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Global estimation of mortality, disability-adjusted life years and welfare cost from exposure to ambient air pollution

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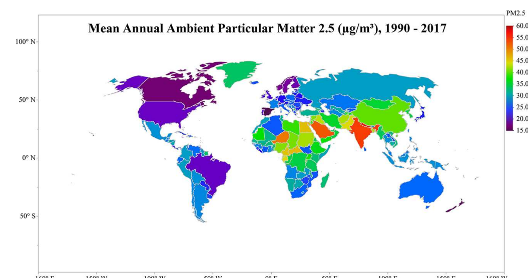
HIGHLIGHTS

- We examined the impact of ambient air pollution on mortality, DALYs and welfare cost.
- We used the novel dynamic panel bootstrap-corrected fixed-effects estimator.
- We found a positive significant association between outdoor air pollution and mortality.
- China is the most vulnerable to economic burden due to ambient air pollution.
- Ambient air pollution has a significant impact on economic development.

GRAPHICAL ABSTRACT



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ABSTRACT

Environmental pollution in the era of sustained economic development is an inevitable occurrence. However, the rising levels of pollutant emissions hamper air quality, hence, affecting health outcomes. Previous studies have assessed the case-by-case effect of ambient air pollution on mortality and morbidity, however, the impact on disability-adjusted life years (DALYs) and welfare cost have not been investigated entirely. Here, we conduct an empirical analysis of the 28-Year trend to analyze the nexus between ambient particulate matter and ozone, mortality, DALYs, and welfare cost across 195 countries and territories by employing novel dynamic panel estimation methods. We find that none of the 195 countries and territories studied between 1990 and 2017 meet WHO guideline for air quality, thus, mitigating ambient air pollution is at risk. However, Spain with an annual average of $PM_{2.5}$ not exceeding 15.12 μg/m^3 is closer to WHO guideline of 10 μg/m^3/annum. Among the countries (China, the US, Russia, India, Germany and Japan) with the highest welfare cost of premature death associated with the exposure to outdoor $PM_{2.5}$ and ozone, China is the most vulnerable to economic burden – spending US$1.58 trillion (constant 2010) in 2017. This study demonstrates that ambient air pollution has a significant impact on economic development (welfare cost) and health outcomes (mortality, premature deaths, and DALYs).

1. Introduction

According to World Health Organization (WHO) and health care ministries across the globe, particulate matter (PM_{10} and $PM_{2.5}$), Sulphur dioxide (SO_2), nitrogen dioxide (NO_2) and ozone (O_3) have a significant impact on the quality of health and well-being (Ritchie and

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Roser, 2019; Katsouyanni, 2003). Ambient air pollution is reported to affect morbidity, disability-adjusted life years (Cohen et al., 2017), life expectancy in total years (premature deaths)(Hay et al., 2017), environmental quality and largely contributing to climate change (Sarkodie et al., 2019). In line with WHO standards for air quality, two main criteria for particulate sizes in the atmosphere exist, thus, particulate matter less than 2.5 μm and 10 μm ($PM_{2.5}$ and PM_{10} in aerodynamic diameter) (Pope III, 1999; World Health Organization, 2016). In 2016, the global age-standardized mortality rate associated with ambient and household air pollution was 114/100,000 population. The 2017 mean annual air pollution ($PM_{2.5}$) exposure was 46 μg/m^3, with 91% population exposed to levels exceeding WHO guidelines for $PM_{2.5}$ not exceeding 10 μg/m^3 (The World Bank, 2019; World Health Organization, 2018).

Environmental pollution is the contribution of both natural occurrences, such as volcanic eruptions, forest fires, among others, and anthropogenic activities (Katsouyanni, 2003) from energy production, industrialization, land use, forestry, agriculture, transportation, buildings and waste generation (IPCC, 2016; Sarkodie and Strezov, 2018). Thus, several studies have examined the extent of pollution on health outcomes (Balakrishnan et al., 2019; Cohen et al., 2017; Huang et al., 2018; Sarkodie et al., 2019). First, studies on the relationship between pollution and health outcomes span from short- to long-term including some cohort studies (Landrigan et al., 2018; Williams et al., 2019). Both minimal and large exposures to ambient pollution have varying impacts on quality of health and well-being, mostly among children and aged (Brunekreef and Holgate, 2002; Landrigan, 2017; Landrigan et al., 2019). Second, the degree to which various harmful ambient compounds namely O_3, NO_2, SO_2, PM_{10}, and $PM_{2.5}$ affect health and well-being have been studied. For instance, several studies have assessed air pollution – years of life lost due to non-accidental cardiovascular and respiratory deaths across the globe and found a significant positive association between pollution and health (Collaboration, 2018; Fitzmaurice et al., 2018; Huang et al., 2018). While there are several studies on the impact of ambient air pollution on environment and health outcomes, literature on the effect of air pollution on financial development is limited (Gakidou et al., 2017; Landrigan et al., 2018; Mostofsky et al., 2012; Solomon et al., 2011). Air pollutants released into the environment due to combustion of fossil fuels for industrial and economic development leads to a trade-off between quality of life and financial development. Thus, a shift from 'money' generating resources such as fossil fuels to curb pollution comes with an economic cost. Apart from direct loss in revenue due to reduced consumption of fossil fuels, an indirect financial cost to the economy emerges from preventive and curative health cost, loss of working hours, migration, and productivity loss (Oliva et al., 2019).

The geographical scope of studies on pollution-health nexus ranges from regions, continents, countries and organizational groups to individual countries, and sometimes across urban areas within specific countries. However, a major challenge for studies on pollution-health association is the non-availability of data. These studies obtained varying data sets, time periods and different estimation models, hence, producing inconsistent results (Katsouyanni, 2003). Meanwhile, there is still much to be considered in the nexus between pollution and health outcomes, as anthropogenic emissions across the globe due to production and consumption is increasing in magnitude (Landrigan et al., 2018). Contrary to previous literature, this study for the first time investigates the impact of air pollution on welfare cost from exposure to ambient particulate matter and ozone. Second, using WHO guideline for air quality as a benchmark, we assess whether countries meet the acceptable level. Third, we identify hotspot countries with air pollution-related mortality and DALYs cases. Thus, this study contributes to the extant literature by investigating the nexus between mortality, disability-adjusted life years and welfare cost. We add to the global debate on health-pollution nexus by employing a dynamic estimation method across 195 countries and territories. The flexibility of the novel dynamic panel bootstrap-corrected fixed-effects estimator makes it possible to examine both parametric and non-parametric inferences. It can be applied unrestrictedly to target series that are either stationary or non-stationary. Using lagged dependent explanatory variables in the estimation technique, omitted variable bias and unobserved common factor are constricted.

2. Materials & method

2.1. Data

Data used in this study were extracted from environmental risk and health database of the Organization for Economic Co-operation Development (OECD, 2018). The variables include exposure to ambient particulate matter [$PM_{2.5}$, (μg/m^3)], mortality from exposure to ambient $PM_{2.5}$ (per million inhabitants), mortality from exposure to ozone (per million inhabitants), premature deaths from exposure to ambient $PM_{2.5}$, premature deaths from exposure to ozone, Disability-Adjusted Life Years (DALYs) from exposure to ambient $PM_{2.5}$ (per thousand inhabitants), DALYs from exposure to ozone (per thousand inhabitants), the welfare cost of premature deaths from exposure to ambient $PM_{2.5}$ (US$, millions, 2010), and the welfare cost of premature deaths from exposure to ozone (US$, millions, 2010). Following routine data preprocessing techniques, unevenly spaced data series were imputed using the imputation algorithm in Orange data mining software version 3.24 by the University of Ljubljana based on a random value method. This imputation algorithm has several advantages, as it keeps the distribution, centring, minimum, maximum and dispersion of the original data intact[1].

2.2. Model estimation

There are several panel estimation techniques available and used in the extant literature, however, this study used the novel dynamic panel bootstrap-corrected fixed-effects estimator to develop mortality-DALYs-$PM_{2.5}$ models with lagged dependent explanatory variables. Contrary to the traditional panel techniques that require only large time dimension (T) for estimations to be asymptomatically valid, the bootstrap-corrected fixed-effects — least squares dummy variable estimator corrects the small T bias in panel dynamic models (Kiviet, 1995; Nickell, 1981) using a simplified algorithm introduced in Everaert and Pozzi (2007). Thus, the bootstrap-corrected fixed-effects estimator is useful in estimating higher-order panel data models that contradict the standard error structure, a situation encountered in this study. Using the suitable resampling option in the dynamic panel estimator, challenges such as, inter alia, cross-sectional dependence and heteroskedasticity that undermine the analytical error correction procedures are controlled.

