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THE ENERGY–POLLUTION–HEALTH NEXUS: A PANEL DATA ANALYSIS OF LOW- AND MIDDLE-INCOME ASIAN NATIONS

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No. 1086
March 2020

Asian Development Bank Institute

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Suggested citation:

Taghizadeh-Hesary, F., E. Rasoulinezhad, N. Yoshino, Y. Chang, F. Taghizadeh-Hesary, and P. J. Morgan. 2020. The Energy–Pollution–Health Nexus: A Panel Data Analysis of Low- and Middle-Income Asian Nations. ADBI Working Paper 1086. Tokyo: Asian Development Bank Institute. Available: https://www.adb.org/publications/energy-pollution-health-nexus-asian-nations

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This research was supported by JSPS Kakenhi (2019–2020) Grant-in-Aid for Young Scientists No. 19K13742 and the Excellent Young Researcher (LEADER) grant of the Ministry of Education (MEXT) of Japan.

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Abstract

An energy resource as a production input plays a major role in various economic sectors, including commodity production, transportation, and electricity generation. However, increased energy consumption may lead to more air pollution, resulting in negative health impacts in a society. The main purpose of this study is to investigate the relationship between energy consumption and health issues (e.g., tracheal, bronchial and lung cancer, respiratory diseases, prevalence of undernourishment, death ratio due to exposure to both outdoor and household air pollution) using generalized method of moments estimation technique for data from 18 Asian countries (both low- and middle-income) over the period 1991–2018. It is found that carbon dioxide (CO_2) emissions per capita in low- and middle-income Asian nations result in the positive prevalence of lung and respiratory diseases. With regard to fossil fuel consumption, the findings demonstrate that this variable increases the risk of lung and respiratory diseases. In addition, the results demonstrate the significant effect of CO_2 emissions and fossil fuel consumption on undernourishment and death ratio. Furthermore, we find that gross domestic product per capita and health care expenditure may help reduce undernourishment and death ratio. The conclusion recommends conducting rapid energy transition programs, improving energy efficiency, and reducing energy intensity in low- and middle-income Asian countries, in order to strengthen their national health security.

Keywords: energy consumption, health issues, low- and middle-income Asian countries, panel data estimation

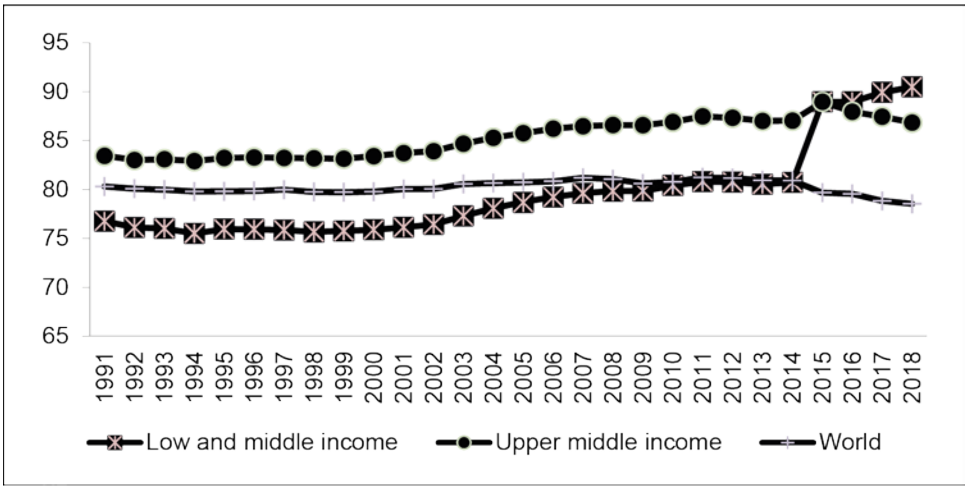
JEL Classification: I15, Q41, C33

Contents

1. INTRODUCTION

Energy consumption has been linked with countries' health security. For instance, a lack of clean energy, especially in low- and middle-income level countries, can potentially expose populations to various noxious gases from the combustion of fossil fuels. Furthermore, energy consumption can directly or indirectly affect human health by inducing air pollution, safe water shortages, or poor medical care infrastructure. Fossil fuel energy consumption increases human health threats, the future costs associated with climate change, and other forms of environmental damage, which are considered together as the health-environmental security of a nation (e.g., Machol and Rizk 2013). This issue is most serious in countries with low- and middle-income levels due to their lack of health infrastructure, poor energy efficiency, and greater contribution of fossil fuel consumption in their total energy consumption basket. Figure 1 illustrates the share of fossil fuel consumption in the total energy consumption basket of low- and middle-income countries. According to the data displayed in Figure 1, fossil fuel contributions to total energy consumption in such nations increased during the period 1991–2018. The share of fossil fuel consumption in these countries reached nearly 90% in 2018, which is greater than the shares of the world's upper-middle-income nations.

