimated F-statistics are greater than upper bound critical values. The test becomes inconclusive if the calculated F-statistics fall within the bounds for the critical values.

After confirming the long run associations among the variables, the next stage is to estimate the long run coefficient, based on the ARDL $(d_1, e_1, e_2, e_3, e_4, e)$. The selection of lag length of ARDL $(m_1, n_1, n_2, n_3, n_4, n_5)$ can be chosen, based on Schwarz Criteria (SC) and Akaike Information (AIC) criterion.

$$\Delta \ln LE_t = \zeta_0 + \sum_{i=1}^{i=d_1} \zeta_{1i} \Delta LE_{t-i} + \sum_{i=0}^{i=e_1} \zeta_{2i} \Delta lnCO2\_Gas_{t-i} + \sum_{i=0}^{i=e_2} \zeta_{3i} \Delta lnCO2\_Coal_{t-i} + \sum_{i=0}^{i=e_3} \zeta_{4i} \Delta lnCO2\_Patrol_{t-i} + \sum_{i=0}^{i=e_4} \zeta_{5i} \Delta lnPCT_{t-i} + \sum_{i=0}^{i=e_5} \zeta_{6i} \Delta lnUP_{t-i} + \upsilon_t \quad (3)$$

In the next stage, the short run coefficients is to be obtained by computing ECM model, accompanied with the long run estimates as follows:

$$\Delta \ln LE_t = \theta_0 + \sum_{i=1}^{i=d_1} \eta_{1i} \Delta LE_{t-i} + \sum_{i=0}^{i=e_1} \eta_{2i} \Delta lnCO2\_Gas_{t-i} + \sum_{i=0}^{i=e_2} \eta_{3i} \Delta lnCO2\_Coal_{t-i} + \sum_{i=0}^{i=e_3} \eta_{4i} \Delta lnCO2\_Patrol_{t-i} + \sum_{i=0}^{i=e_4} \eta_{5i} \Delta lnPCT_{t-i} + \sum_{i=0}^{i=e_5} \eta_{6i} \Delta lnUP_{t-i} + \varphi ECT_{t-1} + \upsilon_t \quad (4)$$

whereas, $\eta_1, \eta_2, \eta_3, \eta_4, \eta_5$ , and $\eta_6$ signify short run coefficients, ECM represents error correction terms, obtained from Equation (2). And $\varphi$ is the adjustment coefficient.

## RESULTS AND DISCUSSIONS

Table 1 presents the outputs of stationary test, which divulges that both dependent and independent variables are non-stationary at level with drift and trend. Therefore, we cannot reject the null hypothesis of a unit root at 5% significance level, yet all the variables become stationary on the first difference; therefore, all the variables can be modeled as I (1). Econometric theory suggests that if the variables are non-stationary at the level and become stationary on the first differences, these variables are integrated in order 1. Hence technique of ARDL is employed to account for same order, while estimating long-run association among dependent and independent variables.

The next step is to choose an appropriate lag length in order to get rid of any serial correlation. In this regard, Akaike information criteria is employed to obtain maximum lag. Table 2 gives the findings from selection of the maximum lag. The minimum value of Akaike Information (AIC) signifies that the maximum lag 4 is an appropriate lag length for our existing model.

**Table 1. ADF unit root test**

| Variables | T-Statistics | P value* |
|---|---|---|
| ADF test at level with trend & intercept | | |
| ln LE | -0.9360 | 0.9431 |
| ln $CO_2$_Gas | -1.5917 | 0.7831 |
| ln $CO_2$_Coal | -3.4684 | 0.1534 |
| ln $CO_2$_Petrol | -2.3619 | 0.3946 |
| ln PCI | -0.7355 | 0.9650 |
| ln UP | -2.1376 | 0.5132 |
| ADF test at level with trend & intercept | | |
| ln LE | -7.0601 | 0.0000 |
| ln $CO_2$_Gas | -4.9528 | 0.0010 |
| ln $CO_2$_Coal | -5.3721 | 0.0003 |
| ln $CO_2$_Petrol | -4.4384 | 0.0044 |
| ln PCI | -6.4224 | 0.0000 |
| ln UP | -7.2602 | 0.0000 |