For brevity, the generic expression of the dynamic panel estimation models constructed based on the bootstrap-corrected fixed-effects is presented as (De Vos et al., 2015):

$$y_{i,t} = \gamma * y_{i,t-1} + \beta * x_{i,t} + \mu_i + \varepsilon_{i,t} \quad (1)$$

For cross-sectional dimension $i = 1, \ldots, N$ and time dimension $t = 2, \ldots, T$, where $y_{i,\ t}$ denotes the dependent variables, $x_{i,\ t}$ represents the strongly exogenous regressors, γ is the autoregressive coefficient of the lagged dependent variable, β is the estimated vector coefficients of the independent variables, μ_i represents the uncorrelated and exogeneous country-specific fixed-effects or unobserved heterogeneity with a zero mean and greater than zero variance, and $\varepsilon_{i,\ t}$ is the unobserved and uncorrelated error term across cross-sectional units and

[1] The characteristics of the data during pre-imputation and post-imputation are presented in Appendix A.

time. To achieve a dynamic stable relationship between $y_{i,\,t}$ and $x_{i,\,t}$, γ is assumed to be less than 1.

Our models can be constructed by rewriting Eq. (1) as:

$$lnTOT_{MORi,t} = \gamma{*}lnTOT_{MORi,t-1} + \beta{*}lnPM25_{i,t} + \mu_i + \varepsilon_{i,t} \tag{2}$$

$$lnTOT\_MOR_{V\,i,t} = \gamma{*}lnTOT_{MORV\,i,t-1} + \beta{*}lnPM25_{i,t} + \mu_i + \varepsilon_{i,t} \tag{3}$$

$$lnTOT_{DALY\,i,t} = \gamma{*}lnTOT_{DALY\,i,t-1} + \beta{*}lnPM25_{i,t} + \mu_i + \varepsilon_{i,t} \tag{4}$$

$$lnTOT\_SC_{V\,i,t} = \gamma{*}lnTOT\_SC_{V\,i,t-1} + \beta{*}lnPM25_{i,t} + \mu_i + \varepsilon_{i,t} \tag{5}$$

$$\begin{aligned} lnTOT_{MORi,t} = {} & \gamma{*}lnTOT_{MORi,t-1} + \beta_1{*}lnTOT_{DALY\,i,t} + \beta_2{*}lnTOT\_SC_{V\,i,t} \\ & + \beta_3{*}lnPM25_{i,t} + \mu_i + \varepsilon_{i,t} \end{aligned} \tag{6}$$

$$\begin{aligned} lnTOT_{MORi,t} = {} & \gamma{*}lnTOT_{MORi,t-1} + \beta_1{*}lnTOT_{DALY\,i,t} + \beta_2{*}lnTOT\_SC_{V\,i,t} \\ & + \beta_3{*}lnTOT\_SC\_V\_lnTOT\_DALY_{i,t} + \beta_4{*}lnPM25_{i,t} + \mu_i \\ & + \varepsilon_{i,t} \end{aligned} \tag{7}$$

For Eqs. (2)–(7): Where *ln* denotes the logarithmic transformation of the data series, $lnTOT_{MOR}$ is the total mortality from exposure to outdoor $PM_{2.5}$ and ozone, $lnTOT\_MOR_V$ denotes premature deaths from exposure to outdoor $PM_{2.5}$ and ozone, $lnTOT_{DALY}$ is the total Disability-Adjusted Life Years from exposure to outdoor $PM_{2.5}$ and ozone, $lnTOT\_SC_V$ is the total welfare cost of premature deaths from exposure to outdoor $PM_{2.5}$ and ozone and *lnPM*25 is the exposure to ambient particulate matter. To control for heteroskedasticity and its corresponding heterogeneity, the model specification included a resampling of error terms using the randomized temporal heteroskedasticity scheme with analytical heterogeneous initialization. This implies that the algorithm resamples the entire time period spanning 1990–2017, followed by resampling of the error terms within the specified time periods ($t = 1, \ldots, 28$). Sampling from a multivariate normal distribution including cross-sectional specific means and variance-covariance matrices were the initial conditions. To make unbiased statistical inferences while preserving the dynamic panel structure of the estimated models, we utilized the nonparametric bootstrap option of the simulation to resample the original data series and subsequently apply the bootstrapping bias-correction to the estimated fixed-effects of each constructed samples (De Vos et al., 2015).

2.3. Model validation

The assurance of quality control measures is essential to the validity and replicability of the estimated models. To ensure the independence of the model residuals, we first assumed cross-section independence of the panel series by testing for unit root using first generational panel unit root tests namely Breitung (Breitung, 1999) and Im-Pesaran-Shin (IPS) (Pesaran et al., 2003) which all requires a balanced panel, a challenge that led to data imputation of the unevenly spaced data series. The unit root tests were conducted to examine the stationarity of panel data series under the null hypothesis of a unit root in the panel. The tests were essential to deal with highly persistent time series that may influence the model estimation, hence, producing misleading results leading to biased statistical inferences. The results of first generational panel unit root tests are presented in Appendix B. The results confirm the presence of unit root among variables except $PM_{2.5}$ at level, however, the null hypothesis of unit root is rejected at first difference in all series. Second, we suspected an issue with cross-section dependence (CD), a challenge with panel data settings, hence, we employed a CD test following the algorithm outlined in Pesaran (2004); Pesaran (2015). The CD test is suitable for both balanced and unevenly spaced panel dataset and examines the average correlation between cross-sectional units assuming a standard normal distribution based on the null hypothesis of either *strict cross-sectional independence* or *weak cross-sectional dependence* (Pesaran, 2004; Pesaran, 2015). Evidence from the test for cross-section dependence in Appendix C reveals that the null hypothesis of either strict cross-sectional independence or weak cross-sectional dependence is rejected — providing strong evidence of correlation across countries. The next step was to examine the likelihood of heterogeneity, another challenge in panel data setting. We used the modified Wald (MWALD) statistics in a fixed-effect regression that assumes normality of errors based on the null hypothesis of homoskedasticity expounded in Greene (2000). The results of the test presented in Table 1 rejects the null hypothesis of homoskedasticity with a *p-value* close to zero, thus, providing strong evidence of heteroskedasticity. With the presence of strong correlation and a violation of normality, the study re-examined the unit root using the second generational panel unit root tests useful in making a critical judgement on the evidence of unit roots in heterogeneous panel with strong correlation across panel units. We utilized both cross-sectionally augmented IPS (CIPS) and cross-section augmented Dickey-Fuller (CADF) based on the null hypothesis of homogeneous non-stationary for the former (Pesaran, 2007) and null hypothesis assuming all series are non-stationary in heterogeneous panel with cross-sectional dependence for the latter (Pesaran et al., 2003). The empirical results of the second generational panel unit root tests in Appendix D corroborate the first generational panel unit root tests.

3. Results

3.1. Rankings

Choropleth maps showing the geographical distribution of various data series are presented in Figs. 2–6. The top ten countries with the highest concentrations of $PM_{2.5}$ include Nepal (57.91 μg/m^3), India (54.48 μg/m^3), Saudi Arabia (52.93 μg/m^3), Niger (50.71 μg/m^3), Central African Republic (46.65 μg/m^3), Egypt (46.3 μg/m^3), Cameroon (45.85 μg/m^3), Gabon (44.24 μg/m^3), Pakistan (44.21 μg/m^3), and Equatorial Guinea (43.4 μg/m^3) while countries with lower $PM_{2.5}$ concentrations include Spain (15.12 μg/m^3), New Zealand (16.17 μg/m^3), Denmark (16.62 μg/m^3), Canada (17.05 μg/m^3), Norway (18.16 μg/m^3), Sweden (18.65 μg/m^3), Finland (19.41 μg/m^3), the US (20.13 μg/m^3), Brazil (20.23 μg/m^3), and Portugal (20.44 μg/m^3) [see Fig. 1]. It can be observed that all countries with higher concentrations are developing economies striving to improve livelihoods through economic advancement, however, the carbon-embedded economic structure comes with an environmental cost. The particulate emissions are primarily from the vast usage of automobiles, combustion of domestic waste in open areas, and industrial factories that do not adhere to regulations that will ensure safe emission levels (Van Vliet and Kinney, 2007).

