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Infant mortality rates and nonrenewable energy consumption in Asia and the Pacific: The mediating role of carbon emissions

Bosede Ngozi **ADELEYE**♦[a,b,c], Muhammad **AZAM**♠[d,e], Evans **OSABUOHIEN**♥[a,b,c], Ifeoluwa **OGUNRINOLA**♣[a,b], Paul **ADEKOLA**•[a,b]

[a]Department of Economics and Development Studies, Covenant University, Nigeria; [b]Centre for Economic Policy and Development Research (CEPDeR), Covenant University, Nigeria; [c]Regional Centre of Expertise (RCE) Ogun, Nigeria

[d]School of Economics, Finance & Banking, College of Business, Universiti Utara Malaysia, Malaysia; [e]Department of Economics, Faculty of Business and Economics, Abdul Wali Khan University Mardan, Pakistan

Abstract

This study aligns with the 2030 United Nations Sustainable Development Goals- 3 which aim to *"ensure healthy lives and promote well-being for all at all ages"*. It contributes to the nascent literature stream on energy-health dynamics by introducing a holistic theoretical model to empirically examine the mediation effect of carbon emissions on the relationship between nonrenewable energy and infant mortality rates. Using an unbalanced panel data on 42 Asia and the Pacific countries from 2005 to 2015 and deploying the structural equation modeling approach, the empirical results are surmised as follows: (i) in regard to the full sample of countries, nonrenewable energy indirectly increases infant mortality rates through increasing carbon emissions. In other words, carbon emissions play a partial mediation role between nonrenewable energy and infant mortality rates; and (ii) for the different income groups, carbon emissions show varying mediation effects. For example, the mediation effects of carbon emissions in lower-middle and upper-middle income countries are found to be similar to those of the full sample of countries. Therefore, based on these findings, we conclude that nonrenewable energy is an essential determinant of infant mortality rates. Policy recommendations are put forward.

Keywords: Carbon emissions; infant mortality rate; per capita income; nonrenewable energy; Asia and the Pacific region

JEL Classification: I00, I10; I15; I18; I19; N55

♦ Corresponding Author ngozi.adeleye@covenantuniversity.edu.ng; ORCID: 0000-0002-1274-714X; website: https://cruncheconometrix.com.ng
♠ drazam75@yahoo.com; ORCID: 0000-0001-7417-3981
♥ evans.osabuohien@covenantuniversity.edu.ng
♣ ifeoluwa.ogunrinola@covenantuniversity.edu.ng
• paul.adekola@covenantuniversity.edu.ng

1 Introduction

The search for resilient sustainable economic development is fast becoming an interesting concern among governments, policy makers, and international institutions to bolster social uplift. In fact, the excessive usage of energy, mainly from carbon associated sources is detrimental to the environment and public health. Economic development is human development [1], as human capital is directly associated to growth and is undeniably one of the most essential ingredients of economic growth and development. Human capital is considered as "a prime engine for economic growth" [2-4]. Therefore, it is essential to survey the factors that determine human capital. The available studies reveal that nonrenewable energy (NRE) and some fossils associated ailments also adversely affect human capital, but such impact ought to be investigated, which is the main objective of this study.

Energy is an imperative element of every society and undertakes a domineering part boosting socio-economic living standard of the society. Energy sources can be categorized into renewable energy (RE) and NRE sources. Whereas the main RE sources are biomass, hydro (water), wind, solar, and geothermal. These sources are limitless in supply and can be replenished/ refilled naturally. While the non-NRE sources are coal, oil, nuclear, and gas. These are scarce in supply and cannot be replaced or recycled [5]. Several erstwhile studies highlighted that the increase in the use of energy for economic activities increases a huge concern of rising environmental depletion [6,7]. To prepare more goods and services-meet the increasing energy demand at local level have enhanced the incineration of fossil fuels such as coal, gas, and oil at the industrial level and solid fuels burning at the household level. Certainly, on one hand the exploitation of fossil fuels is though adding to GDP per head but producing GHGs which affects public health on the other hand [8]. Renewable energy source has some idiosyncratic positive economic heave impacts compared to NRE. In their study, [9] mentioned

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(RE)'s technologies may perhaps be less viable compared to NRE due to a large level of preliminary capital cost.

Growing CO_2 emissions unfavorably affects many health indicators[1], consequently an adverse influence of health indicators lead to a reduction in human capital productivity and therefore a decrease in the socio-economic development. Health indicators such as life expectancy and infant mortality rate are among the key variables. Life expectancy is "the expectation of how long a newborn person can live on average, assuming that current mortality rates remain unchanged"; while infant mortality rate is "the number of children who expires under the age of one for every 1000 live births in a year" [10]. The existing ambient levels of air pollution in the city of Sao Paulo, Brazil are linked with mortality for people above 65 years of age for all non-accidental causes, for cardiovascular and for respiratory illnesses [11]. Evidently, environmental contamination is approaching distressing proportions globally. Environmental contaminants have numerous adversative health effects from early life, some of the utmost important detrimental influences are infant mortality, perinatal illnesses, cardiovascular illnesses, respiratory illnesses, allergies, rise in stress oxidative, endothelial dysfunction, mental illnesses, and many other destructive effects [12, 13]. It is extensively argued that the people of the developing world can be exposed to the different harmful gases coming from the combustion of fossil fuels from production, transport, and power generation due to the absence of the clean energy. Moreover, energy use can directly or indirectly influence human health by causing air pollution, lack of safe water, and inadequate medical care infrastructures. Likewise,

[1] Global health indicators can be divided into directly and indirectly measure health sensations, where directly measure are (e.g., deaths, illnesses, use of services) and indirect measures are (e.g., education, poverty indicators, and societal development); these are also described to as distal and proximal indicators, respectively. According to the World Health Organization (2015) report there are total 100 Core Health Indicators are life expectancy (at birth), adult mortality rate between 15 & 60 years of age, under-five mortality rate, infant mortality rate.

fossil fuel energy that is used in industries increases public health threats, and other environmental harms, which are deemed as national health securities [14].

