The roles of economic growth and health expenditure on CO₂ emissions in selected Asian countries: a quantile regression model approach

Faik Bilgili 1 · Sevda Kuşkaya 2 · Masreka Khan 3 · Ashar Awan 4,5 · Oguzhan Türker 1

Received: 20 January 2021 / Accepted: 22 March 2021 / Published online: 14 April 2021
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Abstract
Continuous economic growth and the rise in energy consumption are linked with environmental pollution. Demand for health care expenditure increased after the COVID-19 pandemic. This study is interesting in modeling the nexus between public and private health expenditure, carbon dioxide emissions, and economic growth. To this end, the present study analyzed the nexus between public and private health care expenditure, economic growth, and environmental pollution for 36 Asian countries for the period 1991–2017. FMOLS, GMM, and quantile regression analysis confirm the EKC hypothesis in Asia. Besides, FMOLS and quantile regressions reached the reducing effects of government and private health expenditures on CO₂ emissions. While quantile regression results show that public and private health expenditures can mitigate CO₂ emissions; however, these results differ for various levels of CO₂. Findings of quantile regression show a significant impact of both public and private health expenditures in reducing CO₂ at the 50th and 75th quantiles but results are insignificant for the 25th quantile. Overall, the paper concludes that both government and private health sectors’ expenditures caused CO₂ emissions to decrease in Asia and that the negative impact of the private health sector on CO₂ emissions is greater than that of the government health sector. The concluding remark is that the higher the health spending, the higher the environmental quality will be in Asia. Hence, the health administrators need to increase public and private health expenditures with an effective cost-service and energy-efficient management approach to reach sustainable health services and a sustainable environment in Asia.

Keywords EKC · Asia · Climate change · CO₂ emissions · Government health expenditure · Private health expenditure

Introduction
Deterioration of the environment and carbon dioxide (CO₂) emissions have been a growing concern in the researcher and policymakers community (Saida and Kais 2018; Cheikh et al. 2020). Air quality and a healthy environment are compromised by many developing and developed countries for the sake of rapid output growth. Due to deteriorating air quality and environment, demand for health expenditures increases to keep healthy life possible (Alimi et al. 2019). Air pollution...
alone causes premature deaths of 7 million people worldwide each year (UNEP 2020). The rise in environmental pollution due to anthropogenic emissions like CO₂ influences the cost of health care expenditure (Ahmad et al. 2021). Health expenditure is continuously increasing because governments have to finance more health care infrastructure and public health insurance. Demand for health care infrastructure and insurance is increasing due to urbanization, industrial development, rise in energy consumption, infrastructure development, and rural to urban migration (Apergis et al. 2020). Higher health expenditures are the indicators of (a) awareness of the society about individual and public health, and (b) high level of the industrial production process, which might cause chemical pollution, air pollution, and carcinogenic nutrition (Gerdtham and Jönsson 2000). Thus, the analysis of the interactions between environment, expenditure on health, and economic growth becomes more vital.

For both the developed and developing world, earlier literature has witnessed a rising interest in the nexus of health expenditure, economic growth, and pollution. The literature on economic growth, health expenditure, and the environment can be seen in three groups. The first group of studies analyzed the relationship between economic growth and the environment. These studies used the Environmental Kuznets Curve (EKC) framework that established an inverse U-shaped relationship between economic growth and environmental degradation. Initially coined by Grossman and Krueger, (1995), EKC argues that with the rise in income, the environment starts decaying, then reaches plateaus, and finally drops (Inglesi-Lotz and Dogan, 2018). The second group of literature focused on expenditure on health and economic growth. This literature touched on issues like income elasticity of health expenditure (Bustamante and Shimoga 2018) and distribution of health expenditures (Fan and Savedoff 2014; Dieleman et al. 2016). The third group of the literature analyzed the interactions among health expenditures and CO₂ emissions Yu et al. (2016). Most of the studies analyzed the impact of CO₂ emission on health care expenditure; however, few studies attempted to see the impact of public and private health care expenditure on CO₂.

The pairwise relationship between economic growth and pollution is studied by previous literature in detail. Studies using EKC offer a good insight into the relationship between environmental Kuznets Curve (EKC), which presents the empirical results of study, (d) “Conclusion and policy implications” section concludes the study with policy recommendations.

Literature review

Theoretical framework

The coronavirus outbreak (SARS-CoV-2) is a specific type of infectious disease, increasing severe acute respiratory syndrome (Abbas 2020). As COVID-19 outbreaks, public outcry over economic freedom became new normal (Su et al. 2020). In the post-COVID scenario, the importance of health infrastructure increased many folds. Recent literature on the novel coronavirus (COVID-19) emphasized increasing health expenditures even at the cost of defense expenditures (Yoosefi Lebni et al. 2020).

The research on the environment, economic growth, and health expenditure can be classified in three spectra of literature. The first spectrum of literature is primarily based on the famous Environmental Kuznets Curve (EKC), which...
proposes an inverse U-shaped relation between per capita income and environmental degradation (Ulucak and Bilgili 2018). Initially coined by Grossman and Krueger (1995), EKC argues that with the rise in income, the environment starts decaying, then reaches plateaus, and finally drops (Murshed et al. 2021). Though many studies confirmed EKC’s existence, many others found different shapes of the EKC and thus left the result inconclusive (Ahmad et al. 2020). Using city-level data for China, Chen et al. (2020) found conventional EKC. On similar lines, Pata (2018), Suki et al. (2020), and He and Lin (2019) also found the existence of EKC for Turkey, Malaysia, and China, respectively. Also, Murshed and Dao (2020) investigated the validity of the EKC hypothesis for Bangladesh, India, Pakistan, Sri Lanka, and Nepal during 1972–2014. The empirical findings indicate that the EKC hypothesis is valid only for Bangladesh and India. In comparison, other studies did not find the existence of EKC in their studies, for instance, Pontarollo and Muñoz (2020) and Zhou et al. (2019).

Many studies have used the EKC framework to analyze the relationship of environmental and economic variables ranging from CO2, carbon footprints, trade openness, urbanizations, democracy, financial crises to energy sources (Grossman and Krueger 1991; Dinda, 2004; Dogan and Seker 2016; Bilgili et al., 2019a; Özcan and Öztürk 2019; Peng et al. 2020).

The health expenditure and CO2 emission nexus

The second spectrum of research has focused on the linkage between health expenditure and environmental variables. This spectrum did not receive much attention from researchers as compared to EKC literature. Recently, Ahmad et al. (2021) studied health care expenditures and CO2 emission. Using the STIRPAT framework, their study found that health care spending in China promoted CO2 emission. Zaidi and Saïdi (2018) found two-way causality between health expenditure and CO2 emission. Khan et al. (2016) found inverted U shape relation between health expenditure and income per capita. They argued that economic maturity to reduce diseases comes in the later stage of economic development. Their results provided evidence for a direct relationship between CO2 emission and health expenditure per capita. Alimi et al. (2019) investigated the impact of carbon emission on health expenditure. Using data for 15 West African countries for 1995–2014, they found environmental degradation increases health expenditures. These results are found for public health expenditure only; however, for private health expenditures, results were insignificant. It was argued by the study that individuals are not likely to spend privately on health problems caused by increased carbon emissions. Using a panel data set of 125 developing countries, Yahaya et al. (2016) found a positive impact of carbon monoxide, CO2, nitrous oxide, and income per capita on health expenditures in the long run. However, in the short run, nitrous oxide and sulfur dioxide showed no impact on per capita health expenditures in developing countries. In a recent study, Ibukun and Osinubi (2020) also confirmed that increased health expenditure are due to deteriorating environmental quality.

Green house gas (GHG) emissions were found as a significant predictor of health expenditure. Among all GHG gases, CO2 is a significant influencer, followed by carbon monoxide (Murshed et al., 2020a). Yahaya et al. (2016) used panel data of 125 countries and found GHG gases increase health care expenditures significantly. This model is further extended by Metu et al. (2017) by adding population density and infant mortality as explanatory variables of health. Gangadharan and Valenzuela (2001) found that a deteriorating environment is harming health indicators. Employing time series data from Nigeria and the ARDL model, it was found that population density and infant mortality positively affect health care expenditures. Further, there is a negative effect of GHG on health care expenditures. Similar results were found by Odusunya et al. (2014) for Nigeria that GHG harms health. However, the results contradicted other country-specific studies; for instance, Abdullah et al. (2016) found a positive relation between GHG and Malaysia’s health care expenditures.

Health expenditures are found to be a driving force in carbon emission. For instance, Blázquez-Fernández et al. (2019) revealed a positive relationship between health expenditures and CO2 emissions. Yazdi and Khanalizadeh (2017) found similar results for the MENA region. Their study obtained empirical evidence for an increase in environmental damage due to rising health expenditure. Using a panel of 20 countries, Burns (2016) presented results in favor of previous evidence that health expenditure drives carbon emissions. While analyzing the impact of electricity production and health expenditures, Zaman and Abd-el Moemen (2017) provided results revealing that health expenditures further decay the environment. Using panel data for 58 Belt and Road Initiative countries and employing GMM and FMOLS, Khan et al. (2019) found health expenditures increase carbon emission. Wang et al. (2019a) analyze the linkages among health expenditure, CO2 emissions, and GDP per capita in 18 OECD countries with the ARDL cointegration model during the period 1975–2017. They found bidirectional causality between health expenditure and CO2 emissions for New Zealand and Norway.