Egypt (27 per 1000 people), Ukraine (26 per 1000 people), Belarus (23 per 1000 people), Russia (22 per 1000 people), Turkmenistan (21 per 1000 people), Nigeria (21 per 1000 people), Bulgaria (20 per 1000 people), Tajikistan (18 per 1000 people), Uzbekistan (17 per 1000 people), and India (17 per 1000 people) are countries with the most estimated cases of DALYs from exposure to ambient $PM_{2.5}$ and ozone whereas Nicaragua (3 per 1000 inhabitants), Paraguay (3 per 1000 people), Libya (3 per 1000 people), Honduras (3 per 1000 people), Mozambique (3 per 1000 people), Malawi (4 per 1000 people), Dominican Republic (5 per 1000 people), Colombia (5 per 1000 people), Uganda (5 per 1000 people), and Madagascar (5 per 1000 people) are countries with the least cases of DALYs for the study period (see Fig. 2).

Ukraine (1130 per million people), Belarus (1012 per million people), Russia (894 per million people), Bulgaria (891 per million people), Latvia (731 per million people), Lithuania (704 per million people), Hungary (685 per million people), Czech (678 per million people), Slovakia (658 per million people) and Serbia (652 per million people) have the highest estimated mortality rate from exposure to ambient $PM_{2.5}$ and ozone whereas Libya (56 per million people), Mozambique (65 per million people), Nicaragua (71 per million people), Malawi (86 per million people), Mali (90 per million people), Honduras (91 per million people), Uganda (93 per million people), Paraguay (93 per million people), Madagascar (95 per million people) and Kenya (100 per million people) have the lowest ambient $PM_{2.5}$ and ozone attributable mortality rates depicted in Fig. 3.

Table 1
Baseline model estimation of ambient air pollution and health outcomes using Drisc-Kraay panel regression.

Estimation	Mortality[a]	Premature	DALYs	Welfare cost	Mortality[b]	Mortality[c]
γ	−0.033***	−0.024***	−0.035***	−0.833***	−0.188***	−0.197***
	[0.011]	[0.002]	[0.010]	[0.045]	[0.034]	[0.036]
DALYs	–	–	–	–	0.168***	0.124***
					[0.031]	[0.022]
Welfare cost	–	–	–	–	0.004***	−0.013***
					[0.001]	[0.005]
Welfare cost × DALYs	–	–	–	–	–	0.009***
						[0.003]
$PM_{2.5}$	0.005**	0.005***	0.004**	0.049	0.005**	0.004**
	[0.002]	[0.002]	[0.002]	[0.031]	[0.002]	[0.002]
1992	0.003***	0.003***	0.003***	0.078***	0.004***	0.004***
	[0.002]	[0.000]	[0.000]	[0.004]	[0.000]	[0.000]
1993	0.005***	0.004***	0.005***	−0.009*	0.007***	0.007***
	[0.000]	[0.000]	[0.000]	[0.005]	[0.000]	[0.000]
1994	−0.003***	−0.004***	−0.003***	0.006	0.001	0.002*
	[0.000]	[0.001]	[0.000]	[0.005]	[0.001]	[0.001]
1995	−0.007***	−0.008***	−0.007***	0.077***	−0.001	0.000
	[0.003]	[0.001]	[0.000]	[0.003]	[0.001]	[0.001]
1996	0.001*	0.000	0.000	0.173***	0.005***	0.007***
	[0.003]	[0.001]	[0.000]	[0.007]	[0.001]	[0.001]
1997	−0.001***	−0.001	0.000	0.076***	0.005***	0.006***
	[0.000]	[0.001]	[0.000]	[0.011]	[0.001]	[0.002]
1998	−0.004***	−0.003***	−0.003***	0.179***	0.004**	0.005**
	[0.000]	[0.001]	[0.000]	[0.007]	[0.002]	[0.002]
1999	−0.008***	−0.008***	−0.008***	0.166***	0.001	0.002
	[0.001]	[0.001]	[0.000]	[0.010]	[0.002]	[0.002]
2000	−0.015***	−0.015***	−0.015***	0.160***	−0.004	−0.003
	[0.003]	[0.001]	[0.000]	[0.011]	[0.002]	[0.003]
2001	−0.005***	−0.005***	−0.005***	0.288***	0.005**	0.006**
	[0.000]	[0.001]	[0.000]	[0.011]	[0.002]	[0.002]
2002	−0.002***	−0.001	−0.004**	0.237***	0.009***	0.010***
	[0.000]	[0.001]	[0.000]	[0.016]	[0.002]	[0.003]
2003	−0.005***	−0.003*	−0.006***	0.232***	0.008***	0.009***
	[0.003]	[0.001]	[0.000]	[0.015]	[0.003]	[0.003]
2004	−0.013***	−0.010***	−0.013***	0.320***	0.002	0.003
	[0.003]	[0.002]	[0.000]	[0.014]	[0.003]	[0.003]
2005	−0.011***	−0.008***	−0.011***	0.487***	0.004	0.005
	[0.003]	[0.002]	[0.001]	[0.018]	[0.003]	[0.003]
2006	−0.003***	0.001	−0.001*	0.471***	0.010***	0.012***
	[0.003]	[0.002]	[0.001]	[0.027]	[0.003]	[0.003]
2007	−0.002***	0.002	−0.001*	0.473***	0.012***	0.013***
	[0.004]	[0.002]	[0.001]	[0.026]	[0.003]	[0.003]
2008	−0.006***	−0.001	0.006***	0.536***	0.009***	0.011***
	[0.004]	[0.002]	[0.001]	[0.027]	[0.003]	[0.003]
2009	−0.008***	−0.003	−0.008***	0.453***	0.009**	0.011***
	[0.004]	[0.002]	[0.001]	[0.030]	[0.003]	[0.004]
2010	−0.010***	−0.005**	−0.012***	0.552***	0.008*	0.010**
	[0.004]	[0.002]	[0.001]	[0.027]	[0.004]	[0.004]
2011	0.006***	0.011***	−0.004***	0.562***	0.022***	0.024***
	[0.004]	[0.002]	[0.001]	[0.031]	[0.003]	[0.004]
2012	−0.020***	−0.015***	−0.022***	0.546***	0.002	0.004
	[0.004]	[0.002]	[0.001]	[0.031]	[0.005]	[0.005]
2013	−0.017***	−0.012***	−0.019***	0.601***	0.006	0.008
	[0.004]	[0.002]	[0.001]	[0.031]	[0.005]	[0.005]
2014	−0.019***	−0.015***	−0.023***	0.678***	0.004	0.007
	[0.004]	[0.002]	[0.001]	[0.033]	[0.005]	[0.005]
2015	0.029***	0.034***	0.024***	0.652***	0.046***	0.048***
	[0.004]	[0.002]	[0.001]	[0.037]	[0.004]	[0.004]
2016	−0.028***	−0.022***	−0.032***	0.779***	0.000	0.003
	[0.004]	[0.003]	[0.001]	[0.036]	[0.006]	[0.006]
2017	0.007***	0.012***	−0.002*	0.691***	0.031***	0.033***
	[0.004]	[0.003]	[0.001]	[0.042]	[0.005]	[0.005]
Constant	0.174***	0.175***	0.061***	5.436***	0.636***	0.767***
	[0.055]	[0.043]	[0.019]	[0.338]	[0.117]	[0.152]
Prob > F	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
R^2	0.151	0.147	0.153	0.419	0.259	0.271
Cointegration[†]	Yes	Yes	Yes	Yes	Yes	Yes

Notes: [.] denotes Drisc/Kraay robust standard errors, γ represents lagged dependent variable; and ***, **, * denote statistical significance at 1, 5, and 10% levels. [†] represents the estimation of cointegration using Westerlund test; YES represents the rejection of the null hypothesis of no cointegration at 1, and 5% significance levels; [a], [b], [c] denote Mortality ~ *f*(Ambient air pollution), Mortality ~ *f*(DALYs, welfare cost and ambient air pollution) and Mortality ~ *f*(DALYs, welfare cost, ambient air pollution and interaction between DALYs and welfare cost). Legend: DALY is the average total Disability-Adjusted Life Year from exposure to $PM_{2.5}$ and ozone, R^2 means R-squared, and Prob > F is the probability of Fisher's test statistic.