Accomplishing sustainable environment poses a dominant stance in the process of national economic development. Indeed, the worsening of environmental quality can be explicated particularly by the rise in CO_2, which is due to the consumption of energy resources for instance coal, natural gas, and oil. Consequently, the deterioration of the environmental quality by the use of pollutant energy sources can have a destructive effect on the quality of human life, thus, it influences the existence of humankind. Environmental pollution can also endanger the lives of mammals and detriment plants. Evidently, growing air pollution such as CO_2, causes stern health problems and creates substantial economic liabilities for healthcare [15-17]. [18] expounded that several environmental factors affect mortality. Many prior studies exploring environmental effects on mortality have concentrated on air pollutants and indicated that exposure to air pollutants is connected with an increased risk of mortality [19-21].

Furthermore, [22] expounded that the World Health Organization (WHO) has found climate change as one of the biggest health hazards of the 21st century, and air pollution as the sole leading environmental health hazard. Several erstwhile studies have underlined that the prominent cause of higher mortality rate is because of the environmental degradation which occurs due to the consumption of NRE resources for instance fossil fuels at micro-level and macro-level [23-25]. Undeniably, unregulated air pollution cause mortality from cardiac, respiratory, and other disorders [26]. Substantial death rates are connected to fossil fuel energy consumption, as combustion emissions from power generation, transport, and industry usually occur in heavily crowded regions [27]. Many other pollutant sources including biomass burning, agriculture, and residential energy usage needs be controlled to accomplish a decrease in mortality up to 5.55 million superfluous deaths per annum (with additional mortality decrease from condensed household air pollution). Substituting fossil by clean, RE sources could reduce the worldwide mortality by 65%, and up to 84% in the U.S. [28]. Environmental pollution has direct and indirect destructive effects on aggregate output via disease and health spending, as well as reducing labour productivity, and other damaging externalities [29]. [30] confirms that excess mortality related to the COVID-19 epidemic is because of air pollution by particulate matter in Italy in the first quarter of 2020.

We have observed that most of erstwhile studies researched the link between environment, economic growth, and public health expenditure. The central focus of this study is to identify and verify the interaction between environmental degradation, infant mortality rate, and NRE consumption in the context of Asia and the Pacific region. The motivation for this study is based on the central role human capital plays in the process of economic growth and development. While the human capital indicators are affected by NRE usage and thereby carbon emissions, the broad objectives of this study are to: (1) examine if NRE has a significant impact on carbon emissions; (2) evaluate whether the impact of NRE on mortality rates is significant in the presence of the mediator (carbon emissions); (3) appraise if the impact of the mediator on mortality rates is significant in the presence of NRE; (4) determine if NRE has a significant indirect (mediated) impact on mortality rates; and (5) assess if (1) to (4) significantly differ across income groups. The remaining study is structured as follows: Section 2 deals with related prior studies on the subject under investigation. Section 3 presents data, empirical model, and estimation strategy. Section 4 interprets the empirical results and shed lights on discussion. Section 5 concludes the study.

2 Literature Review and Hypotheses Development

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In 1997, the importance of clean and sustainable environment was first established legitimately in the Kyoto Protocol which was ratified by both developed and developing economies. The protocol detects greenhouse gases (GHG) emissions, especially carbon dioxide (CO_2) as the leading source of global warming. Moreover, CO_2 emissions from fossil fuels and industrial activities are around 65% of worldwide GHG emissions [31]. The significance of energy consumption documented by [32]is that the energy use is believed as a development gauge in the literature of energy economics. Increase in economic activities, industrialization, and growing urbanization results in an increase demand for energy consumption [33]. [34] expounded that the use of energy is vital to society and offers numerous wellbeing benefits. Though, each source of energy consumption also involves health risks. The authors have also added that the major health effects ensue to the blazing of solid fuels, biomass, and coal, mostly in the form of work-related health risks and overall air pollution. Unavailability of electricity and cleanse fuels in the world's unfortunate households is a predominantly serious risk for health. Energy accessibility is linked with health at the household level "energy security" and "energy poverty or fuel poverty", the former at the household level means a family's prospect of having sufficient energy to warmth the home during cold climate, cook food, and make cool the home during hot weather—a matter of accessibility, inexpensiveness, and capability [35], and the latter, on the other hand means financial lack in affording energy for these elementary uses [36]. Energy poverty is also related with several problems of 'economic poverty', containing poor health and adversative social consequences [37, 38].

2.1 Nonrenewable Energy and Health Outcomes

Also, [25] studied the influence of greenhouses gasses emissions, energy utilization, and economic activities on health risks (i.e., mortality rate and incidence of respiratory disorders) in emerging Asian countries from 1995 to 2018. The empirical evidence establishes that fossil fuel use, GHGs, and natural resources exhaustion are main factors to growing health risks in the long run, while the usage of clean energy and enhancement in per capita output is helping to boost the health status. Results also reveals that greenhouse gasses emission is the only substantial factor accountable for the high mortality rate and incidence of respiratory disorders in the short run. The study of [39] found that NRE (i.e., coal, oil, and gas) rise measles, air pollution, tuberculosis, and mortality rate, which consequently affect human capital in Pakistan from 1995–2017. The ARDL approach verify the long-run and short-run impacts of air pollution, fossils fuels, and diseases on human capital. The Gary Becker hypothesis and the Grossman models of [40] study found that energy predictors have a significant and negative effect on infant mortality rates in 23 African countries during 1999–2014. Moreover, empirical estimates indicate that a high pollution causes an increase in mortality rates. Using the generalized method of moments technique, [41] observed that the maximum variability of mortality could be described by carbon emission variability in Commonwealth of Independent States (CIS) economies during 1993–2018.

Hypothesis 1: Nonrenewable energy is positively related to health outcomes.