*Mackinnon (1996) one-sided p-values

**Table 2. VAR lag order selection criteria**

| Lag | LogL | LR | FPE | AIC | SC | HQ |
|---|---|---|---|---|---|---|
| 0 | 148.1505 | NA | 0.000199 | -5.686022 | -5.456579 | -5.598649 |
| 1 | 259.0544 | 190.7546 | 2.45e-06 | -10.08217 | -9.814492 | -9.980239 |
| 2 | 306.9883 | 80.52894 | 3.76e-07 | -11.95953 | -11.65361 | -11.84303 |
| 3 | 378.1491 | 116.7037 | 2.27e-08 | -14.76596 | -14.42180 | -14.63490 |
| 4 | 382.8608 | 7.538740* | 1.96e-08* | -14.91443* | -14.53203* | -14.76881* |
| 5 | 383.7462 | 1.381290 | 1.97e-08 | -14.90985 | -14.48920 | -14.74966 |

*Lag order, selected by the criterion. LR: Sequential modified LR test statistic (each test at 5% level) and FPE

**Table 3. Bound test of co-integration**

| Test Statistic | Value | K |
|---|---|---|
| F-statistic | 9.643321 | 5 |
| | Critical Value Bounds* | |
| Significance | I0 Bound | I1 Bound |
| 10% | 2.26 | 3.35 |
| 5% | 2.62 | 3.79 |
| 2.5% | 2.96 | 4.18 |
| 1% | 3.41 | 4.68 |

*Pesaran et al., (2001) Critical values 0.08 percent.

**Table 4. Long-term coefficients of ARDL (4,1,1,4,0,3) Model Dependent Variable in LE**

| Regressor | Coefficient | Standard error | t-ratio |
|---|---|---|---|
| Constant | 3.728353* | 0.159638 | 23.354979 |
| ln $CO_2$_Gas | -0.024489* | 0.005061 | -4.838496 |
| ln $CO_2$_Coal | -0.035331* | 0.010404 | -3.395987 |
| ln $CO_2$_Petrol | -0.084033* | 0.006007 | -3.990048 |
| ln PCI | 0.031539* | 0.006931 | 4.550575 |
| ln UP | 0.006863* | 0.002199 | 3.121551 |

*Signify significance level at 5 percent

The nexus between long-run linkage among independent and dependent variables of Equation (1) is set up with the help of ARDL bound test. Table 3 depicts the output of bound test for co-integration. The estimated value of F-Statistic was greater than the tabulated upper bound value at 10%, 5%, 2.5%, and 1% level of significance. For this reason, the null hypothesis of no co-integration got rejected at 5% level of significance. Accordingly, it confirms and validates the long-term nexus among the variables.

Table 4 shows the long run linkage between life expectancy, the determinants of which are computed by the ARDL approach. All coefficients of the variables symbolize the long-term slopes.

The coefficient value of $CO_2$_Gas assumed negative sign and was significant at 5% level of significance. Since emissions of carbon dioxide from natural gas consumption are the covariate, we should make use of the largest influence on the human health in the long run. Elaborate by itself, this factor joins other factors, encompassed in the estimated model, giving rise to the percentage of $CO_2$ emissions, in turn reducing life expectancy by approximately 0.024%. The estimated value of $CO_2$_Coal was -0.035, indicative of the negative impact of carbon emissions from the consumption of coal on human health. In the same way, there exists a negative relation between $CO_2$emissions from the use of petroleum on human health. Moreover, China as an emerging economy with higher levels of $CO_2$ emissions from the consumption of natural gases, coals, and petroleum would also probably tolerate higher levels of other toxic chemicals and waste products, further raising the risk of health issues for its residents. Hence, our findings suggested that along with an increase in carbon emissions, life expectancy trimmed down. On the other side, increased per capita income and urban population enhanced human health, e.g. 1% upsurge in per capita income led to an increase of life expectancy by 0.03%. Likewise, 1% rise in urban population brought increased life expectancy by a meagre rate of 0.006%. Hence, these results clearly show that the variables, related to socio-economic, are extremely effective in determining life expectancy or human health in China. Therefore, an increase in income will rise many expenditures like health expenses, food expenses, etc., further improving human health. Additionally, migration from villages to big cities also improved the quality of life. The results from this study are consistent with the previous studies by Bayati et al. (2013) for Eastern Mediterranean Region, Monsef and Mehrjardi, (2015) for various countries, and Zhou et al. (2018) for China, itself.