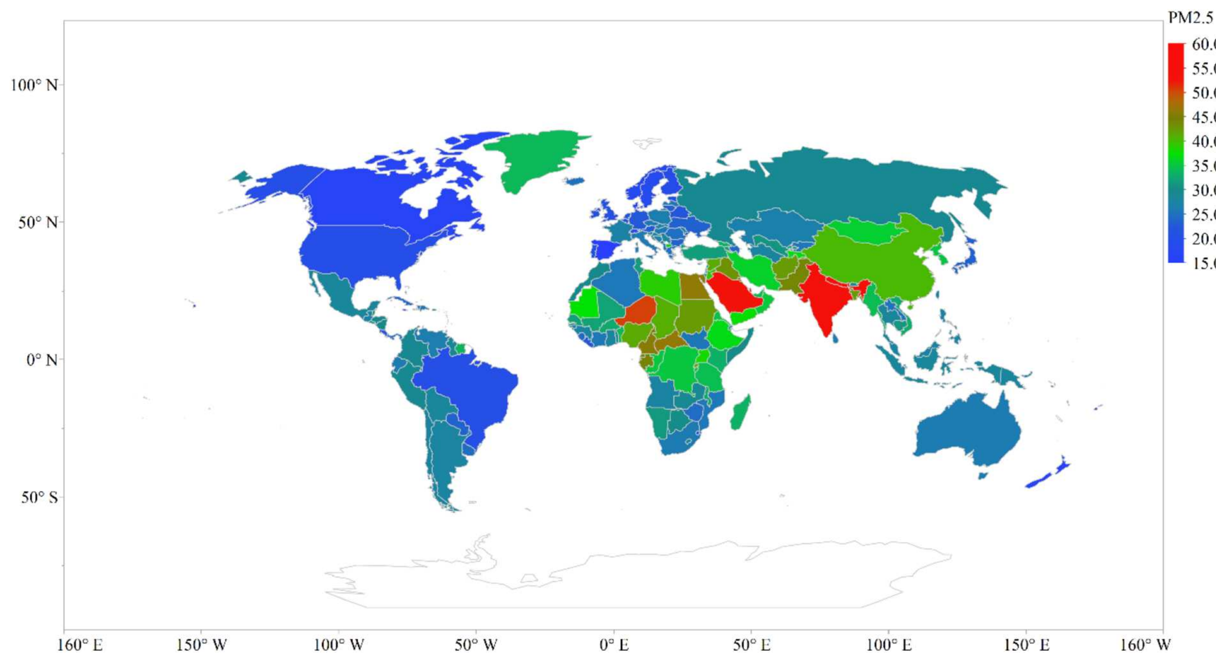

Fig. 1. Geographical distribution of the mean exposure to ambient particulate matter [$PM_{2.5}$, ($\mu g/m^3$)] across 195 countries.

China (821,688 deaths) and India (537,818 deaths) are the two countries with the highest number of estimated premature deaths due to the exposure to ambient $PM_{2.5}$ and ozone (see Fig. 4). The estimated welfare cost of premature death associated with the exposure to outdoor $PM_{2.5}$ and ozone was high in China (605,592 millions, 2010 US$), the US (471,173 millions, 2010 US$), Russia (236,556 millions, 2010 US$), India (214,412 millions, 2010 US$), Germany (157,671 millions, 2010 US$) and Japan (150,151 millions, 2010 US$) [Fig. 5].

3.2. Model-based assessment

En route to the model estimation, the study first tested for stationarity using first generational panel unit root tests (Appendix B). We subsequently tested for a possible cross-sectional dependence in the panel (Appendix C), where the results confirmed the existence of cross-sectional dependence among the panel units. Hence, the first generational unit root tests were incapable of handling cross-sectional dependence, a verdict that led to re-estimation of stationarity using second generational unit root tests (Appendix D). After meeting the preconditions, the study proceeded to test for panel cointegration using Westerlund test under the null hypothesis of no cointegration. This form of residual-based panel cointegration is capable of accounting for country-specific short-run dynamics and country-specific slope parameters (Westerlund, 2005). The empirical results in Table 1 show that the variables in the model specification are cointegrated in all panels.

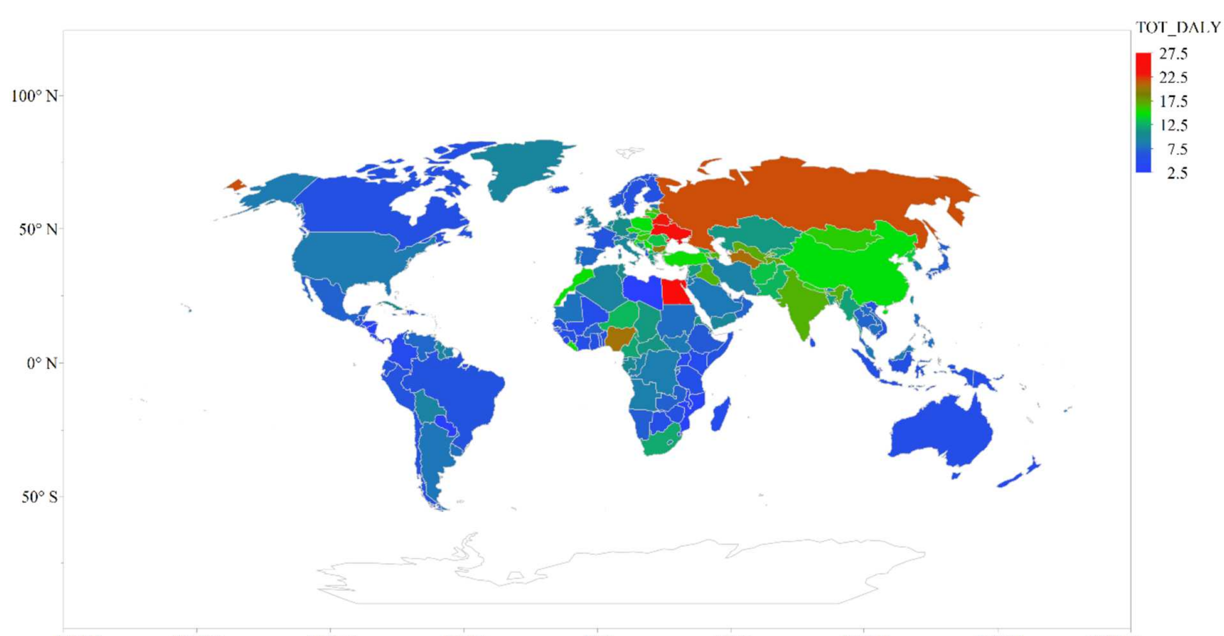

Fig. 2. Geographical distribution of DALYs from exposure to $PM_{2.5}$ and ozone per 1000 inhabitants. Legend: TOT_DALY is the average total Disability-Adjusted Life Year from exposure to $PM_{2.5}$ and ozone.

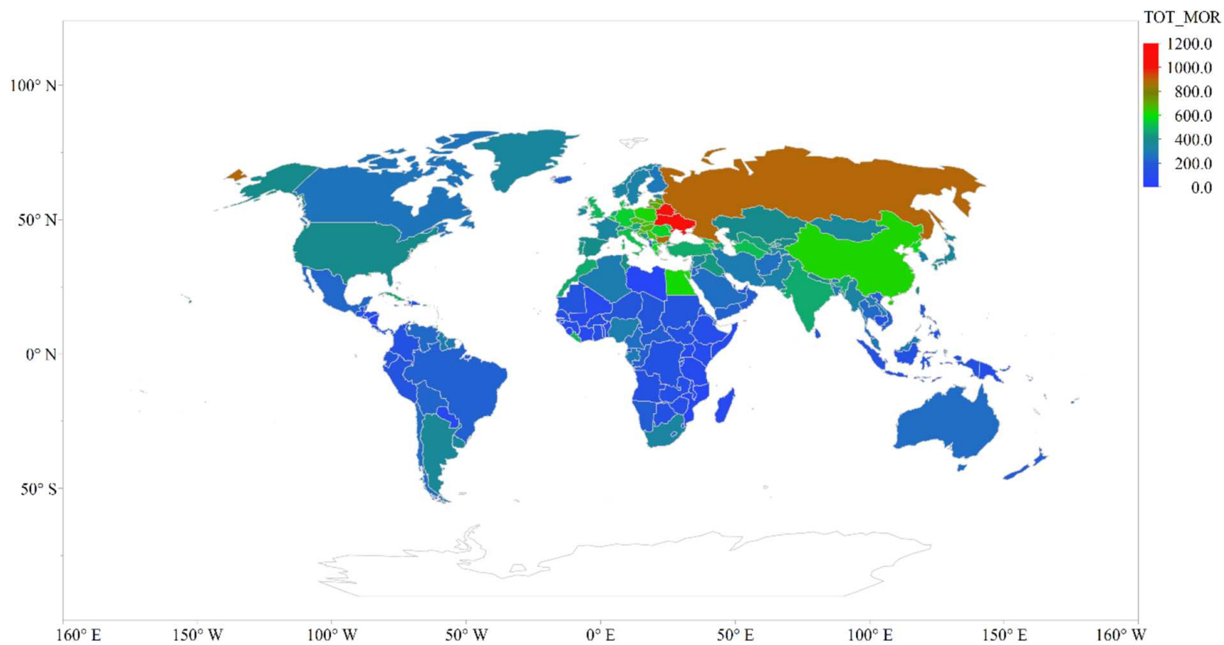

Fig. 3. Geographical distribution of mortality from exposure to $PM_{2.5}$ and ozone per 1000,000 inhabitants. Legend: TOT_MOR is the mean total mortality from exposure to $PM_{2.5}$ and ozone.