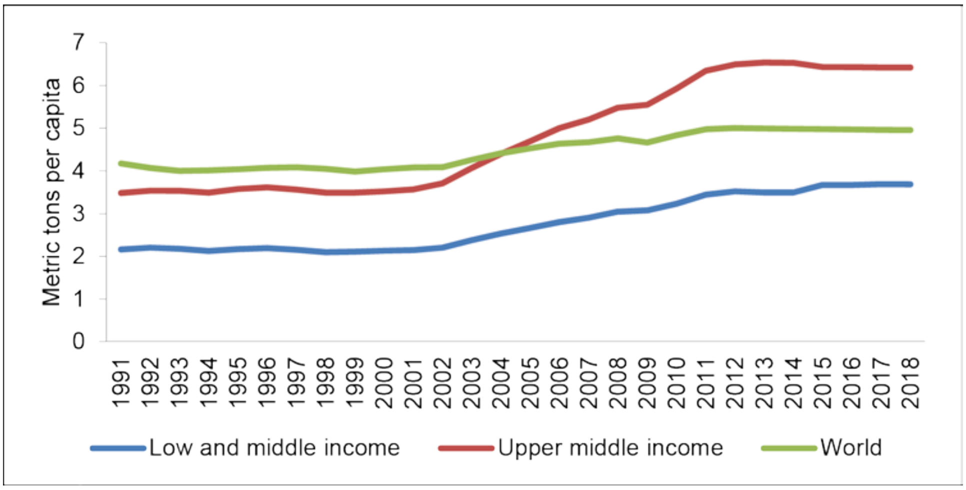
Figure 1: Fossil Fuel Consumption (% of Total) **in Low- and Middle-Income Countries**



Source: Authors' compilation from data gathered from the World Bank.

A higher consumption of fossil fuel energy sources leads to increased air pollution in these countries. Gathering and analyzing data from the World Bank proves that the amount of CO_2 emissions per capita in these nations has risen from over 2 metric tons per capita in 1991 to nearly 3.8 metric tons per capita in 2018, indicating that over the three last decades the issue of air pollution in these nations increased considerably.

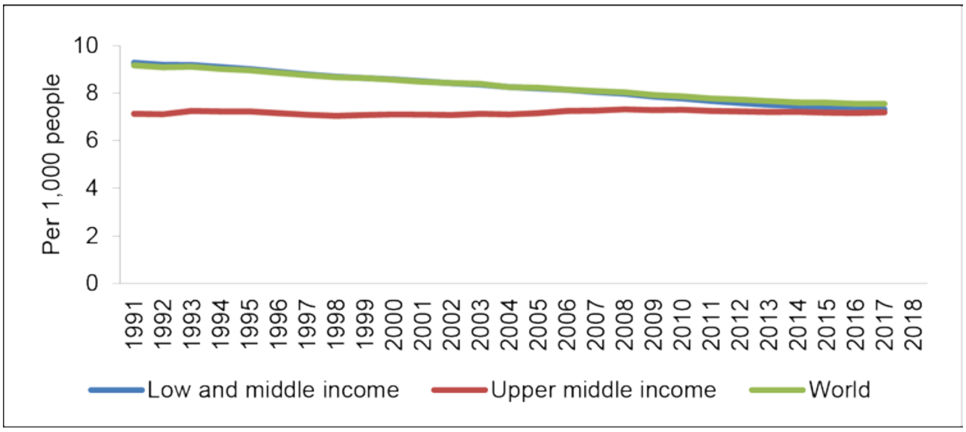
Figure 2: CO_2 Emissions per Capita by Low- and Middle-Income Countries



Source: Authors' compilation from data gathered from the World Bank

The increased share of fossil fuel consumption and air pollutant emissions in these countries may constitute the main cause of their high death rates compared with upper-middle-income countries. Following a Stanford University report (2008), carbon dioxide emissions have a significant association with human mortality. Generally, the resulting air pollution leads annually to about 1,000 additional deaths and many more cases of respiratory illness around the world. According to Figure 3, the death ratio in low- and middle-income countries remained consistently higher than that in upper-middle-income nations over the period 1991–2018.

Figure 3: Death Rate of Low- and Middle-Income Countries



Source: Authors' compilation from data gathered from the World Bank

Despite some earlier studies such as Newborough and Probert (1987); Lambert et al. (2014); Chaabouni et al. (2016); Nasre Esfahani and Rasoulinezhad (2016); Sirag et al. (2017); Apergis, Ben Jebli, and Youssef (2018); and Hanif (2018), we cannot find any in-depth investigation focusing on the relationship between energy consumption, air pollution, and health in low- and middle-income Asian nations. Hence, to our knowledge, this is the first study to assess the negative effects of energy consumption and air pollution on human health in Asia. It may thus play an important role in addressing the importance of energy insecurity and its health effects, particularly in low- and middle-income Asian nations.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and specifies the model. Section 4 presents the empirical findings, and finally Section 5 concludes the paper.