Various econometric methods to study the relationship between CO2 and health expenditure may or may not change the results. For instance, Ullah et al. (2019a) employed 2SLS and 3SLS using 1998–2017 data for Pakistan and found a positive effect of CO2 on health expenditures. His results are similar to Shahzad et al. (2020), which used data 1995–2017 for Pakistan using FMOLS and DOLS. Similarly, Yu et al. (2016) and Xu et al. (2019) found the same results for China that waste gas and waste increase health expenditures. Both
studies used province-level data from China and employed different techniques that are FMOLS and quantile regression models. However, Xu et al. (2019) seem that for regional comparison based on income, quantile regression is a much better choice to achieve the study's objectives. Their study found different results for low-income regions from the medium and upper-income regions in their province-level study.

The energy consumption and CO₂ emission nexus

The third strand of the literature analyzed the link between various forms of energy consumption and CO₂. CO₂ emissions are one of the most important threats to the quality of the environment (Li et al. 2021). Utilizing different methodologies, many scholars analyzed the linkage between energy consumption and CO₂. For instance, Halicioglu (2009) found a positive and significant relationship between CO₂ and energy consumption for Turkey during 1960–2005. Similar results were found by Jayanthakumaran et al. (2012) for India during 1971–2007. Yazdi and Mastorakis (2011) found a long-run relationship between CO₂ and renewable energy consumption for Iran. Using the Granger causality test, the study found bidirectional causality between renewable energy consumption and CO₂ emission. Using panel spatial simultaneous equations models on European Union data during 1995–2014, Radmehr et al. (2021) found unidirectional causality running from renewable energy to CO₂ emission. For OECD countries, non-renewable increases, whereas renewable energy decreases CO₂ (Shafiei and Salim 2014). This study used the Westerlund cointegration test and error correction model for the data during 1980–2011. However, Charfeddine and Kahia (2019) argued that renewable energy has less influence on CO₂ based on their empirical investigation. They used panel vector autoregressive (PVAR) model on data from the Middle East and North Africa (MENA) region during 1980–2015. Using 1980–2011 data from sub-Saharan Africa’s big 10 electricity generators, Inglesi-Lotz and Dogan (2018) argued that non-renewable decrease while renewable energy increase CO₂. Pata and Caglar (2021) analyzed the role of renewable energy in explaining the CO₂ level of China using annual time series data for 1980–2016. The study employed an augmented ARDL model and found that renewable energy does not affect CO₂.

Many other studies showed that energy from renewable sources has an inverse relation with the environment in developed and developing economies (Bilgili et al. 2016; Bilgili and Ulucak 2018; Destek and Sinha 2020). Findings in previous literature show that the positive role of health expenditures is more than the negative effect of renewable energy (Badulescu et al. 2019).

For more than two decades, researchers are actively analyzing the complex relationship between Economics Growth, Environment, and Health Expenditures. Earlier work revolves around the famous Environmental Kuznets Curve (EKC) which proposes an inverse U-shaped relation between per capita income and environmental degradation (Ulucak and Bilgili 2018). Later, the dynamics of growth and health expenditures grasped the attention of researchers. This literature contributed to the debate about whether health expenditure is a luxury good—that is—it receives more share with rising income or it is a normal good which should not be left for market forces and must be treated as a necessity to depend on government interventions (Murthy and Okunde 2016). Thus, a new avenue of research that is yet less explored would be the interaction of health expenditures and climate change.

Literature from public health experts and epidemiologists marked various effects of air pollutants (for instance; nitrous oxide, carbon mono oxide, and sulfur dioxide) which includes lung irritation, aggravation of cardiovascular diseases, pulmonary diseases, respiratory illness, impact on defense system on lungs, and reduced work capacity (Samet et al. 2020).

The impact of climate change on health has become an area of interest recently due to the spread of infectious diseases caused by air pollution (Khan et al. 2019, 2020a,b). Climate change has a direct impact on the ecosystem and member species (Zaidi and Saidi 2018). There is a continuous increase in the strand of literature about determinants of health expenditure. The negative impacts of climate change on health are indisputable. Zaidi and Saidi (2018) found two-way causality between health expenditure and CO₂ emissions.

With increased access to renewable energy, the health situation becomes better because of low energy bills and reduced air pollution. The money saved from energy bills could be used for better health facilities and reduced air pollution enabling citizens to enjoy better health (Apergis et al. 2018a). Khan et al. (2016) found inverted U shape relation between health expenditure and income per capita. They argued that economic maturity to reduce diseases comes in the later stage of economic development. Their results provided evidence for a direct relationship between CO₂ emission and health expenditure per capita. Alimi et al. (2019) empirically investigated the impact of carbon emission on health expenditure. Using data for 15 West African countries for the years 1995–2014, they found environmental degradation increases health expenditures. These results are found for public health expenditure only, however, for private health expenditures, results were insignificant. They argued individuals are not likely to spend privately on health problems caused by increased carbon emissions. Besides, their study found a positive effect of income per capita and expenditures on health. The fertility rate was found to be negatively related to private expenditures on health. The study argued that it might be due to less availability of budget as family size increases. Life expectancy is found positively related to public health expenditures.
Using a panel data set of 125 developing countries, Yahaya et al. (2016) found a positive impact of carbon monoxide, CO$_2$, nitrous oxide, and income per capita on health expenditures in long run. However, in the short run nitrous oxide and sulfur dioxide showed no impact on per capita health expenditures in developing countries. On the other hand, carbon monoxide and carbon dioxide emissions along with income per capita were found significant. Findings in previous literature show that the positive role of CO$_2$ emissions in health expenditures is more than the negative effect of renewable energy (Badulescu et al. 2019). The health expenditures and CO$_2$ emissions might be associated negatively or positively; it depends on GDP (Moosa and Pham 2019).

The nexus of trade openness, CO$_2$, and health care expenditure is also explored by researchers to reveal their dynamics. For instance, Ullah et al. (2019b) found a bi-directional causality between trade openness and health expenditure. Using 2SLS, 3SLS, and Granger causality method, the study found population growth has two-way causality with health expenditures. Using data from China, the results of the study revealed a negative impact of CO$_2$ on health care expenditure, while both were measured in per capita form.

Green house gas (GHG) emissions were found as a major predictor of health expenditure. Among all GHG gases, carbon dioxide emission is a major influencer followed by carbon monoxide. Yahaya et al. (2016) used panel data of 125 countries and found GHG gases increase health care expenditures significantly. This model is further extended by Metu et al. (2017) by adding population density and infant mortality as explanatory variables of health. Employing time series data from Nigeria and ARDL model, they found that population density and infant mortality positively affect health care expenditures. Further, there is a negative effect of GHG on health care expenditures. Similar results were found by Oduusuya et al. (2014) for Nigeria that GHG harms health. However, the results contradicted with other country-specific studies, for instance, Abdullah et al. (2016) found a positive relation between GHG and health care expenditures for Malaysia.

Health expenditures are found to be a deriving force in CO$_2$ emissions. For instance, Blázquez-Fernández et al. (2019) revealed a positive relationship between health expenditures and CO$_2$ emissions. A similar result was found by Yazdi and Kahanlizadeh (2017) for the MENA region. This study obtained empirical evidence for an increase in environmental damage due to rising health expenditure. A panel of 20 countries (Burns 2016) presented results too in favor of previous evidence that health expenditure drives carbon emissions. While analyzing the impact of electricity production and health expenditures, Zaman and Abd-el Moemen (2017) provided results revealing that health expenditures further decay the environment. Using panel data for 58 Belt and Road Initiative countries and employing GMM and FMOLS, Khan et al. (2019) found health expenditures increase carbon emission.

Although most of the studies presented in Table 1 show that the proxy for health used by various studies is per capita health care expenditure, however, some studies used life expectancy as a measure to capture the overall health situation. For instance, Xing et al. (2019) used life expectancy as a dependent variable and analyzed various climate-related proxies as explanatory variables. Various indicators are used in previous literature to proxy climate change. Aldieri and Vinci (2020) provided a list of various studies that used different proxy variables to capture climate change. Among them, temperature and carbon dioxide emissions are two prominent. However, our literature survey provides an extended list which includes sulfur$^1$ and nitrogen emissions, water waste from industry, and PM 10 and 2.5. Various econometric methods to study the relationship between CO$_2$ and health expenditure may or may not change the results. For instance, Ullah et al. (2019a) employed 2SLS and 3SLS using 1998–2017 data for Pakistan and found a positive effect of CO$_2$ on health expenditures. His results are similar to Shahzad et al. (2020) which used data 1995–2017 for Pakistan using FMOLS and DOLS. Similarly, Yu et al. (2016) and Xu et al. (2019) found the same results for China that waste gas and water waste increase health expenditures although they used different estimation models. Both studies used province-level data from China and employed different techniques that are FMOLS and quantile regression models. However, it seems from Xu et al. (2019) that for regional comparison based on income, quantile regression is targeting well the objective of the study. Their study found different results for low-income regions from the medium and upper-income regions in their province-level study.

Data

In estimations, panel data for Asian 36 countries for the period 1991–2017 are employed. The data definition and source are depicted in Table 2 and the list of Asian countries is presented in Table 3. To provide a visual inspection of the variables, the relevant line graphs of the panel variables are presented in figures from A1 to A6 in the appendix section. Besides, figures A7 and A8 in the appendix section show 36 individual countries’ per capita CO$_2$ emissions and 36 individual countries’ per capita health expenditures.