2.2 Nonrenewable Energy and Carbon Emissions

[42] worked on the effect of real income, NRE, and RE use on CO_2 emissions for the United States from 1980–2014. Findings reveal that surges in RE use alleviate environmental degradation whereas expansions in NRE use inflate CO_2 emissions. [43] detected a positive influence of population density, per capita income, and NRE sources on CO_2 emissions in four South Asian countries over 1980-2013. Results also indicate, that the inverse sign of RE sources suggests that per capita CO_2 emissions reduce 0.352% as 1% rise in RE sources. The study of [44] shows that RE use has a statistically insignificant effect on CO_2 emissions in Pakistan from 1970 to 2016; and coal, and natural gas are the key contributors to the level of pollution in the country. [45] found that widespread use of energy from conventional sources

such as burning fossil fuels has destructive impacts on environmental quality by growing the level of CO_2 emissions in 13 developing Asian countries during 1980 to 2014. [46] found that boost in economic growth and fossil fuels consumption contributes to the enlargement in CO_2 emissions, and thereby deteriorate the environment in the 15 developing Asian countries from 1990–2013. [47] expounded that though NRE use accelerates the aggregate production, but it is also a key source of CO_2 emissions in top oil producing African economies over 1980–2015. Lastly, [29] empirically obtained a uni-directional association running from RE to carbon emanations in 21 European Union countries from 1995 to 2014. Our study fills the gap in the literature by engaging a mediation modelling approach to the health-environment dynamics in Asia and the Pacific.

Hypothesis 2: Nonrenewable energy is positively related to carbon emissions.

2.3 Nonrenewable Energy, Carbon Emissions and Health Outcomes

There are many studies on the interrelationship between energy, carbon emissions, and public health, for different countries, they employed different empirical methodologies, while the empirical findings have been yet fused or vague. For instance, [48] showed that a 1 percent reduction in total suspended particulates bring a 0.35 percent decrease in the infant mortality rate. [49] found a statistically positive and significant effects of enhancement socio-economic conditions on public health through pollutants such as PM10 and CO_2 emissions in 60 developing countries from 1990–2010. [16] showed that CO_2 emissions have an adverse impact on public health in China in the long run. [50] concluded that CO_2 emissions do not have effect on health status in twelve (12) countries from the Southern African Development Community (SADC) over 2000–2008. [51] documented that industrialization enhanced the level of CO_2

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emissions in developing countries, and consequently it badly affects the pregnancy outcomes and hygienic states of adolescents. A two-way causal links has been detected between changes in infant mortality rate and increase in CO_2 emissions, and between gross capital formation and changes in child mortality rate, respectively from 1971–2010. [52] tested the influence of environmental degradation measured by PM_{10} on infant mortality rate in Nigeria during 2000 to 2016. The empirical outcomes show that environmental degradation has significantly negative effect on infant mortality.

Hypothesis 3: Carbon emissions is positively related to health outcomes.

Hypothesis 4: Carbon emissions mediates the relationship between nonrenewable energy and health outcomes.

3 Variables, Empirical Model and Analytical Schema

3.1 Variables and Classifications

This study uses an unbalanced panel data of six variables on 42 countries[2] located in Asia and the Pacific region from 2005 to 2015. The variables which are sourced from the World Bank (2020) World Development Indicators (WDI). Infant mortality (*MINF*) is the outcome variable, the main explanatory variable is nonrenewable energy per capita (*ENUPC)*; the mediator variable is carbon emissions per capita (*CO2PC*). We include two covariates: female secondary school enrolment (*SECF*), and access to basic sanitation (*BSAN*). Under-5 mortality (*MU5*) rates is included used to test the robustness of the results.

On *a priori* expectations, nonrenewable energy consumption is expected to yield asymmetric effects on mortality rates. The impact will be positive, if increased use of unfriendly energy sources causes increased environmental pollution and eventually leads to deaths of infants and

[2] See Appendix Table A1 for the list of countries and income classifications.

under-5 children. However, the impact is negative when nonrenewable energy sources are channelled to power health-sustaining outcomes thereby cutting down deaths of infants and children. The effect of carbon emissions on child mortality is expected to be positive as environmental pollution is hazardous to health. As female secondary education improves, it is expected that child mortality rates drop since more knowledgeable mothers are expected to understand the essentials of childcare and upbringing better than those who hold little or no education. Better sanitation is expected to reduce mortality rates. Table 1 details the variables and their respective *a priori* expectations.

Table 1 Variables Description and Expected Signs

S/No.	Code	Short Definition	Expected signs
1	*MINF*	Number of infant deaths	Not Applicable
2	*MU5*	Number of under-five deaths	N/A
3	*ENUPC*	Energy use (kg of oil equivalent per capita)	+/-
4	*CO2PC*	CO2 emissions (metric tons per capita)	+
5	*BSAN*	People using at least basic sanitation services (% of population)	-
6	*SECF*	School enrolment, secondary, female (% gross)	-

Source: Authors' Compilations from the World Bank (2020) World Development Indicators (WDI)

We proceed to show the measures of central tendency and correlation among the variables in Table 2. With the emphasis on the indicators of interest, the average infant mortality rate for the region is 27.07% and the standard deviation of 16.92 shows that the countries are widely dispersed from the sample average. Japan shows the lowest in 2013 to 2015 with 2.1 while Pakistan has the highest infant mortality at 79% in 2005. Singapore show to have the lowest under-5 mortality rate at 27% for years 2013 to 2015 while the country with the is Pakistan at 99.8% in 2005. The mean under-5 mortality rate is 33.27 and the standard deviation of 21.7 evidences wide deviation from the mean. The mean of carbon emissions is 4.17 with a standard deviation of 5.12. Nepal consistently shows the lowest emissions per capita from 2005 to 2009

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averaging between 0.09 and 0.161 while Brunei shows the highest from 2007 to 2014 averaging between 19.29 and 24.63. Lastly, the sample mean energy per capita is 2079.99 with a standard deviation of 2182.92 which reveals that the countries are widely dispersed from the mean. Timor-Leste steadily shows the lowest emissions per capita from 2006 to 2008 averaging between 58.05 and 58.85 while Brunei Darussalam shows the highest from 2006 to 2014 averaging between 6074.57 to 9837.45. (See Appendix Table A2 for detailed summary statistics across the income groups).