2. AIR POLLUTION AND HEALTH ISSUES

Air pollution consists of a mixture of various gaseous and particulate matters (PMs). The latter are usually classified based on their size to better characterize their pathogenicity. Fine PMs with a diameter of 2.5 µm (PM2.5) are the main subgroup that can enter small airways and cause toxicity (Dominici et al. 2006). The gaseous components are mainly composed of polycyclic aromatic hydrocarbons (PAHs), ozone, carbon monoxide, nitrogen oxides (NOx), and sulfur dioxide (Fetterman, Sammy, and Ballinger 2017). According to a World Health Organization (WHO 2016) report, 92% of the global population lives in areas with poor air quality. In 2010, ambient (outdoor) and household (indoor) air pollution constituted the fourth and ninth leading risk factors behind the global disease burden, respectively (Lim et al. 2012a). In Southern Asia, household air pollution arising from solid fuels (e.g., wood, coal, and other biomass) is ranked among the top four risk factors for human health (Lim et al. 2012a). High concentrations of PMs from anthropogenic sources can affect the pulmonary system, the cardiovascular system, the psychoendocrine system, and the reproductive system (see Fetterman, Sammy, and Ballinger 2017). Various studies have assessed the mechanisms underlying these effects. Accordingly, a large number of previous studies have focused on the reactive oxygen species (ROSs) that are produced in response to the components of air pollution (e.g., PMs or NOx) (Fetterman, Sammy, and Ballinger 2017). These are chemically reactive molecules that contain oxygen. ROSs are highly reactive with cellular elements, especially DNA. Through interacting with cellular and mitochondrial DNA molecules, they make several changes that eventually result in human diseases. In addition to air pollution, energy insecurity can affect human health as a result of safe water shortages. Energy insecurity may affect water sources through global warming. Safe and clean water shortages may expose populations to various communicable (or infectious) and noncommunicable diseases (e.g., micronutrient deficiencies). Last but not least, the availability of modern energy sources plays a major role in determining access to standard health care facilities. Women and children are the most vulnerable demographic groups. According to a WHO factsheet, over 289,000 women globally die from pregnancy or delivery complications every year, and approximately 24% of these deaths occur in South Asia (WHO 2014). Most of these deaths are preventable with simple lighting, operating and blood transfusion services (Mills 2012). In the following sections the connecting channels between energy insecurity and human health are presented in detail. These interconnections can be categorized into environmental effects, household effects, and medical care effects. The information presented in Sections 2.1. and 2.2. are related to the first two categories.

2.1 Ambient/Household Air Pollution

Air pollution can affect human health in several ways. Therefore, a few mechanisms are proposed. For instance, PMs can directly target mitochondria (the main actor of cellular metabolism) and cause cellular dysfunction (Meyer et al. 2013). They can also induce genetic and epigenetic alterations, and lead to cancer formation (DeMarini 2015).

PMs and ozone are the two main components of air pollution that can affect the pulmonary system (United States Global Change Research Program, USGCRP 2016). They may either cause or exacerbate pulmonary disorders. Indeed, various pulmonary disorders are linked with exposure to air pollution. First, prolonged exposure to household air pollution (e.g., using traditional stoves for baking bread in low- and middle-income countries) can induce prolonged inflammation in airways and cause chronic obstructive pulmonary disease (COPD). This is mediated by inducing systemic reactive oxygen species (ROS) production (Golshan, Faghihi, and Marandi 2002). Second, air pollution plays a major role in the development of asthma and recurrent wheezing in children with hyperactive airways (Padhi and Padhy 2008; Modig et al. 2009). Third, air pollution may exacerbate the symptoms of patients suffering from rhinosinusitis (WHO 2013). Relatedly, air pollution can induce pneumonia by impairing the immune system (Kreyling, Semmler, and Möller 2004). PMs and nitric oxide (NO) are the two key components of air pollution that are associated with the cardiovascular system. According to a meta-analysis, each 10 µg/m3 increase in PM2.5 concentration can escalate annual cardiovascular mortality by 11% (Hoek et al. 2013). The equivalent rate for NO is equal to 13% (Faustini, Rapp, and Forastiere 2014). Coronary artery disease, cardiac failure, stroke, and arrhythmia are all cardiovascular disorders that are causally linked to air pollution. These effects are mainly caused by the pro-atherogenic feature of resultant ROSs (see Bourdrel et al. 2017).