\(^1\) SO$_2$ is emitted majorly from vehicles and Nitrous Oxide from industrial process.
| Authors                  | Country          | Period          | Estimation Technique                      | Major Findings                                                                                                                                 |
|-------------------------|------------------|-----------------|-------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------|
| Shahzad et al. (2020)   | Pakistan         | 1995–2017       | ARDL, VECM, FMOLS, DOLS, CCR              | Growth and CO\(_2\) emissions have a positive while RE and ICT have a negative impact on health expenditure.                                |
| Ullah et al. (2019a)    | Pakistan         | 1998–2017       | 2SLS, 3SLS, Pairwise Granger Causality test | Trade increases CO\(_2\), CO\(_2\) increases HE. RE has a negative effect on HE and CO\(_2\). HE and GDP have bi-directional causality. |
| Apergis et al. (2018a)  | 42 Sub-Saharan African countries | 1995–2011       | Pedroni’s panel co-integration, FMOLS, DOLS, VECM | In SR granger causality runs from real GDP to CO\(_2\), RE, HE. In LR, unidirectional causality runs from RE to HE and CO\(_2\). HE and RE decrease while real GDP increases carbon emission. |
| Khan et al. (2016)      | Selected developed countries | 2000–2013       | GMM                                        | EKC confirmed, U shape relation between PFC and Pm2.5 with per capita income, CO\(_2\) increases HE; Energy demand increases HE; inverted u shape relationship among per capita health expenditure and GDP. |
| Zaidi and Saidi (2018)  | Sub Saharan African | 1990–2015       | ARDL, VECM                                 | In LR, EG positively impacts HE, CO\(_2\) and Nitrous oxide have a negative impact on HE. In SR, causality runs from HE to GDPPC and two-way causality among CO\(_2\), GDP, and HE and CO\(_2\). |
| Wu et al. (2020)        | Taiwan           | 1995Q1–2016Q4   | Wavelet analysis                           | There is unidirectional causality from HE per capita to CO\(_2\) emission per capita.                                                     |
| Alimi et al. (2019)     | 15 ECOWAS        | 1995–2014       | Pooled OLS, FE, System GMM                 | Carbon emission has a positive effect on public HE, but no effect on private HE.                                                           |
| Abdullah et al. (2016)  | Malaysia         | 1970–2014       | ARDL, ECM                                  | CO\(_2\), SO\(_2\), NO\(_2\) have a negative effect on HE in LR, but a positive effect in SR, GDP, FR, MR effects HE negatively in LR and SR. |
| Yu et al. (2016)        | 31 Chinese provinces | 1997–2014       | FMOLS, Panel based ECM                     | In LR waste gas, dust and smog, and water waste increase HE. In SR, Dust and Smog are insignificant, Waste gas and GDPPC significantly affect HE. |
| Yazdi and Khamalizadeh (2017) | MENA countries | 1995–2014       | ARDL                                        | CO\(_2\) and PM10 have a positive effect on HE in LR.                                                                                     |
| Yahaya et al. (2016)    | 125 Developing country | 1995–2012       | Panel OLS, and Panel DOLS                  | In LR; CO, NOX, CO\(_2\), NO, Y IN SR; SO\(_2\) and NO are insignificant; Y, CO, and CO\(_2\) contribute positively to HE. |
| Blázquez-Fernández et al. (2019) | 29 OECD countries | 1995–2014       | Dynamic panel data                         | GDPPC has a positive effect on HE. Sulfur contributes to HE in linear and Carbon monoxide in the dynamic model.                           |
| Narayan and Narayan (2008) | 8 OECD countries | 1980–1999       | Panel OLS and DOLS                         | In LR, SO, CO, and GDPPC are significant and positive, while NO is insignificant. In SR; GDPPC and CO are significant but SO and NO are not. |
| Chaabouni et al. (2016) | A global panel of 51 countries | 1995–2013       | GMM                                        | There is a unidirectional causal relationship from CO\(_2\) to HE with an exception for low-income countries. For low-income countries, there is bidirectional causality. |
| Moosa and Pham (2019)   | 8 country groups | 1995–2015       | FMOLS                                      | GDPPC is more important in determining HE for Low and middle-income countries than Environment, however, in high-income countries both are important. |
| Badulescu et al. (2019) | 28 EU countries  | 2000–2014       | ARDL                                        | In LR, CO\(_2\), GDPPC contributes positively and Renewable decreases HE. In SR, all results are the same, however, Renewable is not significant. |
| Chaabouni and Saidi (2017) | 3 groups of 51 countries | 1995–2013       | GMM, Dynamic Simultaneous Equation Model   | Bidirectional causality between GDP and CO\(_2\) and between HE and GDP. While unidirectional from CO\(_2\) to HE except for low-income countries. |
| Farooq et al. (2019)    | 30 Chinese provinces | 1996–2015       | Quantile regression                        | CO\(_2\) and population contribute positively, Afforestation negatively in HE. NO\(_2\) and SO\(_2\) have mixed results for various quintiles. Gas and oil consumption has no significant impact on Health. |
| Erdoğan et al. (2019)   | Turkey           | 1971–2016       |                                            |                                                                                                                                         |
According to the EKC hypothesis, environmental quality gets worse (CO₂ emissions will increase) at the initial income stages (at GDP_PC level) of the economies, and, later, it tends to improve as economies grow (CO₂ emissions will decrease). The growth is depicted by squared GDP_PC which is denoted by GDP_PC². Hence, one may test EKC in Eq. (1) to observe if there exists an inverted U-shaped curve between environmental quality and per capita GDP.

\[
\text{CO}_2 \cdot \text{PC}_i = f \left( \text{GDP} \cdot \text{PC}_{i_t}, \text{GDP} \cdot \text{PC}^2_{i_t} \right) \quad (1)
\]

\[
\text{CO}_2 \cdot \text{PC}_i = f \left( \text{GDP} \cdot \text{PC}_{i_t}, \text{GDP} \cdot \text{PC}^2_{i_t}, \text{Electricity Fossil}_{i_t} \right) \quad (2)
\]

\[
\text{CO}_2 \cdot \text{PC}_i = f \left( \text{GDP} \cdot \text{PC}_i, \text{GDP} \cdot \text{PC}^2_i, \text{Electricity Fossil}_i, \right. \\
\left. \text{Government Health Expenditures}_i, \text{Private Health Expenditures}_i \right) \quad (3)
\]
respectively. Later, the EKC function in Eq. (2) includes electricity production from fossil sources. In Eq. (3), the
i
v
capitalized sign of squared per capita income on per capita CO2 emissions. The estimated coefficient of electricity generation from fossil energy on carbon emissions (Eq. 2) is expected to be positive.

The influences of per capita government health expenditures and per capita private health expenditures are of interest to this research to monitor through the EKC model given in Eq. 3.

Table 2: The panel variables

| Data                                      | Definition                                      |
|-------------------------------------------|-------------------------------------------------|
| Per capita CO2 emissions (CO2_PC)         | Tonnes CO2/Population                            |
| Per capita GDP (GDP_PC)                   | GDP per capita (constant 2010 US$)              |
| Squared per capita GDP (GDP_PC^2)         | Squared GDP per capita (constant 2010 US$)      |
| Electricity production (ELECTRICITY_FOSSIL)| Electricity production from oil, gas, and coal sources (% of total) |
| Per capita private health expenditure (PRIV_HEALTH_EXPEND) | Domestic private health expenditure per capita, PPP (current international $) |
| Per capita government health expenditure (GOV_HEALTH_EXPEND) | Domestic general government health expenditure per capita (current US$) |

All data except CO2/Population are obtained from World Bank Development Indicators (2020) [Link to data source]. The data for per capita CO2/Population are extracted from IEA (2020), CO2 Emissions from Fuel Combustion [Link to data source].

Table 3: Asian countries

| 1  | Armenia 13 | Jordan 25 | Russia 26 | Environ Sci Pollut Res (2021) 28:44949–44972 |
| 2  | Azerbaijan 14 | Kazakhstan 26 | Saudi Arabia 27 | |
| 3  | Bahrain 15 | Korea Rep. 27 | Singapore 28 | |
| 4  | Bangladesh 16 | Kyrgyz Rep. 28 | Sri Lanka 29 | |
| 5  | China 17 | Lebanon 29 | Tajikistan 30 | |
| 6  | Georgia 18 | Malaysia 30 | Thailand 31 | |
| 7  | Indonesia 19 | Mongolia 31 | Turkey 32 | |
| 8  | Iraq 20 | Myanmar 32 | Turkmenistan 33 | |
| 9  | India 21 | Nepal 33 | United Arab Emirates 34 | |
| 10 | Iran 22 | Oman 34 | Uzbekistan 35 | |
| 11 | Israel 23 | Pakistan 35 | Vietnam 36 | |
| 12 | Japan 24 | Philippines 36 | Yemen Rep. 37 | |

The paper follows firstly unit root tests, later cointegration tests, and long-run parameter estimations from the Fully Modified OLS (FMOLS) method. The Y_t times series given in Eq. (4) follows an AR(1). The hypotheses presented in Eqs. (5) and (6) yield panel homogeneous panel unit root null and panel heterogeneous unit root null hypotheses, respectively.

\[ΔY_{it} = φ_1 Y_{i,t-1} + v_{it} \quad (4)\]

\[H_0 : \varphi_1 = 0 \text{ for all } i, \text{ whereas } H_A : \varphi_1 = \varphi_A ≠ 0. \quad (5)\]

\[H_0 : \varphi_1 = 0 \text{ for all } i, \text{ as } H_A : \varphi_1 ≠ 0. \quad (6)\]

Under homogeneity, \(\varphi_1\) are identical across members (cross-sections) as explained by Breitung (2000) and Levine et al., 2002). Under heterogeneity assumption, \(\varphi_i\) are not identical across members as are given in Maddala and Wu, 1999 and Im et al., 2003. \(Y_t\) is found stationary through heterogeneous unit root tests if \(\varphi_1 = \varphi_A ≠ 0\) and again \(Y_t\) is found stationary through heterogeneous unit root tests if \(\varphi_1 ≠ 0\). Eq. (7) exhibits the panel regression.