We developed a baseline estimation model using Drisc/Kraay panel fixed-effects regression with robust standard errors. The nonparametric method is robust in both balanced and unbalanced cross-sectionally dependent panels with heteroskedastic and autocorrelated error structure (Driscoll and Kraay, 1998). The empirical results of the model estimates based on Drisc/Kraay panel fixed-effects regression are presented in Table 1. Contrary to the extant literature on pollution-health nexus, we accounted for both country-specific fixed-effects and time effects across countries. It can be observed that the estimated models are statistically significant at 1% level, with corresponding predictive power (R^2) ranging from 15 to 42%. The lagged dependent variable (γ) is negative and statistically significant (*p-value* < *0.01*) across all estimated models, signifying a transitory effect of historical trends of mortality, premature deaths, DALYs, and Welfare Cost. Meaning that the historical instabilities are corrected to equilibrium with time. The intercept parameter for the estimated models is positive and statistically significant at 1% level. Meaning that holding all regressors constant, ambient $PM_{2.5}$ increase mortality by 0.17–0.77%, premature deaths by 0.18%, DALYs by 0.06% and welfare cost by 5.44%. The time effects show heterogeneous parameters from 1992 to 2017, confirming the presence of heterogeneity. To verify the robustness of the Drisc/Kraay panel fixed-effects regression, we employed the average marginal effects of all covariates as a post-estimation method (Fig. 6). Fig. 6 shows that the estimated coefficients are within the 95% confidence interval using the population average over the estimation sample.

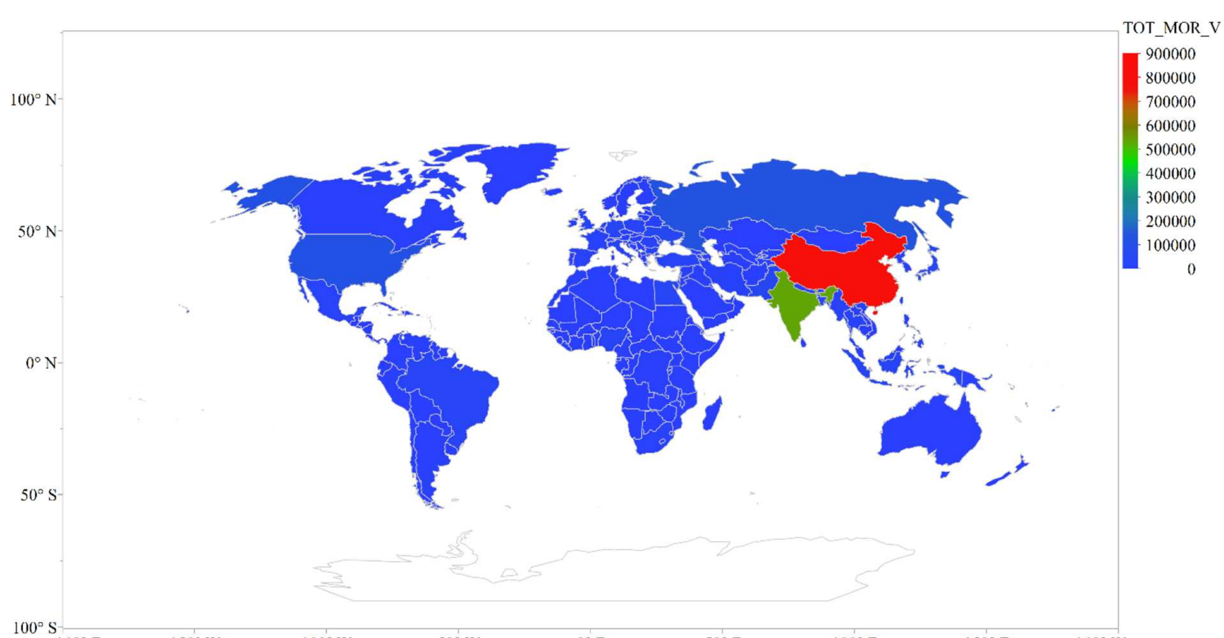

Fig. 4. Geographical distribution of premature death from exposure to $PM_{2.5}$ and ozone per persons. Legend: TOT_MOR_V denotes the average premature deaths from exposure to $PM_{2.5}$ and ozone.

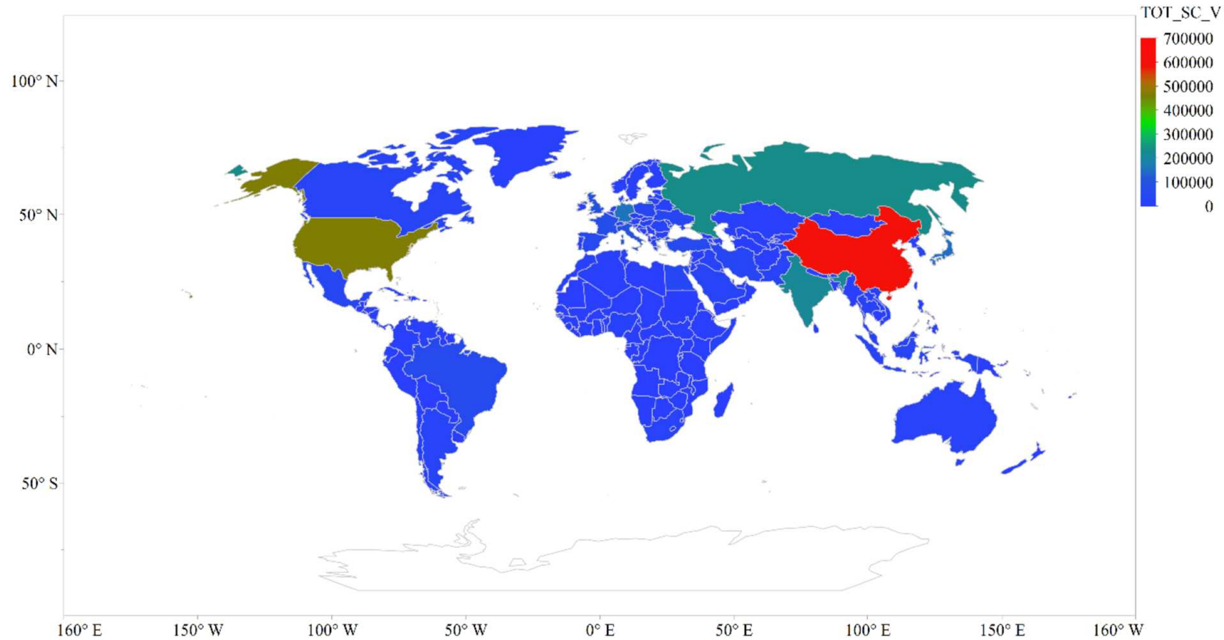

Fig. 5. Geographical distribution of the welfare cost of premature deaths from exposure to $PM_{2.5}$ and ozone (millions, 2010 US$). Legend: TOT_ SC_V is the mean total welfare cost of premature deaths from exposure to $PM_{2.5}$ and ozone.