Table 2 Summary Statistics and Correlation Analysis

Variable	*Summary Statistics*				*Correlation Analysis*	
	Mean	Std. Dev.	Min	Max	lnMINF	lnMU5
$MINF_{it}$	27.074	16.916	2.1	79	1.000	
$MU5_{it}$	33.272	21.715	2.7	99.8	0.998***	1.000
$ENUPC_{it}$	2079.991	2182.923	58.046	9837.447	-0.712***	-0.712***
$CO2PC_{it}$	4.17	5.123	0.098	24.627	-0.643***	-0.655***
$BSAN_{it}$	73.784	24.905	14.131	100	-0.563***	-0.581***
$SECF_{it}$	78.246	23.569	26.892	145.888	-0.690***	-0.701***

Note: *** denotes statistical significance at the 1% level; MINF = infant mortality rates; MU5 = under-5 mortality rate; CO2PC = carbon emissions per capita; ENUPC = nonrenewable energy per capita; BSAN = access to basic sanitation; SECF = female secondary school enrolment; ln = natural logarithm.
Source: Authors' Computations

The right-hand side of Table 2 details the pairwise correlation[3], which measures the relative association among the regressors and dependent variables. Using the natural logarithmic transformation of the variables, except for total natural resource rents which shows a statistically significant positive association at the 1% level, the regressors have statistically significant negative relationships with mortality rates. These provide some evidence that as the

[3] See Appendix A3 for detailed correlation matrix

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indices of these regressors increase, mortality rates decline. However, it becomes imperative to subject these finding to rigorous econometric tests (see Section 4).

3.2 Analytical Schema

This study argues that because nonrenewable energy naturally discharges carbon dioxide, methane, and other gasses into the atmosphere it contributes to changing climate patterns that invariably affect food production, animal ecosystems, human health and essential biodiversity within habitats. In other words, the planet is heated as more nonrenewable fuel is burned causing adverse health outcomes. Another dimension to this nonrenewable energy-emissions path is that fossil fuel which is one of the sources of nonrenewable energy leads to increase in carbon dioxide emissions in the atmosphere considered to be the primary source of "greenhouse" gas effect that causes environmental degradation with attendant harmful health aftermaths.

Hence, the conceptual framework in Figure 3 shows that the impact of nonrenewable energy consumption (X) on mortality rate (Y) is not *somewhat* direct but mediated via a third variable (M). The discourse is probed on whether environmental degradation mediates the impact of nonrenewable energy consumption on mortality rates. That is, does nonrenewable energy consumption exert a significant indirect (mediated) effect on mortality rates? In this energy-mortality rate framework, a third variable is added to the analysis of the initial X → Y relation in order to improve understanding of the connection or to determine if the link is spurious. Mediation analysis is a method to increase information obtained from a research study when measures of the mediating process are available. A mediating variable improves understanding of such a relation because it is part of the causal sequence of X→M →Y. Such that, nonrenewable energy → carbon emissions → mortality rates.

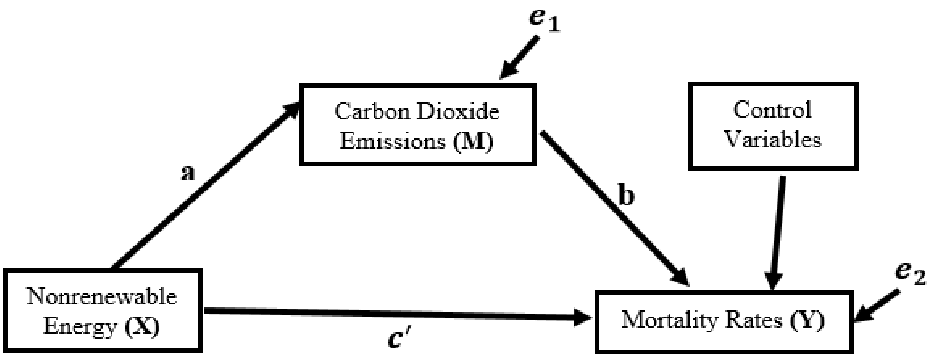

Figure 3: Mediation modelling of nonrenewable energy, carbon emissions and mortality rates.
Source: Authors 'construction

Figure 3 uses the notation most widely applied in mediation modeling [53, 54, 55, 56, 57] (MacKinnon et al., 2007; Baron & Kenny, 1986; Kenny et al. 1998; Judd & Kenny, 1981a,b), with $\boldsymbol{a}$ representing the relation of nonrenewable energy to carbon dioxide emissions, $\boldsymbol{b}$ representing the relation of carbon dioxide emissions to mortality rates adjusted for nonrenewable energy, and $\boldsymbol{c}'$ the relation of nonrenewable energy to mortality rates adjusted for carbon dioxide emissions. The symbols $\boldsymbol{e}_1$ and $\boldsymbol{e}_2$ represent residuals in the carbon dioxide emissions and mortality rates models, respectively. The equations and coefficients corresponding to Figure 3 are discussed in section 3.3. For now, note that there is a direct effect relating nonrenewable energy to mortality rates and a mediated effect by which nonrenewable energy indirectly affects mortality rates through carbon dioxide emissions.