\[Y_{it} = \alpha_i + X_{it}'B_i + \eta_{it} \quad (7)\]

where \(Y, \alpha, X, \) and \(I\) denote \(k × 1\) column vector, \(k × 1\) vector of constants, \(n × m\) matrix of the independent variable(s), \(n × 1\) is slope vector, and \(\eta_{it}\) is \(k × 1\) the residual term vector, respectively. If the residual term \(\eta_{it}\) for an \(i\)th section at time \(t\) follows an \(I(0)\) process, it is stationary, and, if vector \(Y_{it}\) and matrix \(X_{it}\) follow an \(I(1)\) process, they are cointegrated as depicted in Kao et al. (1999) and Pedroni (2001). The cointegration analyses are conducted under a homogeneous variance structure (as \(B_i = B_0\)) and heterogeneous variance structure (as \(B_i ≠ B_0\)). Equation (4) explores the cointegration test conducted through Eq. (8) by following Kao et al. (1999) and Pedroni (1999).
\[ \eta_t = \gamma\eta_{t-1} + u_t \quad (8) \]

The hypotheses presented in Eqs. (9) and (10) depict homogeneous panel cointegration null and panel heterogeneous cointegration null hypotheses, respectively.

\[ H_0: \quad \gamma_1 = \gamma_0 = 1 \text{ for all } i; H_A: \gamma_1 = \gamma_0 < 1 \quad (9) \]

\[ H_0: \quad \gamma_1 = \gamma_0 = 1 \text{ for all } i; H_A: \gamma_1 < \gamma_0 \quad (10) \]

When \( \gamma_A < 1 \), one can reject the null of no cointegration.

**FMOLS methodology**

After the cointegration tests, the paper will conduct the long-run panel coefficient estimations through the FMOLS methodology. To this end, first, the long-run covariance matrix \( \Omega \) is decomposed (Kao et al. 1999).

\[ \Omega = \sum_{j=0}^{\infty} \mathbb{E} \left( \Psi_t \Psi_t' \right) = \begin{bmatrix} \Omega_{tt} & \Omega_{it} \\ \Omega_{it} & \Omega_{tt} \end{bmatrix} \quad (11) \]

where \( \Psi_t = (\mu_t, \varepsilon_t)' \). The symmetric covariance matrix is depicted in Eq. (12)

\[ \Pi = \sum_{j=0}^{\infty} \mathbb{E} \left( \Psi_t \Psi_t' \right) = \begin{bmatrix} \Pi_{tt} & \Pi_{it} \\ \Pi_{it} & \Pi_{tt} \end{bmatrix} \quad (12) \]

Then, the estimators from OLS (\( \hat{B}_{OLS} \)) and Fully Modified OLS (\( \hat{B}_{FMOLS} \)) are revealed by Eqs. (13) and (14) respectively (Basher and Mohsin 2004; Kao et al. 1999; Pedroni 2001).

\[ \hat{B}_{OLS} = \left( \sum_{i=1}^{N} (X_{it} - \bar{X}_t)^T \right)^{-1} \left( \sum_{i=1}^{N} (X_{it} - \bar{X}_t) \right) (Y_{it} - \bar{Y}_T) \quad (13) \]

\[ \hat{B}_{FMOLS} = \left( \sum_{i=1}^{N} (X_{it} - \bar{X}_t)^T \right)^{-1} \left( \sum_{i=1}^{N} (X_{it} - \bar{X}_t) \right) \left( \hat{Y}_{it} - \hat{T}_{it} \right) \quad (14) \]

and where \( \hat{B}_{OLS} \) follows the normal distribution with non-zero mean as \( \hat{B}_{FMOLS} \) follows the asymptotically normal distribution with zero means to correct endogeneity and serial correlation (Kao and Chiang 1997).

The next section yields the outputs from relevant tests and panel FMOLS estimations to observe EKC under both within dimension (homogeneous structure) and between dimension or group mean panel (heterogeneous structure).

**GMM methodology**

Generalized moments method (GMM), which is considered a nested estimation method, is one of the most followed methods of econometric analysis in the literature. The GMM methodology, allowing us to predict the moments of a population distribution relative to the moments estimated from a particular sample, was introduced by Hansen (1982). Also, GMM is widely employed in the literature because it allows different variances and autocorrelation (Mubeen et al. 2020).

In this method, unknown parameters are estimated by setting the sample averages of moment functions through Eq. (15) (Imbens 1997; Golan 2017).

\[ E [\hat{Z}_i] = 0 \quad (15) \]

For instance, one-step GMM (one optimal GMM weighting matrix) is used to predict the optimal linear combination of the moment functions (Imbens 1997; Carmichael and Coën 2020). Through the weight matrices in one-step GMM estimators, the matrices are determined independently of the estimated factors (Windmeijer 2005). The one-step system GMM estimator is obtained with the weighing matrix \( W \) as defined in Soto (2009).

\[ W = \begin{bmatrix} W_d & 0 \\ 0 & W_1 \end{bmatrix} \quad (16) \]

The Arellano and Bond (1991) type one-step estimator uses the identity matrix as a weighting matrix (Cameron and Trivedi 2005). The one-step GMM uses the weighting matrix and the estimator as defined in Eqs. (17) and (18).

\[ W_N = \left[ \sum_{i=1}^{N} Z_i Z_i' \right]^{-1} = \left[ ZZ' \right]^{-1} \quad (17) \]

\[ \hat{\beta}_{2SLS} = \left[ \left( \mu Z(W)^{-1} ZX \right) X(Z(W)^{-1} ZY) \right]^{-1} \quad (18) \]

It can be shown that the estimator is the optimal panel GMM estimator as \( u_i | Z_i \) is iid \([0, \sigma^2 I] \). The GMM estimator can be directly calculated following Eq. (19).

\[ \gamma_j = \begin{bmatrix} \Delta X_{i1}^\prime \text{ dummies} & m_{i1} & m_{i2} & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ \Delta X_{i2}^\prime \text{ dummies} & 0 & 0 & m_{i1} & m_{i2} & \cdots & 0 & \cdots & 0 \\ \Delta X_{i3}^\prime \text{ dummies} & 0 & 0 & 0 & 0 & \cdots & \cdots & \cdots & \cdots \end{bmatrix} \quad (19) \]

The first two columns are normal instruments and the following columns depict the GMM type instruments.

The next section will explore the data and estimated parameters of GLM, GMM, and quantile regressions.

**Quantile regression methodology**

In regression analysis, the ordinary least squares (OLS) regression method’s predictions do not qualify as effective predictions when their assumptions are not met (Osborne 2000). Notably, in the case of heterogeneity structure in the variance, the OLS analysis might fail to estimate the B vector efficiently and
consistently. Under this circumstance, we need alternative regression models such as quantile regression models in which heterogeneity structure and quantile structure of the data are considered (Katchova 2013; John and Nduka 2009). Quantitative regression models are flexible and more robust than the OLS model estimates since no assumptions are made about the distribution of the error term it predicts (Belaïd et al. 2020). The OLS method results in predictions based on the conditional mean (expected mean value) of the dependent variable’s response to the independent variable(s). However, quantile regression aims to estimate the conditional median or other quantiles, such as the 10th quantile, 25th quantile, 75th quantile, and 90th quantile of the response variable (Ong et al. 2015).

The quantile regression introduced by Koenker and Bassett, 1978 and developed Koenker and Hallock (2001) does not require economic variables sequence to conform to a normal distribution. Quantile regression determines the model for the selected quantities in the conditional distribution of the dependent variable (Palma et al. 2020; Sirin and Yılmaz 2020; Xuan and Lin 2020). Hence traditionally, the linear regression model is expressed as the linear regression model equation as follows:

\[ y_i = \alpha_0 + \alpha_1 x_{i1} + \ldots + \alpha_p x_{ip} + \epsilon_i \quad i = 1, \ldots, n \]  

(20)

Parameter \( p \) in Eq. (20) shows the number of parameters in the equation. The term \( i \) is equal to the number of data points. As a similar formation to the linear regression model, the quantile regression model equation for the \( \tau \) th quantile can be written as below:

\[ Q_{\tau}(y_i) = \alpha_0(\tau) + \alpha_1(\tau)x_{i1} + \ldots + \alpha_p(\tau)x_{ip} \quad i = 1, \ldots, n \]  

(21)

Thus, alpha coefficients have become functions that change depending on the quantile (Dye 2020).

Finally, the panel quantile regression model can be depicted by Eq. (22).

\[ Q_{\tau}(z_{it}) = \xi_t + \gamma(\tau)z_{it} + x_{it}^T \beta(\tau), i = 1, \ldots, n; t = 1, \ldots, T_i \]  

(22)

where \( z_{it} \) is the estimated output, \( z_{it-1} \) is the lag of the zit, \( x_{it} \) depicts the exogenous variables, and \( \xi \) denotes the \( N \times 1 \) vector of intercepts. The effects of the covariates \( z_{it-1}, x_{it} \) are allowed to depend upon the quantile, \( \tau \), of interest (Galvao and Montes-Rojas 2010).

As a summary, the graphical representation of the paper’s methodological framework is presented in Fig. 1.

**Estimation output**

Table 4 yields the descriptive statistics for panel variables. Jarque-Bera (JB) probability test results, similar to Dawar et al. (2021), verify the violation of the normality assumption. In case of the normal distribution is not valid, the \( t \) and \( F \) significance tests are still valid when the sample is large enough due to the asymptotic normality of OLS. In quantile regression analysis, the normality assumption is dropped entirely (Wenz, 2018). Machado and Silva (2019) indicate that quantile regressions via moments estimations perform well even if the errors follow high skewness and kurtosis.