Table 5 demonstrates the findings of short-run coefficients and error correction term (ECT). With regard to Equation (4), the computed coefficient of the ECM turned out to be -0.030.

Some diagnostic tests were also carried out, which involved ARCH, Breusch-Godfrey Serial Correlation LM Test, and Ramsey RESET Test. The final findings of all diagnostic tests verified that the estimated model was free of heteroscedasticity and serial correlation. Moreover, Ramsey RESET test identified that there was no specification error in the estimated model. CUSUM square tests and CUSUM were performed to check the stability in estimated model with Figure 1 depicting that CUSUM graph was significant at 5% level of significance, also showing that our model remained stable in all aspects. In Figure 1, the graph of CUSUM and CUSUM of square signify that the blue line is located within red lines, meaning that all parameters were stable.

**Table 5. ECM of the selected ARDL (4,1,1,4,0,3) Model**
**Dependent variable Δ in LE**

| Regressor | Coefficient | Standard error | t-ratio |
|---|---|---|---|
| Δ ln $CO_2$_Gas | -0.000402 | 0.000291 | -1.384303 |
| Δ ln $CO_2$_Coal | -0.000358 | 0.000332 | -1.077999 |
| Δ ln $CO_2$_Petrol | -0.001682* | 0.000448 | 3.753621 |
| ln PCI | 0.000954* | 0.000178 | 5.354966 |
| ln UP | 0.000035 | 0.000034 | 1.025611 |
| ECM (-1) | -0.030239* | 0.004754 | -6.360811 |

* shows level of significance at 5%, R-squared=0.998, F-Statistic=3170786., Breusch-Godfrey Serial Correlation LM Test (Obs R squared) =0.414391, Autoregressive Conditional Heteroscedasticity Test (Obs R squarer) = 4.896631, Ramsey RESET Test (F-Statistic) = 0.606760

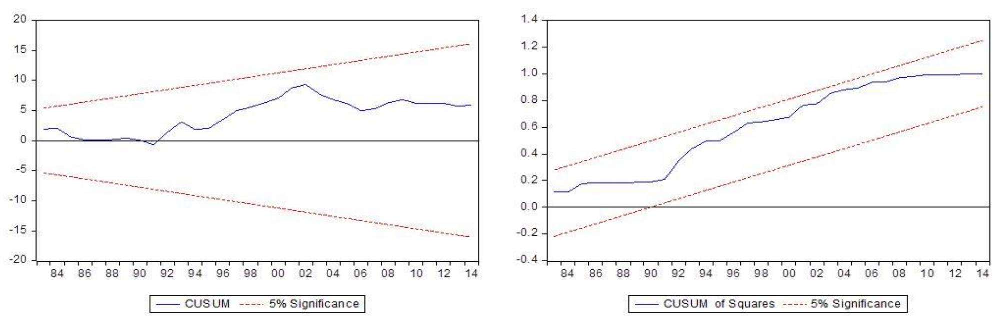


**Fig. 1. CUSUM and CUSUM of Square**

## CONCLUSION

This study used emission of carbon dioxide due to consumption of natural gases, coal, and petroleum as a proxy of environmental quality, since greenhouse gases are reflected to be the foremost contributor to changes in a global climate. The study aimed at finding out whether there exists a long-run relation among carbon emissions from consumptions of different resources, per capita income, urban population, and total human health from a Chinese perspective. ARDL Bound test validated the existence of a long-term linkage among the variables. The empirical findings divulged the long-run negative impact of carbon emissions from consumption of natural gases, coal, and petroleum on human health. A positive and significant influence of per capita income and urban population on human health was also found. Furthermore, the coefficient of ECM was negative and statistically significant, thus validating the existence of a long-term nexus among variables. The results, obtained from this study, suggested that reduction of $CO_2$ emissions, the principal cause of greenhouse gas emissions, should be important in setting up a high quality of life for the citizens. In this regard, burning of carbon must be decreased through adopting substitute means, like burning of crop remnants after harvest, better control of wildfires, diminution in the rate of land deforestation and, conversion and diminution of emissions from commercial fishing operations.

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