3.3 Empirical Models

As discussed in Section 2, supporting empirical evidences [48, 51, 49, 50, 52] (Chay & Greenstone, 2003; Sinha, 2014; Fotourechi, 2016; Mutizwa & Makochekanwa, 2015; Adedotun et al., 2018) showcase the links between emissions and health outcomes and between nonrenewable energy and health. This study connects the distinct relationships by conjuring a mediation hypothesis by which carbon emissions arbitrates the impact of nonrenewable energy

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on infant mortality rates. In other words, attempt is made to evaluate the direct and indirect effects of nonrenewable energy consumption on infant mortality rate using the mediation approach. There are three major approaches to statistical mediation analysis: (*a*) causal steps, (*b*) difference in coefficients, and (*c*) product of coefficients [53] (MacKinnon et al., 2007). This study uses the product of coefficients approach and specify three models:

$$MINF_{it} = \psi_0 + \psi_1 ENUPC_{it} + \psi_2 Z'_{it} + \gamma_t + e_{it} \tag{1}$$

$$CO2PC_{it} = \eta_0 + \eta_1 ENUPC_{it} + \eta_2 Z'_{it} + \gamma_t + \tau_{it} \tag{2}$$

$$MINF_{it} = \alpha_0 + \alpha_1 ENUPC_{it} + \alpha_2 CO2PC_{it} + \alpha_3 Z'_{it} + \gamma_t + v_{it} \tag{3}$$

In the aforementioned three empirical models, Equations (1) and (3) are the determinative equations of the infant mortality rate and Equation (2) is the determinative equation of carbon emissions where, ψ_0, η_0, and α_0 are intercepts, $MINF$ is the dependent variable measured by mortality rates for infants; $ENUPC$ is the independent variable measured by nonrenewable energy per capita; $CO2PC$ is the mediator measured by carbon emissions per capita; $Z'$is a vector of covariates that affect mortality rates (female secondary education and access to basic sanitation); γ_t is the time fixed effect; e_{it} , τ_{it}, and v_{it} are the random disturbances. In simple terms, $\boldsymbol{\psi_1}$ in Equation (1) is the coefficient relating the nonrenewable energy to mortality rates; $\boldsymbol{\alpha_1}$ Equation (3) is the coefficient relating nonrenewable energy to mortality rates adjusted for the mediator, $\boldsymbol{\alpha_2}$ is the coefficient relating the mediator to mortality rates adjusted for nonrenewable energy, $\boldsymbol{\eta_1}$ Equation (2) is the coefficient relating nonrenewable energy to the mediator, carbon emissions. Equations (1), (2) and (3) which are depicted in Figure 3 capture the respective $\boldsymbol{c'}$, $\boldsymbol{a}$, and $\boldsymbol{b}$ paths.

The coefficient $\boldsymbol{\psi_1}$ indicates the *total* effect of the nonrenewable energy consumption on mortality rates. The coefficient $\boldsymbol{\alpha_1}$ in represents the *direct* effect of the nonrenewable energy

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consumption on the mortality rate controlling for the influence of carbon emissions. The *indirect*[4] (mediation) effect equates to $\boldsymbol{\eta_1} * \boldsymbol{\alpha_2}$ using the product coefficient approach and the total effect is equal to the sum of the mediation effect and direct effect, i.e. $\boldsymbol{\psi_1} = (\boldsymbol{\eta_1} * \boldsymbol{\alpha_2}) + \boldsymbol{\alpha_1}$. Note that the mediation equations may be altered to incorporate additional covariates. To check for results robustness, *under-5 mortality rate* is used as the outcome variable to observe if the empirical outcomes are sustained. Lastly, to engage the sub-sample analysis by income groups, the data is categorised into 3 groups of High Income, Lower-Middle Income and Upper-Middle Income countries.

Numbering starts from [58]

3.5 Estimation Approach

This paper uses the mediation modeling approach within the structural equation modeling (SEM) framework to address the study objectives. SEM is widely used in social, behavioural and economic sciences to evaluate linear relationships among variables. Several overviews and variations of SEM can be found in [58] Aigner and Goldberger (1977), [59] Goldberger and Duncan (1973), [60] Saris and Stronkhorst (1984), [61] Saris (1980), [62] Anderson (1984), [63] Jöreskog (1981), [64] Bentler (1986), [65] Satorra (1990), and [53] Mackinnon et al (2007) to mention a few. The mediation modeling technique, on the other hand, handles how the predictor variable X impacts the outcome variable Y [66, 67, 54] (Hayes, 2009, 2013; Baron and Kenny, 1986). [68] Edelman et al. (2005) and [69] Hojnik et al. (2018) explain that mediation equations specify the existence of a significant intervening mechanism (in our case, carbon emissions) between the predictor variable (nonrenewable energy consumption) and the outcome variable (infant mortality rate). As such, the mediator variable (carbon emissions)

[4]Mediation effect exists if the coefficients of the nonrenewable energy ($\boldsymbol{\eta_1}$) and carbon emissions ($\boldsymbol{\alpha_2}$) are statistically significant.

accounts for a significant proportion of the relationship between the nonrenewable energy and the outcome variable.

Given the above, the data is analyzed using the structural equation *sem* routine in Stata version 16. SEM is chosen because of its precision for producing unbiased estimates of mediation impacts [70] (Cheung & Lau, 2008). Adapting the two-step method recommended by [71] Anderson and Gerbing (1988), the structural and regression models are estimated in separate steps. First, a structural model representing the hypothesized structural relationship between nonrenewable energy and carbon emissions is evaluated (that is, Equation 2). Second, the regression model is analyzed to test the adequacy of the hypothesized relation [Equation 3]. In addition, based on the non-normal distribution of the data, the mediation (indirect) effect is tested using the Satorra-Bentler robust standard errors technique [65, 64] (Satorra, 1990; Bentler, 1986). This approach is justified in obtaining parameter estimates such as fitting the model and evaluating the estimates' sampling variability as well as the null distribution of test statistics. Lastly, the goodness-of-fit of both models is evaluated. To know if the data fits well with the hypothesized model, three critical fit indices widely used in structural equation modeling analysis are applied: the comparative fit index ([72] Bentler, 1990), Tucker–Lewis index [73, 74] (Bentler & Bonett, 1980; Tucker & Lewis, 1973) and root mean square error of approximation [75, 76] (Steiger, 1990; Steiger & Lind, 1980). RMSEA is an absolute fit index, in that it assesses how far a hypothesized model is from a perfect model. On the contrary, CFI and TLI are incremental fit indices that compare the fit of a hypothesized model with that of a baseline model (i.e., a model with the worst fit).

4 Results and Discussions

This section presents empirical findings which fill essential gaps in the health-energy literature on Asia and the Pacific by showcasing findings on whether carbon emissions mediate the impact of nonrenewable energy on mortality rates and whether this impact differs across income groups. Estimations begin with the structural and regression models in Table 3 followed by the decomposition of effects and diagnostics in Table 4. Corresponding robustness results are displayed in Tables A4 and A5 while Table 5 summarizes the validation of the hypotheses. Results are interpreted in turns.