Before panel data estimations, cross-sectional dependence tests and slope heterogeneity tests need to be run to avoid obtaining biased and inconsistent parameter predictions. Table 5 yields the results of cross-sectional dependence and slope heterogeneity tests. Breusch and Pagan, 1979) LM, Pesaran scaled LM, and Pesaran CD (Pesaran 2004) tests reject the null hypothesis of cross-sectional independence and, thereby, reveal the existence of cross-sectional dependence in the panel of 36 Asian countries for the period 1991–2017. The dependence might stem from some common factors such as oil prices, advances in technology, or epidemic/pandemic processes in the World. In the case of cross-sectional dependence, the fixed or panel effect panel estimations might yield biased and/or inconsistent estimators. One way to deal with cross-sectional dependence is to add the common factors in panel regression estimation. Or, one might obtain a “common correlation effect” in panel estimation to reach unbiased estimators (Henningsen and Henningsen 2019). One might also consider panel estimations through the bootstrap technique with, e.g., 1000 replications to observe the possible bias factor in estimations.

In panel data estimations, it might be assumed that all estimated coefficients are the same for each cross-sectional unit (Juhl and Lugovskyy 2014). However, population data might violate this assumption. Under this circumstance, type II error (the non-rejection of a false null hypothesis) might occur and yield biased estimated parameters. Pesaran-Yamagata Delta and Pesaran-Yamagata Adj. Delta tests (Pesaran and Yamagata 2008; Ditzen and Bersvendsen 2021) reject the null hypothesis of homogenous slopes implying that all slope coefficients are identical across the cross-sectional unit.

Panel quantile regressions can handle inconsistency issue stemming from slope heterogeneity by estimating the parameters at, e.g., lower tail, median tail, and upper tail of the conditional distribution. Therefore, the estimated quantile coefficient vector becomes function(s) of the quantile(s), and each variable’s beta coefficient will vary across quantiles. Table A1 in the appendix gives the results of quantile slope equality tests. The coefficients of GDP, Government health expenditure, and Private health expenditure at the lower tail (25th quantile), and median (50th quantile) are found significantly different. The coefficients of GDP, Electricity fossil, and Government health expenditures, at the median tail (50th quantile) and upper tail (75th quantile), are found significantly different. Overall, the null of coefficients are equal to each other is rejected by the Wald test by 1% level.
Before the estimations, one also needs to conduct the unit root tests and cointegration tests considering cross-sectional dependence to observe if variables follow I(0), or I(1) or higher order of integration process and whether variables are cointegrated or not. Therefore, we follow, next, the panel stationary and cointegration tests considering cross-sectional dependence. Table A2 reveals the panel unit root tests with cross-sectional dependence (Hadri, 2000; Breitung and Das 2005).

Breitung and Das (2005) panel unit root tests follow the null hypothesis that all the panels contain a unit root. The Hadri (2000) Lagrange multiplier (LM) considers the null hypothesis that all the panels are (trend) stationary. In both Breitung and Das (2005) and Hadri’s (2000) test, one can prefer the option(s) to include (i) panel-specific means (fixed effects), (ii) time trends, (iii) subtract cross-sectional means, and (iv) allow for cross-sectional dependence in the model of the data-generating process as described in Stata 15. Table 6 outputs indicate that the variables in levels are found nonstationary while first-differenced variables are found stationary; therefore, they are I(1).

Tables 7, 8, 9, and 10 yield the results of panel cointegration tests considering cross-sectional dependence (Westerlund 2005, 2007). The null of no cointegration is rejected by Z value of Pt of Table 7 at 1%. Westerlund tests were repeated with 500 replications (Table 8) and by 1000

### Table 4  Descriptive statistics of variables

| Descriptive statistics | CO2_PC | GDP_PC | GDP_PC2 | Electricity_Fossil | Gov_Health_Exp | Priv_Health_Exp |
|------------------------|--------|--------|---------|-------------------|----------------|----------------|
| Mean                   | 5396.205 | 9140.991 | 2.55E+08 | 73.35533          | 270.7941       | 309.6483       |
| Median                 | 3329.000 | 3469.251 | 12035822 | 83.72224          | 62.17705       | 193.2163       |
| Maximum                | 30033.000 | 65478.71 | 4.29E+09 | 100.0000          | 4374.526       | 1857.079       |
| Minimum                | 58.00000 | 190.0151 | 36105.74 | 0.000000          | 0.383601       | 17.49712       |
| Std. Dev.              | 5892.149 | 13113.58 | 6.53E+08 | 29.28478          | 550.3033       | 291.3505       |
| Skewness               | 1.726434 | 2.174567 | 3.704797 | −1.174789         | 4.045765       | 1.693184       |
| Kurtosis               | 6.020613 | 7.415922 | 17.83120 | 3.328509          | 22.86770       | 6.593192       |
| Jarque-Bera            | 852.3792 | 1555.821 | 11132.10 | 211.0662          | 11658.35       | 616.5735       |
| Probability            | 0.000000 | 0.000000 | 0.000000 | 0.000000          | 0.000000       | 0.000000       |
| Observations           | 972     | 972     | 972      | 900               | 608            | 607            |
replications (Table 9) and rejected again null of no
cointegration by Pt and Pa statistics at 5% significance level.
Finally, the variance ratio test (Table 10) verifies the existence
of cointegration at 5% significance. Eventually, the tests yield
the evidence that variables are I(1) and have a long-run rela-
tionship with a non-zero rank in the estimated matrix.

Eventually, statistical evidence reaches the conclusion that
the variables are I(1) and cointegrated which in turn indicates
that variables have a long-run relationship. Upon unit root and
cointegration test findings, one can conduct the estimations
through FMOLS, GMM, and quantile regressions.

The estimation results are presented in Tables 11, 12, and
13. Table 11 demonstrates that the Environmental Kuznets
Curve (EKC) hypothesis holds in panel Asian data. It means
that as countries develop with higher income, environmental
quality gets better. Here, environmental quality is presented
by air pollution which is denoted by CO₂ emissions. At initial
per capita income levels (GDP_PC), as income increases, the
CO₂_PC level increases as well. At later stages, as countries
improve their per capita incomes (GDP-PC 2), an increase in
GDP_PC2 causes CO₂_PC to diminish. Eventually, there ex-
ists an inverted U-shaped curve under EKC.

Table 11 gives the estimation outputs through panel
FMOLS, GMM, quantile regression (QREG) analysis. The
estimations of GDP_PC on CO₂_PC from FMOLS, GMM,
(QREG) (25), QREG (50), and QREG (75) are 0.34, 0.28,
0.53, 0.76, and 1.04, respectively. They are all significant at
the 1% level. On the other hand, the impact of GDP_PC²
obtained from FMOLS, GMM, QREG (25), QREG (50), and
QREG (75) are −1.88E-06, −1.37E-06, −7.43E-06, −1.15E-05,
and −1.00E-05, respectively. As expected hypo-
thetically, the squared GDP_PC influences CO₂_PC emis-
sions negatively, and all coefficients are found significant at
the 1% level.

Table 12 outputs indicate that in all estimations: (1) EKC
holds. Again, an inverted U-shaped EKC appears. (2) The
electricity production from fossil fuels (from oil, gas, and coal
sources) contributes positively to CO₂_PC emissions.
According to panel FMOLS, GMM and QREG estimations,
the electricity generation based on fossil sources has a signif-
ificant positive effect on carbon emissions. The estimated coef-
ficients of electricity fossil are 24.89, 26.71, 3.17, 5.41, and
33.47, respectively. They are all significant at the 5% level.

Later, we re-launched the panel data to observe the impact
of health expenditures on environmental quality in Asian
countries. We included the variables of government health
expenditures and private health expenditures into the EKC
model as depicted in Eq. (3). The results are given in Table 13.
Table 13 also indicates that the EKC hypothesis holds in 36
Asian countries. This output from Tables 11, 12, and 13 that
EKC holds are confirmed by Zhao et al. (2020), Katircioglu
et al. (2020), Shujah-ur-Rahman et al. (2020), Ahmed et al.
(2020). FMOLS regression estimations yielded significant
negative influences on health expenditures on carbon
emissions.

A unit increase in the per capita government health expen-
ditures decreases per capita carbon emissions by 0.60 units
while a unit increase in the per capita private health expendi-
tures lowers per capita carbon emissions by 2.73 units.

| Table 5 | Test for cross-sectional dependence and slope heterogeneity tests |
|---------|---------------------------------------------------------------|
|         | Value   | df  | Prob     |
| Breusch-Pagan LM | 3661.461 | 630  | 0.0000  |
| Pesaran scaled LM | 85.40173 | 630  | 0.0000  |
| Pesaran CD       | 11.34145 | 630  | 0.0000  |
| Pasaran-Yamagata Delta | 11.643  | 630  | 0.0000  |
| Pesaran-Yamagata Adj. Delta | 15.525  | 630  | 0.0000  |

| Table 6 | Panel unit root tests by allowing cross-sectional dependence (Hadri 2000; Breitung and Das 2005) |
|---------|----------------------------------------------------------------------------------|
|         | Level    | z-Statistic | P value | Difference | z-Statistic | P value |
|         |          |            |         |            |            |         |
|         | CO₂_PC   | 58.1400    | 0.0000  | CO₂_PC     | −3.3115    | 0.9995  |
|         | GDP_PC   | 78.6599    | 0.0000  | GDP_PC     | −1.9466    | 0.9742  |
|         | GDP²_PC  | 75.5128    | 0.0000  | GDP²_PC    | −0.5807    | 0.7193  |
|         | Electricity_Fossil | 34.0356 | 0.0000  | Electricity_Fossil | −4.7830 | 1.0000  |
|         | Gov_Health_Expend | 49.9433 | 0.0000  | Gov_Health_Expend | −3.2450 | 0.9994  |
|         | Priv_Health_Expend | 42.7222 | 0.0000  | Priv_Health_Expend | −4.2588 | 1.0000  |

| Table 7 | Westerlund (2007) ECM panel cointegration tests |
|---------|------------------------------------------------|
|         | Statistic | Value | Z value | P value |
|         |           |       |         |         |
|         | Gt        | −2.229 | −0.175  | 0.430   |
|         | Ga        | −2.228 | 7.211   | 1.000   |
|         | Pt        | −16.351 | −4.403  | 0.000   |
|         | Pa        | −4.097 | 2.885   | 0.998   |

ₐGt and Ga represent group mean statistics, whereas Pt and Pa denote panel statistics as indicated in Westerlund (2007)
 budgets improves air quality, this improvement occurs better due to private health expenditures.