To validate the presence of heterogeneity in the panel estimation, we used the modified Wald test (MWALD test) estimation technique to examine groupwise heteroskedasticity. The results of the MWALD test presented in Table 2 reject the null hypothesis of homoskedasticity, thus, violating the normality assumption across cross-sectional units. The baseline models were re-estimated using dynamic panel bootstrap-corrected fixed-effects to control for cross-sectional dependence, panel heterogeneity, and small sample period bias. The specification of the estimated models included randomized temporal heteroskedasticity resampling error term with analytical heterogeneous initialization via a bootstrapping algorithm to correct both country-specific fixed-effects and time effects. The estimated parameters from the dynamic panel bootstrap-corrected fixed-effects are presented in Table 2. Contrary to the negative parameter of the lagged-dependent variable (γ) in Table 1, the results in Table 2 produce a positive and statistically significant (*p-value* < 0.01) coefficient of γ<1, confirming a dynamic stable relationship between the target variables and regressors. The estimates of the regressors in the bootstrap-corrected fixed-effects specification are qualitatively similar to the baseline regression estimates but vary in quantities. The coefficient linked to the relationship between ambient $PM_{2.5}$ and mortality is positive and statistically significant at 5% (Table 1) and 1% (Table 2) level across models. Thus, a 1% increase in exposure to ambient air pollution increases mortality by 50 in every 1000,000 inhabitants. This confirms our *a priori* expectation of ambient air pollution attributable to mortality. The nexus between premature deaths and ambient $PM_{2.5}$ produces similar significant results; the coefficient is positive and statistically significant at 1%. Consequently, increasing exposure to ambient $PM_{2.5}$ by 1% spur premature deaths across countries. We find a positive and significant (*p-value < 0.05*) coefficient between DALYs and exposure to outdoor air pollution. This means that increasing the exposure to ambient air pollution increases the global burden of disease. In terms of the impact of exposure to outdoor air pollution on welfare cost, we find that a percentage increase escalates the welfare cost of premature deaths by 0.05%. In the fifth model, we plugged in ambient air pollution, DALYs and welfare cost in a mortality function to control for omitted variable bias. We observe that the magnitude of impact on mortality ranges from DALYs > ambient $PM_{2.5}$ > welfare cost. Thus, DALYs from exposure to outdoor $PM_{2.5}$ increases mortality by 0.17% whereas outdoor air pollution and welfare cost increase mortality by 0.005% and 0.004%, respectively. In the sixth model, an interactive effect between DALYs from exposure to outdoor $PM_{2.5}$ and welfare cost was introduced in addition to model five. We find that the initially significant positive coefficient of welfare cost turns significant negative with a positive interactive effect. This means that welfare cost of premature deaths from exposure to outdoor $PM_{2.5}$ and ozone serves as a mitigation effect of ambient $PM_{2.5}$ attributable deaths in countries where DALYs and welfare cost interplay. We validated the estimated models using the bootstrap-stimulated distribution post estimation technique with autoregressive (AR) coefficients presented in Fig. 7. The histogram shows the bootstrap distribution residuals of the estimated models. We can observe the overlay of the kernel fit and normal distribution confirming residual independence and heterogeneous time effects.

4. Discussion

We examined the relationship between exposure to ambient air pollution, mortality, DALYs, and welfare cost using the dynamic bootstrap-corrected fixed-effects estimator. Our estimation reveals that using dynamic models are essential to capture unobserved common factors and variable dynamics of a varied population compared to static models. Our dynamic model successfully controlled for the minimal sample bias (*T*), omitted variable bias, heterogeneity, country and year-specific effects and provided significant statistical inferences.

Exposure to ambient air pollution is a major public health concern, due to its impact on health outcomes. Our annual estimation of ambient air pollution from 1990 to 2017 reveals that no nation from the 195 countries and territories has $PM_{2.5}$ (annual mean) below WHO guideline of 10 $\mu g/m^3$ for air quality. However, Spain is the only country closer to the guideline with an annual average of $PM_{2.5}$ not exceeding 15.12 $\mu g/m^3$. The intensity of ambient air pollution is relatively high in South Asia, Africa and Saudi Arabia while a visible sign of low $PM_{2.5}$ levels is observed in high-income countries corroborating the previous findings (Brauer et al., 2016). It is reported that the high levels of particulate matter can be linked to rapid urbanization and its associated energy intensity (Sarkodie et al., 2020), fossil fuel-dominated energy consumption (Sarkodie et al., 2019), agriculture, forestry and land use (Vadrevu et al., 2017), transportation (Zhang et al., 2019) and

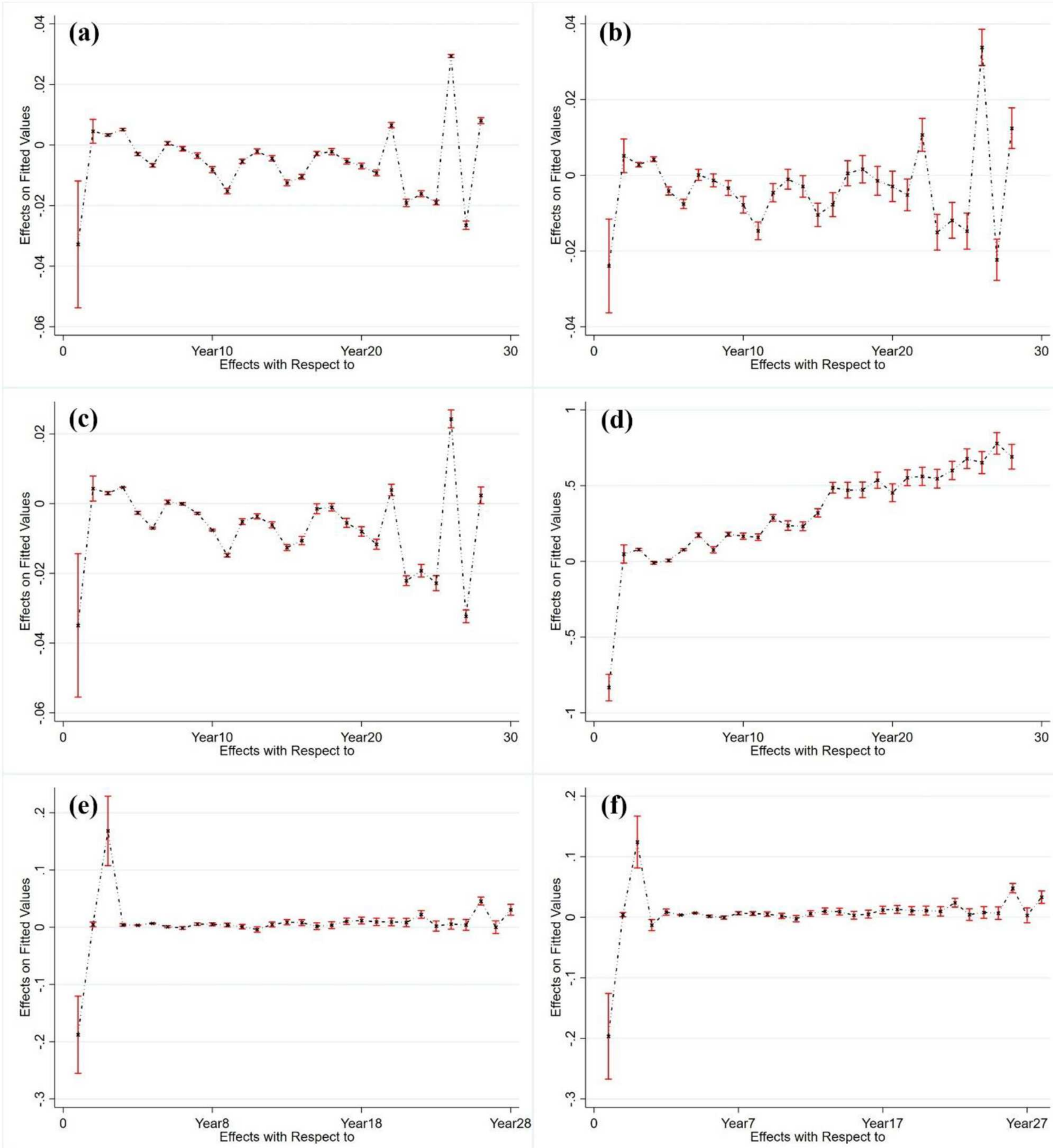

Fig. 6. Average marginal effects of all covariates with 95% CI using the population average over the estimation sample for the: (a) relationship between mortality and $PM_{2.5}$ (b) relationship between premature deaths and $PM_{2.5}$ (c) relationship between DALYs and $PM_{2.5}$ (d) relationship between welfare cost of premature deaths from exposure to $PM_{2.5}$ and O_3 and $PM_{2.5}$ (e) relationship between mortality versus $PM_{2.5}$, DALYs, and the welfare cost of premature deaths from exposure to $PM_{2.5}$ and O_3 (f) relationship between mortality versus $PM_{2.5}$, DALYs, the welfare cost of premature deaths from exposure to $PM_{2.5}$ and O_3, and the interactive effective of DALYs and welfare cost of premature deaths from exposure to $PM_{2.5}$ and O_3. Notes: The red spikes denote the 95% Confidence Interval (CI). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

industrialization (Liu et al., 2016). Countries with persistently high levels of $PM_{2.5}$ depend primarily on solid fuels such as traditional biomass — inter alia, charcoal, straw, and fuelwood; and coal (Liu et al., 2016). The dependence on solid fuels is reported to have contributed to 3 million deaths and 86 million disability-adjusted life years in 2015 (Cohen et al., 2017). Households in low-income countries cannot easily afford alternatives to traditional biomass and often rely on these unsustainable forms of energy consumption for cooking and heating purposes (Meng et al., 2019). Urbanized areas are largely the industrial hub of many countries, which comes with an environmental cost. While rapid urbanization is reported to decline the reliance on solid fuels, hence, reducing household air pollution, urban-driven fossil fuel consumption due to economic development exacerbates ambient air pollution in developing countries (Zhao et al., 2018). In contrast, migration-induced urban population density is reported to have a mitigating effect on pollutant emissions in high-income countries, stemming from

Table 2
Parameter estimates of ambient air pollution and health outcomes using dynamic panel bootstrap-corrected fixed-effects.