A number of studies have postulated a convergence between air pollution and mental disorders, including depression and anxiety (Szyszkowicz et al. 2009; Szyszkowicz et al. 2010; Lim et al. 2012b). Dubos (1969) has highlighted the impact of poor indoor air quality on people's insufficient adaptation. Colligan (1981) has found that indoor air pollution can affect psychological reactions in two ways: first through affecting mental efficacy (e.g., memory status, interpersonal relations, mood status), and second through sympathetic arousal and increasing heart and breathing rate. The latter may induce an unconscious sense of anxiety, fear or panic. According to a Korean study, air pollution might be a risk factor for a number of psychological disorders, ranging from anxiety to suicidal ideation (Shin et al. 2018). Similarly, Costa (2017) has labelled air pollution as a risk factor for autistic disorders in children. In all the studies reviewed here, air pollution is recognized as a risk factor for a wide range of mental disorders.

Furthermore, several prospective studies have explored the relationship between long-term exposure to air pollution and type 2 diabetes mellitus (Andersen 2012; Wang et al. 2014). This might be mediated by the systemic inflammatory effect of ROSs, which in turn causes insulin resistance in peripheral tissues. Another proposed mechanism pertains to mitochondria impairment, which leads to glucose intolerance (Xu et al. 2011). Although there is little information available for this notion, the existing evidence distinguishes air pollution as a risk factor for type 2 diabetes mellitus. A number of studies have established that air pollution is a risk factor for cancer. Certainly, almost all organs are at risk from exposure to air pollution. The evidence reviewed by Fetterman, Sammy, and Ballinger (2017) has demonstrated the key role played by air pollution in inducing cancer in the lungs, kidneys, bladder, prostate, central nervous system, endocrine system, oropharynx, skin, cervix, ovary, liver, and rectum. Many mechanisms have been proposed in the literature for this relationship. To better understand how air pollution acts as a carcinogen, it is advisable to first define one of the most crucial organelles of human cells, the mitochondria. These represent the central regulator of cellular metabolism. They are the main cellular organelles that extract energy packs (i.e., adenosine triphosphate, ATP) from organic compounds (including fatty acids). Furthermore, they are the major cellular component to organize biosynthetic pathways (i.e., the production of amino acids, lipids, nucleotides, etc.). In other words, mitochondria are the key bioenergetic and biosynthetic organelles of human cells. ROSs interconnect air pollution to cancer through impairing the function of cellular mitochondria (Fetterman, Sammy, and Ballinger 2017). Targeting mitochondria with ROSs may induce cancer formation through preventing genome stability (Ishikawa et al. 2008). Several studies have demonstrated the relationship between air pollution and infertility. Indeed, recent systematic reviews such as that conducted by Carre (2017) have clearly shown the negative impact of air pollution on fertility. Both male and female gametogenesis are at risk of this effect. Various components of air pollution can affect either the quality or the quantity of gametes. Moreover, they can compromise fetal development, leading to increased miscarriage rates. Systemic oxidative stress, hormonal disturbance, and genetic and epigenetic alterations are four proposed mechanisms for air pollution-induced reproductive disorders (Carre 2017). Given the impacts of air pollution on the genetic and epigenetic features of gametes, its negative effects on fetal development are to be expected. A number of studies have attempted to explore this relationship. For instance, Pederson et al. (2013) have highlighted the effect of air pollution on low birth weight. Moreover, Suades-Gonzales et al. (2015) have found a negative effect of perinatal exposure to PAHs, nitrogen dioxide (NO2) and PMs on children’s neuropsychiatric development. For further information, see also Costa’s (2017) review regarding its crucial impact on the development of autistic disorders.

2.2 Water Insecurity and Medical Care Effects

Energy insecurity interconnects with medical care infrastructure in several ways. First, it can provide basal necessities to acquire safe medical care (e.g., lighting, sterilizers, air conditioners). Moreover, energy plays an important role in performing various diagnostic procedures (e.g., laboratories, clinical imaging, electrocardiography). Another application of energy in medical care pertains to therapeutic procedures (e.g., radiotherapy). It is also central to the cold chain in refrigerating blood, vaccines and medicines (Porcaro et al. 2017).

Another important factor is water insecurity. This condition plays a direct role in both the outbreak of various infectious disease (e.g., cholera) and the development of food insecurity. The latter may in turn induce growth defects, developmental abnormalities, or micronutrient deficiency, causing various chronic disorders (e.g., anemia, osteoporosis, immune deficiency) (Maggini, Pierre, and Calder 2018). In addition, food insecurity during pregnancy may result in anxiety and depression (Laraia, Siega-Riz, and Gundersen 2010).