GMM predictions reveal, on the other hand, that governmental health disbursements do not cause a recovery in environmental degradation, while private health outlays enhance the air quality in Asia. FMOLS and GMM outputs might yield the conclusion that the private expenses on hospitals, medical services, and products might have a greater positive effect on environmental quality than the governmental medical expenses on environmental quality.

The quantile regression results may provide clarity and/or support for the different results of FMOLS and GMM. The quantile regression estimates at the 25th quantile result in the conclusion that neither government nor private health expenditures have significant power on reducing CO₂ emissions. The quantile estimates also explore an insignificant effect of electric power generated from fossils on CO₂ emissions. The quantile regression predictions at 50th and 75th quartile (considering the 50th and 75th quartiles of CO₂ data) yielded, on the other hand, both government and private health investments and outlays could diminish the CO₂ emissions in Asia. In general, the FMOLS, GMM, and quantile regression analysis indicate that overall health expenditures including both government and private sectors played an important role directly or indirectly to reduce carbon emissions in selected Asian countries. After estimating the models, one also needs to observe variance inflation factor (VIF) statistics which depict the level of correlation/multicollinearity between the regressors in an equation. If there exists no multicollinearity, VIF takes the value less than 3. However, it is acceptable if it is less than 10. Table A2 in the appendix reveals that centered VIF values of regressors, except GDP_pc, are less than 10. So, the regression suffers from multicollinearity slightly in terms of GDP_pc. The correlation matrix depicted in Table A3 yields also a correlation between GDP_pc and squared GDP_pc (GDP_pc²) and between health expenditures with GDP_pc. The multicollinearity problem may not be a serious problem when R² is high and individual t statistics are significant (Johnston 1984). Blanchard (1987) also states that multicollinearity is essentially a data deficiency problem and sometimes researchers might have no choice over the available data for parameter estimations (Kennedy 1998). However, considering multicollinearity a problem in estimations, further study might launch ridge regressions or regression with centered variables or a new model by dropping a variable or some variables from the initial model(s) to eliminate the multicollinearity issue.

### Further interpretations and discussions

The ongoing COVID-19 pandemic has re-shifted the policy focus on the nitty-gritty of healthcare systems globally. To build an environmentally sustainable healthcare system, it is essential to understand the nexus between healthcare expenditure and environmental impacts. Government current and capital health expenditures are to provide government health care services that are financed by compulsory health insurance schemes, compulsory medical saving accounts (CMSA), unspecified government schemes, compulsory contributory schemes, and taxes implemented on private and government sectors. Private current and capital health expenditures are financed by voluntary health care payment schemes, NPISH financing schemes (including development agencies), enterprise financing schemes, unspecified voluntary health care payment schemes, and household out-of-pocket payments (WHO 2020).

Results of quantile regression in Table 10 show that the effect of public and private health expenditure on CO₂ emission is significant for 50th and 75th quantiles; however, it is

| Table 8 | Westerlund (2007) ECM panel cointegration tests |
|---------|-----------------------------------------------|
| Statistic | Value | Z value | P value | Robust P value |
| Gt | – 2.229 | – 0.175 | 0.430 | 0.204 |
| Ga | – 2.228 | 7.211 | 1.000 | 0.476 |
| Pt | – 16.351 | – 4.403 | 0.000 | 0.020 |
| Pa | – 4.097 | 2.885 | 0.998 | 0.016 |

| Table 9 | Westerlund (2007) ECM panel cointegration tests |
|---------|-----------------------------------------------|
| Statistic | Value | Z value | P value | Robust P value |
| Gt | – 2.194 | – 0.015 | 0.506 | 0.193 |
| Ga | – 1.718 | 4.698 | 1.000 | 0.482 |
| Pt | – 10.256 | – 2.841 | 0.002 | 0.014 |
| Pa | – 2.405 | 2.551 | 0.995 | 0.016 |

### Further interpretations and discussions

The ongoing COVID-19 pandemic has re-shifted the policy focus on the nitty-gritty of healthcare systems globally. To build an environmentally sustainable healthcare system, it is essential to understand the nexus between healthcare expenditure and environmental impacts. Government current and capital health expenditures are to provide government health care services that are financed by compulsory health insurance schemes, compulsory medical saving accounts (CMSA), unspecified government schemes, compulsory contributory schemes, and taxes implemented on private and government sectors. Private current and capital health expenditures are financed by voluntary health care payment schemes, NPISH financing schemes (including development agencies), enterprise financing schemes, unspecified voluntary health care payment schemes, and household out-of-pocket payments (WHO 2020).

Results of quantile regression in Table 10 show that the effect of public and private health expenditure on CO₂ emission is significant for 50th and 75th quantiles; however, it is
insignificant for lower quantiles. A possible explanation lies in the argument that when carbon emission is lower than a certain level, the health sector is also underdeveloped, and consequently share of the health sector in carbon emission is also low or insignificant.

Figure 2, following the estimation outputs, depicts the graphical expression revealing the potential impacts of variables on CO2 emissions. With the rise in public and private health care expenditure, our results from the quantile regression document a negative effect on carbon emission. One possible justification could be that a higher level of public and private expenditures is related to CO2 emission efficiency. Buildings, transportation, and equipment involved in health care systems improve from energy efficiency, CO2 emissions, and waste points of view. Khan et al. (2020a) noted that there could be two ways higher health expenditures could reduce CO2 emissions. Direct effect (Halkos and Paizanos 2013) that high health expenditures have redistribution effects, which raise people’s income which in turn raises the demand for a cleaner environment. After people’s demand for the normal public good is fulfilled, demand for the environment will increase in case people see it as a luxury good. The indirect effect is associated with the level of Environmental Kuznets Curve; at some level, government invests in reducing air pollution while at some level environment is compromised for achieving growth (Chaabouni et al. 2016). Energy usage, which has a great impact on the environment, is closely related to the GDP level (Abbasi et al. 2020, 2021).

Our results are different in terms of signs from Khan et al. (2020a) which found a positive association between CO2 and health expenditures for B&RI countries. Khan et al. (2020a) also documented that their results are different for different countries at various levels. Furthermore, their methodology did not use a separate measure for public and private health expenditures. Our study also employed the quantile regression method which has not been used by previous studies mention in our literature review section. Therefore, our study offers new insights into the role of public and private health care expenditure on environmental degradation. Besides the output that both government sector and private health

| Dependent variable: CO2-PC | Coefficient | Std. error | t-stat | Prob. |
|----------------------------|-------------|------------|--------|-------|
| **Panel FMOLS**<sup>a,b,c,d,e,f,g</sup> |             |            |        |       |
| GDP_PC  | 0.340558 | 0.039497 | 8.622437 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.88E-06 | 7.06E-07 | -2.670099 | 0.0077 |
| **Panel GMM**<sup>a,b,i</sup> |             |            |        |       |
| GDP_PC  | 0.284117 | 8.31E-05 | 3418.667 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.37E-06 | 8.27E-10 | -1653.708 | 0.0000 |
| **Panel quantile regression (0.25)**<sup>a,b,i</sup> |             |            |        |       |
| GDP_PC  | 0.530069 | 0.026371 | 20.10048 | 0.0000 |
| GDP_PC<sup>b</sup> | -7.43E-06 | 6.80E-07 | -10.91799 | 0.0000 |
| **Panel quantile regression (0.50)**<sup>a,b,i</sup> |             |            |        |       |
| GDP_PC  | 0.760386 | 0.022561 | 33.70431 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.15E-05 | 9.28E-07 | -12.33841 | 0.0000 |
| **Panel quantile regression (0.75)**<sup>a,b,i</sup> |             |            |        |       |
| GDP_PC  | 1.041590 | 0.040445 | 25.75333 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.00E-05 | 6.40E-07 | -15.63943 | 0.0000 |

<sup>a</sup> Cross-sections included: 36  
<sup>b</sup> Total panel (balanced) observations: 936  
<sup>c</sup> Panel method: Pooled estimation  
<sup>d</sup> Cointegrating equation deterministic: C  
<sup>e</sup> Additional regressors deterministic: @TREND  
<sup>f</sup> Coefficient covariance computed using the sandwich method (heterogeneous variance structure)  
<sup>g</sup> Long-run covariance estimates (Bartlett kernel, Newey-West fixed  
<sup>h</sup> Instrument specification: @DYN (CO2_PC,-2) GDP_PC  
<sup>i</sup> Constant added to the instrument list  
<sup>j</sup> Huber heterogeneous standard errors and covariance  
<sup>k</sup> Sparsity method: Kernel (Epanechnikov) using residuals
sector expenditures caused environmental pollution to decrease in Asia, this paper also yields the output that the negative impact of the private health sector on CO2 emissions (in absolute value) is greater than that of the government health sector. Several studies are examining the environmental impacts of health expenditure, energy use, and economic growth. Some of them prove the validity of the environmental Kuznets curve (EKC) hypothesis. Bibi and Jamil (2020) examine the association between air pollution and economic growth based on the idea of the EKC hypothesis. The result is that the EKC hypothesis is supported in all the above-mentioned regions except in the Sub-Saharan Africa region. This result is confirmed by Isik et al. (2019) for 14 states of the USA. Amri (2018) examines the linkage between CO2 emissions, trade, financial development, and energy consumption and tests the EKC hypothesis in Tunisia. Empirical results demonstrate the rejection of the EKC hypothesis. According to another significant finding, trade, financial development, and energy consumption affect negatively environmental quality. There exist also other EKC studies in the literature. For example, Dogan and Inglesi-Lotz (2020) state that EKC is not confirmed in European countries when economic structure and role of industrialization are considered. Koc and Bulus (2020), by employing GDP, renewable energy, and trade openness as regressors, investigate EKC for South Korea and, in conclusion, do not verify the hypothesis. Arain et al. (2020) present a connection between FDI, renewable energy consumption, economic growth, and carbon emission in the Chinese economy. According to the results, renewable energy consumption improves the economic