4.1 Full Sample and Income Groups Results, Main Analysis

From the structural model in the upper part of Table 3, the coefficient of *ENUPC* is positive and statistically significant at the 1% level across all model specifications. This indicates that a percentage change in nonrenewable energy significantly increases carbon emissions by 1.13, 1.23, 1.084, and 1.083 in the full sample, high, lower-middle and upper-middle income countries, respectively, on average, *ceteris paribus*. This outcome aligns with related studies [44, 46, 47, 77, 78] (Zaidi et al. 2018; Hanif et al. 2019; Awodumi & Adewuyi, 2020; Nathaniel & Adeleye, 2021; Adeleye et al. 2021). From the regression model with *MINF* as the dependent variable, the coefficient of *ENUPC* is negative and statistically significant at the 1% and 5% levels for the full sample and upper middle income countries. This suggests that a percentage change in nonrenewable energy significantly decreases infant mortality rates by 0.52 and 0.79 per cent for the full sample and upper-middle income countries, respectively, on average, *ceteris paribus*. This outcome contradicts [25, 39] Anser et al. (2020) and Asghar et al. (2020).

Table 3 Empirical Results (Full Sample and Income Groups)

Variables	Main	High Income	Lower-Mid Inc	Upper-Mid Inc
	[1]	[2]	[3]	[4]
	Structural Model: Dep. Var: ln*CO2PC*			
$\ln ENUPC_{it}$	1.1309***	1.2313***	1.0841***	1.0830***
	(32.59)	(135.81)	(10.88)	(28.05)

Constant	-7.1204***	-8.1194***	-6.8692***	-6.5135***
	(-26.77)	(-117.27)	(-10.71)	(-21.51)
Regression Model: Dep. Var: ln*MINF*$_{it}$				
lnENUPC$_{it}$	-0.5222***	0.2588	-0.0238	-0.7859**
	(-8.02)	(0.82)	(-0.21)	(-2.21)
lnCO2PC$_{it}$	0.0878*	-0.4708*	0.1136**	0.5749**
	(1.76)	(-1.90)	(2.04)	(2.08)
lnSECFit	-0.8190***	0.6938**	-0.7392***	0.9073
	(-7.96)	(2.53)	(-6.57)	(1.52)
lnBSAN$_{it}$	0.0309	-23.6148***	-0.1588	-2.0540***
	(0.24)	(-19.63)	(-1.31)	(-6.32)
Constant	9.9347***	105.8284***	7.4410***	12.7425***
	(12.19)	(20.25)	(8.77)	(5.00)
Observations	171	171	171	171
Log-likelihood	-561.91	-142.4754	-142.4754	-142.4754
Wald Test (lnCO2PC$_{it}$)	1062.16***	18445.12***	118.37***	786.65***
Wald Test (lnMINF$_{it}$)	334.46***	1709.94***	94.12***	150.48***

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; Estimations with Satorra-Bentler standard errors; ln = natural logarithm; MINF = infant mortality rates; MU5 = under-5 mortality rate; CO2PC = carbon emissions per capita; ENUPC = nonrenewable energy per capita; SECF = female secondary school enrolment; BSAN = access to basic sanitation..
Source: Authors' Computations

Also, the coefficient of *CO2PC* is negative and statistically significant at the 10% level for high income countries while positive and statistically significant at the 10% and 5% levels for the full sample, lower-middle and upper-middle income countries. This shows that while emissions decrease mortality rates in high income countries the reverse is the case for other specifications. The negative outcome contradicts expectations while the positive outcomes align with [41] Rasoulinezhad et al. (2020). On the control variables, basic sanitation and female secondary education evidence mortality-decreasing properties for the full sample and lower-middle income countries [40] (Shobande, 2020) but education exacerbates mortality rate in high income countries. For the most part, these findings align with *a priori* expectations

4.2 *Total, Direct, and Indirect (Mediation) Effects*

The results shown in the upper part of Table 4 decompose the total effects into direct and mediation effects. The direct effects are represented by the coefficient of *ENUPC* on mortality rate as interpreted in section 4.1. This paper's contribution is highlighted by its findings on the mediation effects. We show that the mediation effect is negative and statistically significant at the 10% level for high income countries while positive and statistically significant at the 10% and 5% levels for the full sample, lower-middle and upper-middle income countries. This imply that nonrenewable energy indirectly reduces mortality rates in high income countries but increases for the full sample, lower-middle and upper-middle income countries. These are significant incursions into the health-environment literature. The total effect is the sum of the direct and indirect effects who intuitive interpretation is that overall, nonrenewable energy exert mortality-reducing outcomes in three out of four models supporting Figure 2, in hindsight.

Table 4 Decomposition of Effects and Diagnostics, Main Results

Nonrenewable energy consumption	Full Sample	High	Lower-mid	Upper-mid
	Standardized	Standardized	Standardized	Standardized
Direct Effects	-0.522***	0.2588	-0.024	-0.786**
z stat	(-8.02)	(0.82)	(-0.21)	(-2.21)
Mediation Effects	0.099*	-0.579*	0.123**	0.623**
z stat	(1.76)	(-1.89)	(2.25)	(2.15)
Total Effects	-0.423***	-0.321***	0.099	-0.163*
z stat	(-10.08)	(-14.80)	(1.24)	(-1.75)
Diagnostics/Goodness-of-fit	Full Sample		Income Groups	
RMSEA	0.016		0.018	
Comparative fit index (CFI)	0.994		0.981	
Tucker-Lewis index (TLI)	0.981		0.934	
Standardized root mean squared residual	0.018		0.044	
Coefficient of determination (CD)	0.922		0.915	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; Estimations with Satorra-Bentler standard errors; RMSEA = Root mean squared error of approximation.
Source: Authors' Computations

For the diagnostics, having deployed the Satorra-Bentler robust standard errors, the goodness-of-fit of the models is evaluated. [79] Hu and Bentler (1999) suggested the following criteria

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for a good model fit: RMSEA < 0.06, CFI and TLI > 0.95 and our models align with these thresholds. The CD mirrors the R-squared and indicates that about 92% variation in mortality rate is explained by the regressors. Overall, we conclude that the specified models are not statistically different from the hypothesized models. To test the robustness of our results, the dependent variable is replaced with under-5 child mortality rate and the outcomes shown in Appendix Tables A4 and A5 are not significantly different from those of Tables 3 and 4. Hence, the initial findings and discussions hold.