3. DATA AND MODEL SPECIFICATION

Following on from the above review of the energy–pollution–health nexus, the empirical specification to capture the impact of energy consumption on the health issues of 18 selected low- and middle-income Asian nations [1] (World Bank classification at https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups) over the period 1991–2018 is based on the following simple function:

Health issue = F (influential factors on health of society)

The influential factors on the health of a society are based on previous studies (e.g., see Sirag et al. (2017); Apergis, Ben Jebli, Youssef (2018); and Hanif (2018)), and comprise tracheal, bronchial and lung cancer (TLC), respiratory diseases (RD), prevalence of undernourishment (PU), and death ratio due to exposure to outdoor and household air pollution (DR). All these variables are gathered from the World Bank database. In order to remove redundant information, highlight hidden features, and visualize the main relationships between observations, we use the principal component analysis (PCA) technique to simplify our health variables. Unlike other linear transformation methods, PCA does not have a fixed set of basis vectors. Rather, these depend on the data set, and PCA has the additional advantage of indicating what is similar and different about the various models created (Bruce-Ho and Dash-Wu 2009). Through the results of this method, shown in Table 1, we can reduce the four health variables (TLC, RD, PU, DR) into two components of lung and respiratory diseases (LRD) and undernourishment and death ratio (UDR).

Table 1: PCA Technique Result

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	1.830	45.760	45.760	1.830	45.760	45.760
2	1.210	30.238	75.998	1.210	30.238	75.998
3	.529	13.231	89.228			
4	.431	10.772	100.000			

Source: Authors' compilation.

Table 2: Component Matrix of PCA

	Component	
	1	**2**
TLC	–.549	–.677
RD	–.280	.859
PU	.858	–.058
DR	.845	–.096

Note: TLC, RD, PU, and DR represent tracheal, bronchial and lung cancer, respiratory diseases, prevalence of undernourishment, and death ratio due to exposure to outdoor and household air pollution, respectively.

Source: Authors' compilation.

[1] Namely Afghanistan, Tajikistan, Bangladesh, Indonesia, India, the Kyrgyz Republic, Cambodia, Myanmar, the Philippines, Uzbekistan, Viet Nam, the People's Republic of China, Iran, Kazakhstan, Sri Lanka, Malaysia, Pakistan, and Thailand.

Besides arranging the dependent variable, we need to explore explanatory variables. Following earlier studies such as Chaabouni et al. (2016), we choose CO_2 emissions (metric tons per capita), fossil fuel consumption (% of total energy basket), gross domestic product (GDP) per capita (current US $), health care expenditure per capita (current US $), and urban population growth (annual %), collected from the World Bank database and the British Petroleum (BP 2019) *Statistical Review of World Energy 2019*.

Table 3 presents the primary descriptive characteristics of our data. TLC is measured as a percentage, with our sample of 20 low- and middle-income Asian countries yielding a mean of 0.02% over the period 1991–2018. The mean of our sample's RD is 190,328 people lost per day, with a maximum and a minimum of 352,912 and 8,093 lost per day during 1991–2018, respectively. The PU and DR in the 20 selected countries during the period have means of 17.3% and 20.19%, respectively. The average CO_2 emissions per capita and share of fossil fuel consumption in the total energy basket in our selected sample are 9.19 metric tons per capita and 95.39%, respectively, whereas GDP per capita has a maximum of $11,238.64 and a minimum of $43.29. Urbanization in the selected countries presents an average of 12.49%, with a maximum and a minimum of 17.33% and 1.24%, respectively. Health expenditure per capita presents an average of $415.90 over the period.

Table 3: Variables' Descriptive Statistics

Variables	Unit	Obs.	Mean	Std. Dev.	Max.	Min.
TLC	%	560	0.027	1.92	0.411	0.0012
RD	People lost per day	560	190,328	5.9	352,912	8,093
PU	%	560	17.3	32.39	19.29	12.06
DR	%	560	20.19	41.02	39.44	11.03
CO_2	Metric tons per capita	560	9.19	12.23	21.94	6.12
FFC	%	560	95.39	140.39	100	24.55
GDP	Current US$	560	5,627.39	1,302.93	11,238.64	43.29
URB	%	560	12.49	40.29	17.33	1.24
HEX	Current US$	560	415.90	1,921.44	2,913.92	32.91

Notes: TLC = Tracheal, bronchial and lung cancer, RD = Respiratory diseases, PU = Prevalence of undernourishment, DR = Death ratio due to exposure to outdoor and household air pollution, CO_2 = CO_2 emissions per capita, FEC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health expenditure per capita.

Source: Authors' compilation.