### Table 12 Panel FMOLS, GMM, and quantile regression outputs following Eq. (2)

| Dependent variable: CO2-PC | Coefficient | Std. error | t-stat | Prob. |
|---------------------------|-------------|------------|--------|-------|
| Panel FMOLS<sup>a,b,c,d,e,f,g</sup> | | | | |
| GDP_PC | 0.294130 | 0.035630 | 8.255118 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.22E-06 | 5.49E-07 | -2.225666 | 0.0263 |
| Electricity_Fossil | 24.88699 | 3.768459 | 6.604022 | 0.0000 |
| Panel GMM<sup>a,b,h,i</sup> | | | | |
| GDP_PC | 0.295856 | 0.000532 | 555.8879 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.25E-06 | 4.97E-09 | -250.9368 | 0.0000 |
| Electricity_Fossil | 26.70729 | 0.091923 | 290.5401 | 0.0000 |
| Panel quantile regression (0.25)<sup>a,b,j,k</sup> | | | | |
| GDP_PC | 0.481137 | 0.031865 | 15.09914 | 0.0000 |
| GDP_PC<sup>b</sup> | -6.45E-06 | 7.60E-07 | -8.485483 | 0.0000 |
| Electricity_Fossil | 3.172770 | 1.153612 | 2.750291 | 0.0061 |
| Panel quantile regression (0.50)<sup>a,b,j,k</sup> | | | | |
| GDP_PC | 0.687465 | 0.035834 | 19.18451 | 0.0000 |
| GDP_PC<sup>b</sup> | -1.01E-05 | 1.27E-06 | -7.942059 | 0.0000 |
| Electricity_Fossil | 5.410547 | 1.309292 | 4.132423 | 0.0000 |
| Panel quantile regression (0.75)<sup>a,b,j,k</sup> | | | | |
| GDP_PC | 0.623495 | 0.102264 | 6.096909 | 0.0000 |
| GDP_PC<sup>b</sup> | -3.87E-06 | 1.54E-06 | -2.516744 | 0.0120 |
| Electricity_Fossil | 33.47263 | 4.375306 | 7.650354 | 0.0000 |

<sup>a</sup> Cross-sections included: 36

<sup>b</sup> Total panel (balanced) observations: 792

<sup>c</sup> Panel method: Pooled estimation

<sup>d</sup> Cointegrating equation deterministic: C

<sup>e</sup> Additional regressors deterministic: @TREND

<sup>f</sup> Coefficient covariance computed using the sandwich method (heterogeneous variance structure)

<sup>g</sup> Long-run covariance estimates (Bartlett kernel, Newey-West fixed)

<sup>h</sup> Instrument specification: @DYN (CO2_PC,-2) GDP_PC

<sup>i</sup> Constant added to the instrument list

<sup>j</sup> Huber heterogeneous standard errors and covariance

<sup>k</sup> Sparsity method: Kernel (Epanechnikov) using residuals
growth rate, as inward FDI enhances the environmental degradation in the medium and long run in China. Salahuddin and Gow (2019) examine the empirical effects of economic growth, financial development, and energy consumption on environmental quality in Qatar. The empirical results yield that there is bidirectional causality between economic growth, energy consumption, and financial development and all three indicators of environmental quality. Our results confirm the findings of some seminal works in the literature. Wang et al. (b)

Table 13 Panel FMOLS, GMM, and quantile regression outputs following Eq. (3)

| Dependent variable: CO2-PC | Coefficient | Std. error | t-stat | Prob. |
|---------------------------|-------------|------------|--------|-------|
| Panel FMOLS\textsuperscript{a,b,d,e,f,g} |             |            |        |       |
| GDP\_PC | 0.719818 | 0.045065 | 15.97303 | 0.0000 |
| GDP\_PC\textsuperscript{b} | −5.31E-06 | 5.37E-07 | −9.885870 | 0.0000 |
| Electricity\_Fossil | 10.50434 | 3.033516 | 3.462761 | 0.0006 |
| Gov\_Health\_Expend | −0.595650 | 0.153190 | −3.888313 | 0.0001 |
| Priv\_Health\_Expend | −2.732644 | 0.405639 | −6.736649 | 0.0000 |
| Panel GMM\textsuperscript{a,b,h,i} |             |            |        |       |
| CO2\_PC(-1) | 0.809282 | 0.001465 | 552.5077 | 0.0000 |
| GDP\_PC | 0.152405 | 0.001493 | 102.0645 | 0.0000 |
| GDP\_PC\textsuperscript{b} | −1.19E-06 | 1.04E-08 | −115.2795 | 0.0000 |
| Electricity\_Fossil | 2.944487 | 0.284901 | 10.33514 | 0.0000 |
| Gov\_Health\_Expend | 0.147838 | 0.015304 | 9.659976 | 0.0000 |
| Priv\_Health\_Expend | −1.022370 | 0.006690 | −152.8315 | 0.0000 |
| Panel quantile regression (0.25)\textsuperscript{a,b,j,k} |             |            |        |       |
| GDP\_PC | 0.600204 | 0.084088 | 7.137765 | 0.0000 |
| GDP\_PC\textsuperscript{b} | −8.34E-06 | 1.64E-06 | −5.100121 | 0.0000 |
| Electricity\_Fossil | 2.000591 | 1.725928 | 1.159139 | 0.2469 |
| Gov\_Health\_Expend | −0.561268 | 0.501371 | −1.119465 | 0.2634 |
| Priv\_Health\_Expend | −0.892004 | 0.751940 | −1.186269 | 0.2360 |
| Panel Quantile Regression (0.50)\textsuperscript{a,b,j,k} |             |            |        |       |
| GDP\_PC | 0.949234 | 0.059301 | 16.00703 | 0.0000 |
| GDP\_PC\textsuperscript{b} | −1.24E-05 | 1.34E-06 | −9.309408 | 0.0000 |
| Electricity\_Fossil | 3.171701 | 1.669577 | 1.899704 | 0.0580 |
| Gov\_Health\_Expend | −2.276137 | 1.181928 | −1.925782 | 0.0546 |
| Priv\_Health\_Expend | −2.510034 | 0.687600 | −3.650428 | 0.0003 |
| Panel Quantile Regression (0.75)\textsuperscript{a,b,j,k} |             |            |        |       |
| GDP\_PC | 1.272247 | 0.158397 | 8.031999 | 0.0000 |
| GDP\_PC\textsuperscript{b} | −1.29E-05 | 2.13E-06 | −6.050764 | 0.0000 |
| Electricity\_Fossil | 21.50194 | 5.150120 | 4.175036 | 0.0000 |
| Gov\_Health\_Expend | −6.047287 | 0.965807 | −6.261381 | 0.0000 |
| Priv\_Health\_Expend | −4.324684 | 1.307909 | −3.306563 | 0.0010 |

\textsuperscript{a} Cross-sections included: 36
\textsuperscript{b} Total panel (balanced) observations: 573
\textsuperscript{c} Panel method: Pooled estimation
\textsuperscript{d} Cointegrating equation deterministic: C
\textsuperscript{e} Additional regressors deterministic: @TREND
\textsuperscript{f} Coefficient covariance computed using the sandwich method (heterogeneous variance structure)
\textsuperscript{g} Long-run covariance estimates (Bartlett kernel, Newey-West fixed)
\textsuperscript{h} Instrument specification: @DYN (CO2\_PC,-2) GDP\_PC
\textsuperscript{i} Constant added to the instrument list
\textsuperscript{j} Huber heterogeneous standard errors and covariance
\textsuperscript{k} Sparsity method: Kernel (Epanechnikov) using residuals
find a strong causality between CO₂ emissions, health expenditures, and economic growth through the estimations of the autoregressive distributive lag (ARDL) model for Pakistan. The findings confirm our results for the 50th and 75th quantiles except for the 25th quantile.

Sileem (2016) investigates the association between environmental degradation and health costs for MENA countries the empirical results yield that CO₂ emissions contribute to the increase in public health expenditure. Qureshi et al. (2015) observe the co-movements of health expenditures and environmental indicators for 5 Asian countries and reveal that GDP per unit use of energy, forest area, and energy consumption increase the health expenditures significantly.

The result of Sileem (2016) and Qureshi et al. (2015) are similar to our findings. We find that the higher the health spending, the higher the environmental quality will be in Asia. The highlights of this work are confirmed also by Atuahene et al. (2020), Zaidi and Saidi (2018), Chaabouni et al. (2016), Ghorashi and Alavi Rad (2017), and Apergis et al. (2020). To interpret further, we might need to look at closer the trend of demand for health in Asia with increasing life expectancy, health awareness, environmental awareness, aging, and others. The medical-health expenditures increased in Asia. Asian countries have demanded more medical and insurance services in the last two decades. For instance, in South Asia (Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, and Sri Lanka) life expectancy and health care have improved over the past decade, after previously poor health conditions and services. They reached improved life-expectancy, reduction of maternal, infant, and under-five mortality, and control of communicable diseases in the last decade (Chin et al. 2017). China, Japan, Singapore, Thailand, and South Korea have reached over 95% health coverage. Indonesia started to launch the UHC program in 2014 to achieve UHC within 5 years (Evans et al. 2016).