4.3 Hypotheses Validation

The summary of the regression analyses of the four hypotheses tested in the study is shown in Table 5. Hypothesis 1 is rejected for the full sample and upper-middle income countries while partially sustained[5] and partially rejected[6] for high income and lower-middle income countries. Hypothesis 2 is sustained for all. Hypothesis 3 is rejected for high income countries but sustained for others. Lastly, hypothesis which is the contribution of this study is rejected for high income countries but sustained for others.

Table 5 Hypotheses Validation

Hypotheses	**FS**	**HI**	**LMI**	**UMI**
Hypothesis 1: Nonrenewable energy is positively related to health outcomes (direct effect).	R	PS	PR	R
Hypothesis 2: Nonrenewable energy is positively related to carbon emissions.	S	S	S	S
Hypothesis 3: Carbon emissions is positively related to health outcomes.	S	R	S	S
Hypothesis 4: Carbon emissions mediates the relationship between nonrenewable energy and health outcomes (direct/indirect effect).	S	R	S	S

Note: FS = Full Sample; HI = High Income; LMI = Lower-Middle Income; UMI = Upper-Middle Income; R = Rejected; PR = Partially rejected; S = Sustained; PS = Partially sustained
Source: Authors' Compilation

[5] Partially sustained = coefficient is positive but statistically not significant.
[6] Partially rejected = coefficient is negative but statistically not significant.

5 Conclusion and Policy Recommendations

The nexus between energy-emissions, emissions-health and energy-health have been well researched with varying and inconclusive outcomes. Though the energy-health nexus has been explored, However, the existing literature has not explored the nexus to the best of our knowledge, no single study to date has explored the mediating role of carbon emissions in the relationship between nonrenewable energy and mortality rates. Our study addresses this research gap. We contribute to the emerging literature stream on energy-emissions-health dynamics by introducing a theoretical model to empirically examine the mediation effect of carbon emissions on the relationship between nonrenewable energy and mortality rates. Using an unbalanced panel data on Asia and the Pacific countries from 2005 to 2015 and deploying the structural equation modeling approach, the results are surmised as follows: (i) in regard to the full sample of countries, nonrenewable energy potentially indirectly increases infant mortality rates through increasing carbon emissions. In other words, carbon emissions play a partial mediation role between nonrenewable energy and infant mortality rates; and (ii) for the different income groups, carbon emissions show varying mediation effects. For example, the mediation effects of carbon emissions in lower-middle and upper-middle income countries are found to be similar to those of the full sample of countries. Therefore, based on these findings, we conclude that nonrenewable energy is an essential determinant of infant mortality rates. These findings suggest that since non-renewable energy indirectly increases infant mortality rates through increasing carbon emissions measures towards shifting to renewable energy sources need to be pursued by the various governments and stakeholders in the heath sector. This is because wind, solar, and hydroelectric systems generate electricity with no associated air pollutants. Geothermal and biomass systems emit some air pollutants, though total air emissions are generally much lower than those of fossil fuel, petroleum, coal and natural gas. In other words, adopting environmental quality policies will further reduce infant mortality rates in these countries.

Declarations
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Appendix

Table A1 List of Countries and Classifications

S/No.	Country	Sub-Region	Income Group
1	Australia	East Asia & Pacific	High Income
2	Bangladesh	South Asia	Lower-Middle Income
3	Bhutan	South Asia	Lower-Middle Income
4	Brunei Darussalam	East Asia & Pacific	High Income
5	Cambodia	East Asia & Pacific	Lower-Middle Income
6	China	East Asia & Pacific	Upper-Middle Income
7	Fiji	East Asia & Pacific	Upper-Middle Income
8	Hong Kong SAR, China	East Asia & Pacific	High Income
9	India	South Asia	Lower-Middle Income
10	Indonesia	East Asia & Pacific	Upper-Middle Income
11	Japan	East Asia & Pacific	High Income
12	Kazakhstan	Central Asia	Upper-Middle Income
13	Kiribati	East Asia & Pacific	Lower-Middle Income
14	Korea, Rep. (South)	East Asia & Pacific	High Income
15	Kyrgyz Republic	Central Asia	Lower-Middle Income
16	Lao PDR	East Asia & Pacific	Lower-Middle Income
17	Macao SAR, China	East Asia & Pacific	High Income
18	Malaysia	East Asia & Pacific	Upper-Middle Income
19	Maldives	South Asia	Upper-Middle Income
20	Marshall Islands	East Asia & Pacific	Upper-Middle Income
21	Micronesia, Fed. Sts.	East Asia & Pacific	Lower-Middle Income
22	Mongolia	East Asia & Pacific	Lower-Middle Income
23	Myanmar	East Asia & Pacific	Lower-Middle Income
24	Nauru	East Asia & Pacific	High Income
25	Nepal	South Asia	Lower-Middle Income
26	New Zealand	East Asia & Pacific	High Income
27	Pakistan	South Asia	Lower-Middle Income
28	Palau	East Asia & Pacific	High Income
29	Papua New Guinea	East Asia & Pacific	Lower-Middle Income
30	Philippines	East Asia & Pacific	Lower-Middle Income
31	Samoa	East Asia & Pacific	Upper-Middle Income
32	Singapore	East Asia & Pacific	High Income
33	Solomon Islands	East Asia & Pacific	Lower-Middle Income
34	Sri Lanka	South Asia	Lower-Middle Income
35	Taiwan, China	East Asia & Pacific	High Income
36	Timor-Leste	East Asia & Pacific	Lower-Middle Income
37	Tonga	East Asia & Pacific	Upper-Middle Income
38	Turkmenistan	Central Asia	Upper-Middle Income
39	Tuvalu	East Asia & Pacific	Upper-Middle Income