We may empirically investigate the following model based on our two components of dependent variables and five above-mentioned explanatory variables:

Model I based on the first dependent variable (Component 1: lung and respiratory diseases, LRD):

$$LnLLRD_{it} = \alpha_1 LnCO2_{it} + \alpha_2 LnFFC_{it} + \alpha_3 LnGDP_{it} + \alpha_4 LnURB_{it} + \alpha_5 LnHEX_{it} + \varepsilon_{it} \tag{1}$$

Model II based on the second dependent variable (Component 2: undernourishment and death ratio, (UDR):

$$LnLUDR_{it} = \alpha_1 LnCO2_{it} + \alpha_2 LnFFC_{it} + \alpha_3 LnGDP_{it} + \alpha_4 LnURB_{it} + \alpha_5 LnHEX_{it} + \varepsilon_{it} \tag{2}$$

The coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ and α_5 represent the long-run elasticity estimates of health problems with respect to CO_2 emissions per capita, fossil fuel consumption, GDP per capita, urban population growth, and health expenditure per capita. Based on the relevant literature, we expect that increased CO_2 emissions, fossil fuel consumption, and urbanization lead to an increase in different diseases, while the impacts of GDP per capita and health expenditure per capita as tools that can facilitate progress are expected to reduce diseases. Table 4 lists the expected coefficients of the variables.

Table 4: Expected Signs of Variables

Variable	Expected Sign of Coefficient
CO_2 emissions per capita	+
Fossil fuel consumption	+
GDP per capita	–
Urban population growth	+
Health expenditure per capita	–

Source: Authors' compilation.

In order to estimate the coefficients based on Model I and Model II, the generalized method of moments (GMM) is utilized in a panel-gravity framework for energy consumption–environment pollution–health issues among the 20 selected low-and middle-income countries in Asia. The reliability of the GMM method has been proved by many scholars, such as Arellano and Bond (1991), Martinez-Zarzoso, Nowak-Lehmann, and Horsewood (2009), Kahouli and Maktouf (2015), and Lin (2015). Arellano and Bond (1991) have argued that the GMM estimator including the lagged endogenous variable as an explanatory variable is more convenient for panel data because it yields more consistent and robust results in the presence of arbitrary heteroskedasticity. In general, a regression model in the form of GMM is written as follows:

$$Y_{it} = \alpha + \beta Y_{it-1} + \gamma X_{it} + \eta_{it} + \varepsilon_{it} \tag{3}$$

Where Y indicates the dependent variable (LRD in Model I; UDR in Model II), and X represents all explanatory variables (CO_2 emissions per capita; fossil fuel consumption; GDP per capita; urban population growth; health expenditure per capita). η_{it} represents the country-specific effects, and ε_{it} is the error term.

To attain reliable empirical estimations, we need to conduct some preliminary tests. As the first pre-estimation test, the variance inflation factor (VIF) will be performed to ascertain whether there is any multicollinearity among the series. The second preliminary test is the Hausman test to check for the existence of heterogeneity, which would clarify the presence of random or fixed effects in our panel. Given that the economies of the selected sample have experienced various exogenous and endogenous shocks, the next pre-estimation test is to check cross-section dependency among the series. The second-generation unit root test will constitute the last preliminary test to identify whether the series are I(1) stationary or I(0) non-stationary.

Furthermore, we will conduct two different diagnostics tests after running the GMM estimations. The first is the Arellano-Bond test for zero autocorrelation in the first-differenced errors, and the second is the Sargan test to verify the overidentifying restrictions.

4. EMPIRICAL RESULTS

The VIF (checking multicollinearity among series) and Hausman (checking the nature of the panel data series) tests were conducted to identify the consistency of the GMM approach. Tables 5 and 6 present their findings.

Table 5: VIF and Hausman Test Results (Model I)

Samples	Independent Variables	Explanatory Variables					
		LLRD	LCO2	LFFC	LGDP	LURB	LHEX
20 low- and middle-income Asian countries	LLRD	–	1.10	1.42	1.02	1.18	1.53
	LCO2	1.11	–	1.10	1.21	1.10	1.51
	LFFC	1.29	1.53	–	1.39	1.39	1.40
	LGDP	1.31	1.33	1.39	–	1.42	1.21
	LURB	1.01	1.15	1.21	1.30	–	1.31
	LHEX	1.19	1.61	1.40	1.29	1.32	–
	Mean VIF	1.18	1.34	1.30	1.24	1.28	1.39
	Chi2(5)	13.21					

Note 1: LRD = Lung and respiratory diseases, CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Source: Authors' compilation.