Estimation	Mortality	Premature	DALYs	Welfare Cost	Mortality	Mortality
γ	0.310***	0.274***	0.315***	0.211**	0.841***	0.831***
	[0.036]	[0.034]	[0.030]	[0.085]	[0.028]	[0.028]
DALYs	–	–	–	–	0.147***	0.108***
					[0.026]	[0.024]
Welfare cost	–	–	–	–	0.004***	−0.012***
					[0.001]	[0.004]
Welfare cost × DALYs	–	–	–	–	–	0.008***
						[0.002]
$PM_{2.5}$	0.001***	0.001***	0.001***	0.048***	0.005***	0.005***
	[0.000]	[0.000]	[0.000]	[0.014]	[0.001]	[0.001]
1992	–	–	–	0.073	0.004**	0.004**
				[0.061]	[0.002]	[0.002]
1993	0.000	0.000	0.000	−0.012	0.007***	0.007***
	[0.002]	[0.002]	[0.002]	[0.065]	[0.002]	[0.002]
1994	−0.008***	−0.009***	−0.007***	0.003	0.000	0.001
	[0.002]	[0.002]	[0.002]	[0.075]	[0.002]	[0.002]
1995	−0.010***	−0.011***	−0.010***	0.078	−0.002	−0.001
	[0.002]	[0.002]	[0.002]	[0.062]	[0.002]	[0.002]
1996	−0.001	−0.002	−0.000	0.169**	0.005**	0.006***
	[0.002]	[0.002]	[0.002]	[0.079]	[0.002]	[0.002]
1997	−0.006***	−0.006***	−0.003	0.066	0.005*	0.006**
	[0.002]	[0.002]	[0.002]	[0.067]	[0.003]	[0.003]
1998	−0.008***	−0.008***	−0.006**	0.171**	0.003	0.004*
	[0.002]	[0.002]	[0.003]	[0.073]	[0.002]	[0.002]
1999	−0.012***	−0.013***	−0.010***	0.154*	0.000	0.001
	[0.002]	[0.002]	[0.002]	[0.090]	[0.003]	[0.003]
2000	−0.017***	−0.018***	−0.015***	0.148**	−0.005*	−0.004
	[0.002]	[0.002]	[0.003]	[0.066]	[0.003]	[0.003]
2001	−0.005**	−0.006***	−0.003	0.279***	0.004	0.005*
	[0.002]	[0.002]	[0.002]	[0.083]	[0.003]	[0.003]
2002	−0.005**	−0.006***	−0.005**	0.225**	0.008***	0.009***
	[0.002]	[0.002]	[0.002]	[0.106]	[0.003]	[0.003]
2003	−0.008***	−0.009***	−0.007***	0.211***	0.007**	0.008***
	[0.002]	[0.002]	[0.002]	[0.070]	[0.003]	[0.003]
2004	−0.016***	−0.016***	−0.013***	0.303***	0.001	0.002
	[0.002]	[0.002]	[0.002]	[0.105]	[0.003]	[0.003]
2005	−0.011***	−0.012***	−0.009***	0.469***	0.002	0.004
	[0.002]	[0.002]	[0.002]	[0.099]	[0.003]	[0.003]
2006	−0.004*	−0.005**	−0.000	0.445***	0.009***	0.011***
	[0.002]	[0.002]	[0.002]	[0.105]	[0.003]	[0.003]
2007	−0.006***	−0.007***	−0.003	0.448***	0.010***	0.012***
	[0.002]	[0.002]	[0.002]	[0.099]	[0.003]	[0.003]
2008	−0.009***	−0.010***	−0.007***	0.510***	0.008**	0.009***
	[0.002]	[0.002]	[0.002]	[0.128]	[0.004]	[0.003]
2009	−0.010***	−0.011***	−0.008***	0.422***	0.007**	0.009**
	[0.002]	[0.002]	[0.004]	[0.124]	[0.004]	[0.004]
2010	−0.012***	−0.013***	−0.011***	0.534***	0.006*	0.008**
	[0.002]	[0.003]	[0.002]	[0.097]	[0.004]	[0.004]
2011	0.005*	0.003	−0.006**	0.533***	0.021***	0.022***
	[0.003]	[0.003]	[0.003]	[0.111]	[0.004]	[0.004]
2012	−0.026***	−0.027***	−0.025***	0.521***	0.000	0.002
	[0.003]	[0.003]	[0.004]	[0.138]	[0.005]	[0.005]
2013	−0.015***	−0.017***	−0.014***	0.568***	0.003	0.005
	[0.003]	[0.003]	[0.003]	[0.104]	[0.004]	[0.004]
2014	−0.018***	−0.021***	−0.017***	0.650***	0.002	0.004***
	[0.003]	[0.003]	[0.003]	[0.140]	[0.004]	[0.004]
2015	0.031***	0.028***	0.031***	0.619***	0.044***	0.046
	[0.006]	[0.006]	[0.006]	[0.107]	[0.006]	[0.006]
2016	−0.041***	−0.042***	−0.041***	0.747***	−0.003	0.000***
	[0.004]	[0.004]	[0.004]	[0.125]	[0.004]	[0.004]
2017	0.012***	0.008***	0.012***	0.652***	0.028***	0.030
	[0.003]	[0.002]	[0.002]	[0.111]	[0.004]	[0.004]
Convergence	Yes	Yes	Yes	Yes	Yes	Yes
MWALD test (Prob>chi^2)‡	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***

Notes: [.] denotes Bootstrapped standard errors, Bootstrap 95% (percentile-based) confidence intervals and Inference performed with non-parametric bootstrap; γ represents the lagged dependent variable; ***, **, * denote statistical significance at 1, 5, and 10% levels; [a], [b], [c] denote Mortality ~ *f*(Ambient air pollution), Mortality ~ *f*(DALYs, welfare cost and ambient air pollution) and Mortality ~ *f*(DALYs, welfare cost, ambient air pollution and interaction between DALYs and welfare cost). ‡ denotes the modified Wald test used as a post-estimation technique to examine groupwise heteroskedasticity under the null hypothesis, H_0: $\sigma^2_{(i)} = \sigma^2$ for all i. Legend: DALY is the average total Disability-Adjusted Life Year from exposure to $PM_{2.5}$ and ozone, MWALD means the modified Wald statistics, and Prob>chi^2 is the probability of Chi-squared test.

environmental policy stringency and pollution-abatement technologies (Sarkodie et al., 2020; Sarkodie et al., 2019; Zhao et al., 2018). Agriculture, forestry and land use activities contribute immensely to ambient air pollution in developing countries whose agrarian economy depends on vintage technologies. Pre-harvesting, harvesting and post-harvesting activities such as burning of crop residues, burning forest products and forest fires increase anthropogenic emissions and are more severe in countries with high level of deforestation (Phairuang et al., 2017). The