40	Uzbekistan	Central Asia	Lower-Middle Income
41	Vanuatu	East Asia & Pacific	Lower-Middle Income
42	Vietnam	East Asia & Pacific	Lower-Middle Income

Source: Authors' Compilations

Table A2 Summary Statistics - Full Sample and Income Groups

Variable	*Full Sample*				*High Income Countries*			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
MINF	27.074	16.916	2.1	79	12.903	13.16	2.1	47.4
MU5	33.272	21.715	2.7	99.8	15.211	15.44	2.7	56.2
ENUPC	2079.991	2182.923	58.046	9837.447	4297.067	2276.238	283.493	9837.447
CO2PC	4.17	5.123	0.098	24.627	9.102	5.823	0.305	24.627
BSAN	73.784	24.905	14.131	100	95.196	10.225	65.596	100
SECF	78.246	23.569	26.892	145.888	95.407	17.481	50.082	145.888
Variable	*Lower-Middle Income Countries*				*Upper-Middle Income Countries*			
	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
MINF	36.402	15.009	7.5	79	21.708	11.837	6.7	57.8
MU5	45.49	19.909	8.8	99.8	25.835	14.435	7.9	70.2
ENUPC	564.614	446.598	58.046	1828.103	2315.542	1584.675	315.133	4893.41
CO2PC	1.215	1.811	0.098	15.139	4.612	4.492	0.69	15.646
BSAN	55.902	22.206	14.131	100	87.186	11.938	50.504	99.557
SECF	63.815	22.084	26.892	101.77	87.838	12.188	59.839	115.764

Note: *** denotes statistical significance at the 1% level; MINF = infant mortality rates; MU5 = under-5 mortality rate; CO2PC = carbon emissions per capita; ENUPC = nonrenewable energy per capita; BSAN = access to basic sanitation; SECF = female secondary school enrolment; ln = natural logarithm.
Source: Authors' Computations

Table A3 Correlation Analysis

Variables	1	2	3	4	5	6
(1) lnMINF	1.000					
(2) lnMU5	0.998***	1.000				
(3) lnCO2PC	-0.643***	-0.655***	1.000			
(4) lnENUPC	-0.712***	-0.712***	0.948***	1.000		
(5) lnSECF	-0.690***	-0.701***	0.634***	0.640***	1.000	
(6) lnBSAN	-0.563***	-0.581***	0.626***	0.701***	0.750***	1.000

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; ln = natural logarithm; MINF = infant mortality rates; MU5 = under-5 mortality rate; CO2PC = carbon emissions per capita; ENUPC = nonrenewable energy per capita; SECF = female secondary school enrolment; BSAN = access to basic sanitation.
Source: Authors' Computations

Table A4 Full Sample and Income Groups, Robustness Results

Variables	Main	High Income	Lower-Mid Inc	Upper-Mid Inc

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	[1]	[2]	[3]	[4]
	Structural Model: Dep. Var: lnCO2PC			
$lnENUPC_{it}$	1.1309***	1.2313***	1.0841***	1.0830***
	(32.59)	(135.81)	(10.88)	(28.05)
Constant	-7.1204***	-8.1194***	-6.8692***	-6.5135***
	(-26.77)	(-117.27)	(-10.71)	(-21.51)
Regression Model: Dep. Var: lnMU5				
$lnENUPC_{it}$	-0.5106***	0.3124	-0.0267	-0.7809**
	(-7.62)	(0.99)	(-0.23)	(-2.16)
$lnCO2PC_{it}$	0.0759	-0.5101**	0.1029*	0.5604**
	(1.46)	(-2.06)	(1.73)	(2.00)
$lnSECF_{it}$	-0.8126***	0.8223***	-0.7375***	0.7640
	(-7.65)	(2.94)	(-6.13)	(1.27)
$lnBSAN_{it}$	-0.0446	-24.1973***	-0.2137	-2.0654***
	(-0.34)	(-19.92)	(-1.63)	(-6.31)
Constant	10.3436***	107.7152***	7.8778***	13.5719***
	(12.09)	(20.48)	(8.68)	(5.22)
Observations	171	171	171	171
Log-likelihood	-563.36	-148.98	-148.98	-148.98
Wald Test (lnCO2PC)	1062.16***	18445.12***	118.37***	786.65***
Wald Test (lnMINF)	341.91***	1731.64***	69.11***	162.94***

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; Estimations with Satorra-Bentler standard errors; ln = natural logarithm; MINF = infant mortality rates; MU5 = under-5 mortality rate; CO2PC = carbon emissions per capita; ENUPC = nonrenewable energy per capita; SECF = female secondary school enrolment; BSAN = access to basic sanitation.
Source: Authors' Computations

Table A5 Decomposition of Effects and Diagnostics, Robustness

Nonrenewable energy consumption	Full Sample	High	Lower-mid	Upper-mid
	Standardized	Standardized	Standardized	Standardized
Direct Effects	-0.511***	0.312	-0.027	-0.781
z stat	(-7.62)	(0.99)	(-0.23)	(-2.16)
Mediation Effects	0.858	-0.628**	0.112*	0.607**
z stat	(1.46)	(-2.05)	(1.87)	(2.06)
Total Effects	-0.425***	-0.316***	0.085	-0.174*
z stat	(-10.05)	(-14.83)	(1.04)	(1.86)
Diagnostics/Goodness-of-fit	Full Sample		Income Groups	
RMSEA	0.016		0.018	
Comparative fit index (CFI)	0.994		0.981	
Tucker-Lewis index (TLI)	0.980		0.934	
Standardized root mean squared residual	0.018		0.042	
Coefficient of determination (CD)	0.922		0.91	

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively; Estimations with Satorra-Bentler standard errors; RMSEA: Root mean squared error of approximation.
Source: Authors' Computations