Table 6: VIF and Hausman Test Results (Model II)

Samples	Independent Variables	Explanatory Variables					
		LUDR	LCO2	LFFC	LGDP	LURB	LHEX
20 low- and middle-income Asian countries	LUDR	–	1.42	1.53	1.19	1.29	1.02
	LCO2	1.19	–	1.47	1.32	1.19	1.35
	LFFC	1.43	1.42	–	1.29	1.04	1.28
	LGDP	1.39	1.12	1.30	–	1.38	1.44
	LURB	1.12	1.26	1.32	1.03	–	1.13
	LHEX	1.23	1.11	1.14	1.21	1.43	–
	Mean VIF	1.27	1.26	1.35	1.20	1.26	1.24
	Chi2(5)	12.14					

Note 1: URD = Undernourishment and death ratio, CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Source: Authors' compilation.

Based on Tables 5 and 6, we can conclude that there is low multicollinearity between the cross-sections. Moreover, the findings of the Hausman test (Chi2) depict the panel data with random effects. Next we should check the existence of cross-section dependence in the series. Table 7 presents the results of the cross-section dependence (CSD) test for our variables:

Table 7: Cross-section Dependence Test Results

Samples	Variables	CSD Test	Corr.	Abs. (Corr.)	Significant at 1% Level
20 low- and middle-income Asian countries	LLRD	7.14	0.363	0.363	Yes
	LUDR	9.19	0.413	0.413	Yes
	LCO2	10.01	0.392	0.392	Yes
	LFFC	8.43	0.488	0.488	Yes
	LGDP	9.28	0.317	0.317	Yes
	LURB	9.15	0.349	0.349	Yes
	LHEX	8.18	0.418	0.418	Yes

Note 1: LRD = Lung and respiratory diseases, URD = Undernourishment and death ratio, CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Source: Authors' compilation.

The results of the CSD test, presented in Table 7, confirm that cross-sections are present in all series, meaning that our samples share the same characteristics. Generally, in situations where there is low multicollinearity and cross-section dependence in the series, it is necessary to check if the variables are stationary. Thus, here we conduct the second-generation panel unit root test (Pesaran's 2007 Cross-Sectional Augmented IPS (CIPS) test) with the null hypothesis of all series being I(1). The findings of the test are reported in Table 8 and affirm that all series are I(0).

Table 8: Pesaran (2007) Panel Unit Root Test Results

Samples	Variables	Without Trend	With Trend
20 low- and middle-income Asian countries	LLRD	0.501	1.419
	LUDR	0.482	1.432
	LCO2	0.422	–0.814
	LFFC	0.366	–0.728
	LGDP	0.318	–0.782
	LURB	0.441	–0.681
	LHEX	0.512	1.482

Note 1: LRD = Lung and respiratory diseases, URD = Undernourishment and death ratio, CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB: Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Source: Authors' compilation.

By considering the results of the preliminary tests, the Arellano-Bond dynamic GMM estimations for two models (Model I and Model II) are conducted. The results of the GMM estimations for the 20 low- and middle-income Asian countries are reported in Tables 9 and 10 as follows:

Table 9: Estimation Result for Model I (Dependent Variable: LRD)

Explanatory Variables	Coefficients	Significant at 1% Level
Constant	0.19	No
LCO2	1.73	Yes
LFFC	1.38	Yes
LGDP	–0.11	Yes
LURB	0.58	Yes
LHEX	–0.41	Yes
No. of observations	560	
Range	1991–2018	
Cross-sections included	20	
Wald Chi2 (5)	616.28	Yes

Note 1: CO2 = CO2 emissions per capita, FEFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Source: Authors' compilation.

According to Table 9, CO_2 emissions per capita in low- and middle-income Asian nations lead to increased lung and respiratory diseases. Indeed, a 1% increase in CO_2 emissions per capita leads to an increase in such diseases by approximately 1.73%. With regard to fossil fuel consumption, the estimation proves that this variable leads to greater lung and respiratory diseases. A 1% increase in fossil fuel consumption may accelerate lung and respiratory diseases in these nations by nearly 1.38%.

Table 10: Estimation Result for Model II (Dependent Variable: URD)

Explanatory Variables	Coefficients	Significant at 1% Level
Constant	1.29	No
LCO2	1.24	Yes
LFFC	1.19	Yes
LGDP	–0.39	Yes
LURB	0.19	Yes
LHEX	–0.21	Yes
No. of observations	560	
Range	1991–2018	
Cross-sections included	20	
Wald Chi2 (5)	702.39	Yes

Note 1: CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Source: Authors' compilation.

Table 10 reports the estimated coefficients of variables with regard to undernourishment and death ratio. The results demonstrate that greater CO_2 emissions and fossil fuel consumption leads to increases in undernourishment and death ratio. A 1% increase in CO_2 emissions increases undernourishment and death ratio by nearly 1.24%. Furthermore, GDP per capita and health care expenditure lead to reduced undernourishment and death ratio. The estimation reveals that through a 1% increase in GDP per capita and health care expenditure, undernourishment and death ratio in low-and middle-income Asian countries may decline by approximately 0.39% and 0.21%, respectively.