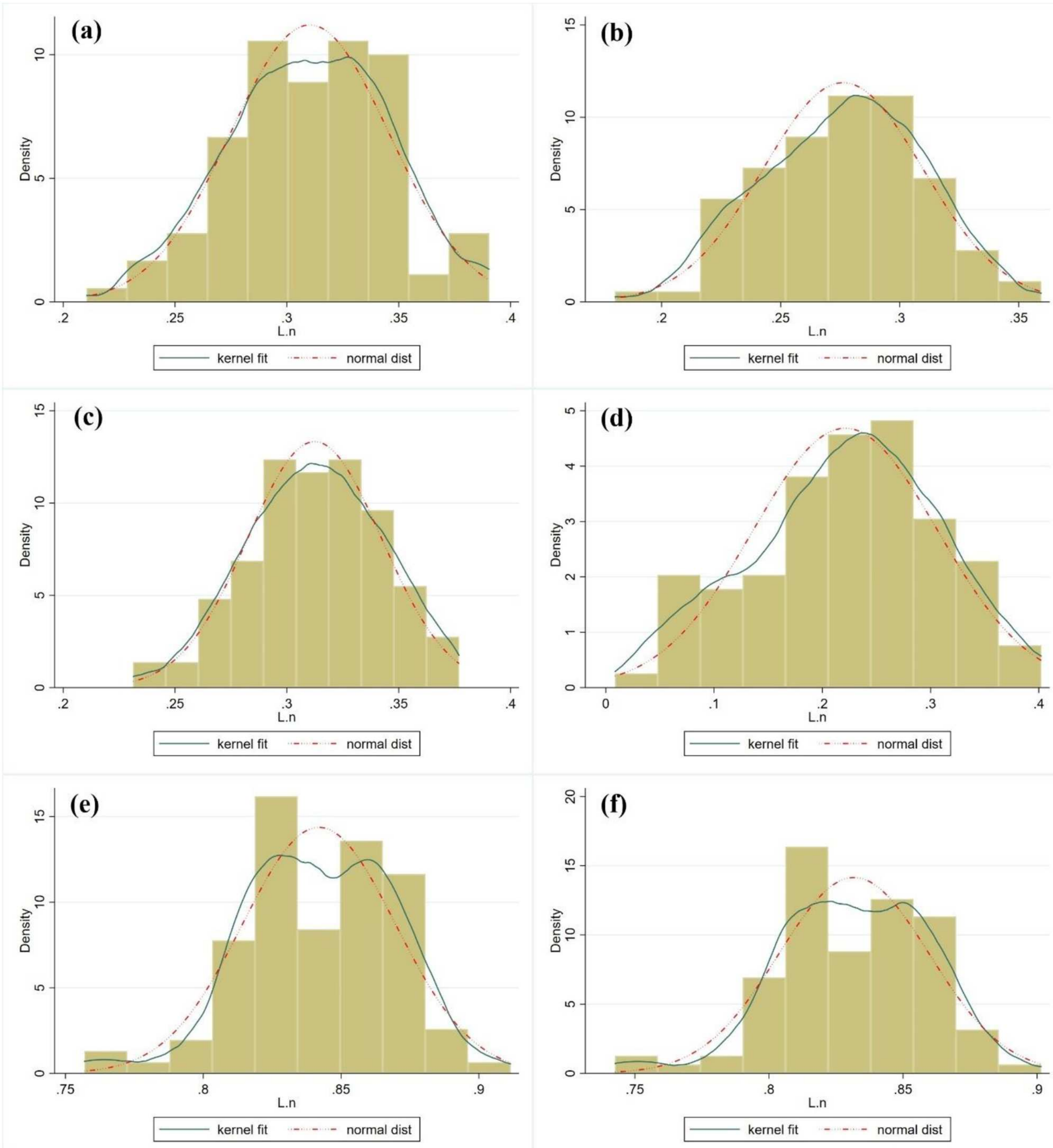

Fig. 7. Post estimation bootstrap-stimulated distribution of autoregressive (AR) coefficients and their sum for the: (a) relationship between mortality and $PM_{2.5}$ (b) relationship between premature deaths and $PM_{2.5}$ (c) relationship between DALYs and $PM_{2.5}$ (d) relationship between welfare cost of premature deaths from exposure to $PM_{2.5}$ and ozone and $PM_{2.5}$ (e) relationship between mortality versus $PM_{2.5}$, DALYs, and the welfare cost of premature deaths from exposure to $PM_{2.5}$ and ozone (f) relationship between mortality versus $PM_{2.5}$, DALYs, the welfare cost of premature deaths from exposure to $PM_{2.5}$ and ozone, and the interactive effective of DALYs and welfare cost of premature deaths from exposure to $PM_{2.5}$ and ozone.

effect of land use on ambient air pollution depends on the share of land occupied by water bodies and land allocated for green space, residential, industrial and agricultural activities. Transportation and industrial activities spur the levels of $PM_{2.5}$ especially in urban areas in countries with industrialized economy. The combustion of fossil fuels in power plants for manufacturing and power generation; and fuel for road, air and maritime transportation propel ambient air pollution (Brauer et al., 2016; Hu et al., 2017). Aside the drivers outlined, it is reported that other underlying factors affecting the levels of ambient air pollution across countries include topography (altitude, slope), meteorology (precipitation, wind speed, temperature and humidity), and traffic emissions (road network) (Huang et al., 2017).

It is observed that the distribution of premature deaths, total mortality and DALYs from exposure to $PM_{2.5}$ and ozone vary significantly across the globe. The panel regression model found strong evidence that ambient air pollution intensifies premature deaths, total mortality, and DALYs. It is reported that exposure to ambient air pollution contributed to 4 million global deaths and 103 million DALYs in 2015 (Cohen et al., 2017). China, India, Russia and the US have the highest number of premature deaths due to exposure to ambient $PM_{2.5}$ and ozone whereas Africa and Australia have low levels of reported cases of ambient $PM_{2.5}$ and ozone attributable premature deaths. In terms of total global deaths, Eastern Europe has the highest mortality rates (≤1130 per million inhabitants) from both $PM_{2.5}$ and ozone while Africa has the lowest vulnerability to ambient $PM_{2.5}$ and ozone attributable mortality rates. However, North Korea, China and India have the highest vulnerability to ozone attributable mortality. The confirmed cases of DALYs attributable to $PM_{2.5}$ and ozone are high in some countries in Eastern Europe, Central and South Asia whereas generally lower cases are reported in Africa, America and the Caribbean.

The health outcomes associated with ambient air pollution have significant policy implication on the welfare cost. Carbonized and energy-intensive economic structure is associated with a trade-off between economic development and environmental quality. China, the US, Russia, India, Germany and Japan are countries with the highest welfare cost of premature death associated with the exposure to outdoor $PM_{2.5}$ and ozone. Our study reveals that China is the most vulnerable to economic burden due to premature death associated with exposure to outdoor $PM_{2.5}$ and ozone. In 2017, China's economic loss (welfare cost) increased to US$1.58 trillion (constant 2010) compared to India [US$581 billion (constant 2010)], the US [US$516 billion (constant 2010)], Russia [US$236 billion (constant 2010)], Japan [US$180 billion (constant 2010)], and Germany [US $170 billion (constant 2010)] (OECD, 2018). A similar study found economic loss due to outdoor $PM_{2.5}$ and ozone attributable premature deaths higher in China compared to Europe and the US (Matus et al., 2012). These countries are within the top 7 nations in the world whose economic development is driven by high energy demand – leading to high CO_2 emissions from fuel combustion (Enerdata, 2019). The 2019 global statistics on CO_2 emissions from fuel combustion ranks China, the US, India, Russia, Japan and Germany as top tier – with corresponding emissions of 9467 $MtCO_2$, 5118 $MtCO_2$, 2277 $MtCO_2$,1755 $MtCO_2$, 1123 $MtCO_2$, and 733 $MtCO_2$, respectively (Enerdata, 2019).

5. Conclusion

In recent years, climate change, ambient and household air pollution and its association with health outcomes have received much attention. The historical trend of premature deaths, total mortality, DALYs and welfare cost has a persistent effect on future occurrences across countries, hence, has policy implications. Here, we investigated the global effect of ambient air pollution on mortality, premature deaths, disability-adjusted life years and welfare cost. The empirical testing results showed a significant positive association between outdoor air pollution, mortality, premature deaths, DALYs and welfare cost. Several high-income economies have in recent years made effort to reduce air pollution and improve air quality, hence, declining premature deaths, mortality, DALYs and welfare cost. In contrast, emerging and industrialized economies including China and India are still experiencing the outgrowth of air pollution. This has in effect increased the confirmed cases of DALYs and welfare cost of premature deaths attributed to ambient air pollution and ozone. The seemingly high levels of ambient air pollution in developing countries can be ascribed to several socio-economic factors. Our study demonstrated that unsustainable and carbon-intensive economic development has environmental, economic and health outcomes. Thus, mitigating air pollution by decarbonizing the economic structure is useful in reducing the overall pollutant emissions.

CRediT authorship contribution statement

Phebe Asantewaa Owusu: Conceptualization, Formal analysis, Data curation, Writing - original draft.**Samuel Asumadu Sarkodie:**Formal analysis, Data curation, Writing - original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.140636.

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