5. ROBUSTNESS ANALYSIS

To ascertain the estimation results from the GMM technique, reported in Tables 9-10, we next carry out an alternative panel data technique, namely fully modified least squares (FM-OLS), to check the robustness of our major findings. As shown in Tables 11-12, the estimation findings do not significantly differ, suggesting the robustness of our results.

Table 11: Robustness Check with FM-OLS for Model I (Dependent Variable: LRD)

	Independent Variables				
Sample	**LCO2**	**LFFC**	**LGRO**	**LURB**	**LHEX**
Low- and middle-income group	1.01 ***	0.98***	–0.01***	0.14***	–0.04***

Note 1: CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Note 3: ** and *** indicate statistically significant at 1% and 5% levels.

Source: Authors' compilation.

Table 12: Robustness Check with FM-OLS for Model II (Dependent Variable: URD)

	Independent Variables				
Sample	**LCO2**	**LFFC**	**LGRO**	**LURB**	**LHEX**
Low- and middle-income group	1.32***	1.19***	–0.02***	0.05**	–0.13***

Note 1: CO2 = CO2 emissions per capita, FFC = Fossil fuel consumption, GDP = GDP per capita, URB = Urban population growth, and HEX = Health care expenditure per capita.

Note 2: (L) indicates variables in the natural logarithms.

Note 3: ** and *** indicate statistically significant at 1% and 5% levels.

Source: Authors' compilation.

6. CONCLUDING REMARKS

In this empirical study, we have attempted to analyze the energy–pollution–health nexus in 18 low- and middle-income Asian countries (namely Afghanistan, Tajikistan, Bangladesh, Indonesia, India, the Kyrgyz Republic, Cambodia, Myanmar, Pakistan, the Philippines, Uzbekistan, Viet Nam, the People's Republic of China, Iran, Kazakhstan, Sri Lanka, Malaysia, and Thailand), based on annual data over the period 1991– 2018. With regard to the methodology, through the use of the PCA technique we reduced the four health variables (TLC, RD, PU, DR) into two components – lung and respiratory diseases (LRD) and undernourishment and death ratio (UDR) – as dependent variables. Furthermore, the generalized method of moments (GMM) was utilized to estimate the coefficients of the dependent variables (CO_2 emissions per capita, fossil fuel consumption, GDP per capita, urban population growth, health care expenditure per capita).

Based on the results, we have found that CO_2 emissions per capita in low- and middle-income Asian nations have led to increased lung and respiratory diseases. Moreover, the estimation has proved that fossil fuel consumption stimulates lung and respiratory diseases. In addition, we found significant impact of urban population growth on increase of lung and respiratory diseases in low- and middle-income Asian nations. The results have demonstrated the role of CO_2 emissions and fossil fuel consumption in increasing undernourishment and death ratio. Furthermore, GDP per capita and health care expenditure have been found to reduce undernourishment and death ratio.

Our finding about the effects of CO_2 emissions on accelerating the spread of disease in countries is in line with Chaabouni et al. (2016); Aung et al. (2017); Chaabouni and Saidi (2017); Rasoulinezhad and Saboori (2018); and Apergis, Ben Jebli, and Youssef (2018). Furthermore, the positive relationship between urbanization and the spread of disease has been confirmed by Moore, Gould, and Keary (2003), although this result contradicts the findings of Geobel, Dodson, and Hill (2010) regarding the role of urbanization in affecting women's health in a South African city. In terms of the positive association between GDP per capita and health satisfaction, our result is in line with Ettner (1996) and Frijters, Haisken-DeNew, and Shields (2005), while it is in contrast with Pickett and Wilkinson (2015), who discussed the effects of income inequality as opposed to GDP per capita.

Consequently, we suggest that low- and middle-income countries adopt various policies to improve energy transition necessitating a shift from fossil fuel energy sources to renewable ones. Using fossil fuel energy sources destroys human living environments and leads to the spread of serious diseases such as cancer. Moreover, we recommend that these countries can carry out new policies in order to have easy access to electricity from green sources as well as increased renewable supply through improved technologies, sustainable economic growth, and the greater incorporation of green sources in daily social life. To this end, these countries must receive scientific, financial and technological assistance from developed countries or countries with successful histories of energy transition. In addition, given the negative implications of urbanization for human health, improving urban lifestyles is highly recommended, which may lead to a better human health in cities.

Despite some limitations such as data access, we believe that this paper makes an important contribution to the existing literature on the relationship between energy consumption and health issues in low- and middle-income Asian countries. We encourage the development of future studies that employ different control variables such as trade openness, interest rates, and inflation as part of an econometric model, that consider direct and indirect effects, and that conduct causality tests in order to distinguish short- and long-run linkages between dependent and independent variables.

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