During the post-Soviet period, there exists some increase in health expenditure in Central Asia also. The medical-health care expenses increased in Kazakhstan, Tajikistan, and Uzbekistan while there is a recent decline in Kyrgyzstan (Kosherbayeva et al. 2020). The health expenditures overall increased in all individual 36 Asian Countries as seen in Figure A6.

The increasing health care expenditures might be explained by some factors such as an increase in health awareness (Burns et al. 2013; Fitzpatrick et al. 2010; Gupta et al. 2012) and income. Barkat et al. (2019) observe health care expenditures in eighteen Arab countries during the period 1995-2015 and reveal that income is not the only determinant of health expenses but also medical progress and an aging population have significant effects on the increase of health care expenditure in the Arab countries. It is expected that the medical technology market in the Asian continent will become the world’s second-largest medical market due to the growing population and general awareness of health issues in Asia (GBP International 2020). This market has been in transition from an oligopoly market structure to a competitive market structure. Accordingly, the demand for health care services increased prominently in Asia. The governmental health institutions and the firms running at this competitive market offer varying medical utilization services, such as varying insurance packages with varying levels of provider coverage as is in western countries such as the USA, Netherlands, Germany, and Switzerland, and others (Broek-Altenburg and Atherly 2020). The transition of medical services and reforms in Asia from a supply-oriented structure to a demand-oriented structure might have encouraged the private sector to spend/invest more in the health sector. Both government and the private sector should consider managing the cost and utilization of medical services. Besides the private sector’s increasing volume of investment in the health sector, the private sector could manage better the cost-utilization packages by considering environmentally friendly hospital buildings, medical waste, and/or the electricity usage from renewable energy sources like solar, wind, and biomass energy. Health spending needs to consider a favorable ecological footprint level with efficient energy usage (Bilgili and Ulucak 2018). The energy from waste, wind, biomass, and other renewables can help societies lower carbon emissions (Kuşkaya and Bilgili 2020; Bilgili et al. 2017, 2019b).

Traditionally in developing countries, private sector healthcare is more efficient and up to date in terms of services and technologies (Smith et al. 2001). One example of the increasing expenditure in the private healthcare sector in
Asia is India. Indian private hospitals and diagnostic centers are well-known for their medical technologies and efficient services at a relatively cheaper cost (Sengupta and Nundy 2005). Patients in Pakistan as well are more satisfied with the services in the private sector than the public sector (Javed et al. 2019). It is relatively more bureaucratic to procure and modernize technological services in the public healthcare sectors in Asian countries (UNECE 2012). Nonetheless, recently, healthcare sectors in Asia have shown high prospects of incorporating teleservices (Suzuki et al., 2020). The private sector has a proven track record in adopting innovative and environment-friendly technology such as teleservice which cut down emissions drastically (De Costa and Diwan 2007; Sood et al. 2007). Thus, the findings of this paper on the more efficient environmental-friendly outcomes of private healthcare expenditure are compatible with the existing evidence.

Health spending in private sectors is increasing day by day and according to the present research, it has better environmental outcomes. Drawing on the findings of this study, it is recommended that governments and multilateral organizations must identify the best practices in the private healthcare sectors in Asia. Afterward, the best practices which might include eco-friendly investment in technologies and services could be replicated in public health sectors for better environmental outcomes. Partnerships between the two sectors are also suggested. But, some decades ago, when private health sector investments were not sufficient, the government health care investments and expenses played an essential role to provide their societies with efficient health services in Asia. Besides, one might claim that especially in the last decade, the private health sector, as well as the government health sector, follows an environmentally friendly efficient health management policy with recent medical technological products in Asia. Waste management has generally improved in Asian countries with some differences in effectiveness (Agamuthu et al. 2009; Shekdar 2009; Ngoc and Schnitzer 2009; Dahiya 2012; Rasul 2016) and might have played an important role in health management in Asia in general. The performance of the private health sector might be intrinsically linked to the structure and performance of the public health sector, which might suggest that deriving population benefit from the private health-care sector requires a regulatory response focused on the health-care sector as a whole (Morgan et al. 2016). Multilateral organizations as the World Health Organization and the United Nations have emphasized public-private partnerships in healthcare sectors for this reason (UNECE 2012). Finally, one might claim that the further comparison of the environmental effects of health investments and management policies between government and private sector in Asia is of interest to search through some disaggregated microdata.

### Conclusion and policy implications

#### Conclusion

This research paper investigates the impact of health expenditures on CO₂ emissions in panel 36 Asian countries within the framework of the Environment Kuznets Curve (EKC) hypothesis. The panel sample period spans from 1991 to 2017. The paper, by employing FMOLS, GMM, and quantile regression methodologies, confirms the EKC in Asia. Empirical results show that as the income level of panel Asian countries grows, the environmental pollution (CO₂ emissions) gets lower.

The parameters from FMOLS highlight that both public and private health care expenditures contribute to lower CO₂ emissions in panel Asian countries. On the other hand, the parameters from GMM highlight that only private health care expenditures contribute to lower carbon emissions. The difference in parameters obtained from two distinct methodologies was further investigated using the quantile regression method. Results revealed that there is a significant effect of both public and private health expenditures in lowering CO₂ emissions for the 50th and 75th quantiles; however, the effect is insignificant for the 25th quantile. This shows that countries with a lower level of CO₂ emissions have a weak relation with health expenditures. This is worth considering finding as the effect of public and private health care expenditure on CO₂ emissions has not been studied for Asia by previous literature using the quantile regression method. Besides, this paper reached statistical evidence that both government sector and private health sector expenditures caused environmental pollution to decrease in Asia and that the negative impact of the private health sector on CO₂ emissions (in absolute value) is greater than that of the government health sector.

#### Policy implications

According to the findings of the study, high government and private health expenditures increase environmental quality. Accordingly, the paper suggests that policymakers aiming for sustainable economic growth should increase health expenditures by protecting and improving the quality of the environment. Therefore, both government and the private sector should consider managing the cost and utilization of medical services. Besides the private sector’s increasing volume of health (health care and capital) expenditures, the private sector could manage better the cost-utilization packages by considering environmentally friendly hospital management, hospital buildings, medical waste, and/or the electricity usage from renewable energy sources (like solar energy).
Our study proposes the following policy recommendations: (a) electricity production from fossil fuels should be replaced with renewable sources. It will eventually lower carbon emission without compromising on economic growth and financial support required for health care system, (b) while making buildings and procuring health-related capital such as machines and vehicles, the energy efficiency should be considered, (c) electricity based on renewables such as solar should be provided to health care units. This will reduce their financial burden as well as carbon emissions, (d) both government and the private sector should also consider managing the cost and utilization of medical services.

**Limitation and suggestions for future research**

The existence of some unavailable observations in the data of 36 Asian countries reduces the number of balanced panel observations employed in panel data estimates. In the future, new parameter estimates can be obtained by increasing the number of observations. The paper might invite future studies to follow the panel data for the European or American or African continent to confirm/disconfirm the findings of this study.

The present study used electricity from fossil fuels and health expenditures. Future researches may employ other forms of energy and health infrastructure variables (as regressors) and ecological footprint (as regressand) in the models. Also, potential future research might be recommended to use alternative methodologies such as nonlinear asymmetric approaches, regime shift bias, and/or threshold convergence analyses to check the validity of the empirical findings of this article.

While there are limited numbers of applications for quantile unit root and cointegration tests for time series, to the best of our knowledge, these applications do not cover the testing analyses for panel quantiles. Future works might conduct panel quantile unit root tests and cointegration tests by developing an algorithm considering data structure (asymptotic properties) at the lower tail, median tail, and upper tail, or at different threshold regimes for each cross-section in panel data.

To reach more unbiased, consistent, and efficient estimators, future works might also launch some bootstrap or Monte Carlo experiments to obtain bias-corrected coefficients and standard errors. Throughout regression estimations with replications, one might assert that expected values of estimated parameters will be most likely equal to their population parameters. Through updated time-periods and Monte Carlo experiments, panel regressions can also handle small sample and high variance issues to reach consistent and efficient estimations.

**Supplementary Information** The online version contains supplementary material available at https://doi.org/10.1007/s11356-021-13639-6.

**Author contribution** FB analyzed and interpreted the FMOLS, GMM, and quantile regression estimations to obtain the potential effects of private and government health expenditures on CO₂ emissions. SK performed preliminary analyses for the panel data of 36 Asian Countries and prepared the methodologies of FMOLS, GMM, and quantile regression models in the methodology section. MK reviewed the literature and wrote the introduction section and underlined the motivation of the manuscript. AA reviewed the relevant literature by focusing on the topics of ‘nexus between health expenditures and air pollution’. OT expanded the discussion section by comparing our findings with the findings of other works in the literature. All authors read and approved the final manuscript.

**Funding** Funding information is not applicable/No funding was received.

**Data availability** We authors confirm that the datasets analyzed during the current study are listed in the reference list and are publicly available as follows:

- All data except CO₂/Population are obtained from World Bank Development Indicators (2020) https://databank.worldbank.org/source/world-development-indicators#
- The data for per capita CO₂/Population are extracted from IEA (2020), CO₂ Emissions from Fuel Combustion. http://wds.iea.org/wds/pdf/Worldco2_Documentation.pdf https://www.iea.org/tandc/termsandconditions/

**Declarations**

**Ethics approval and consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Conflict of interest** The authors declare no conflict of interest.

**Authors’ agreement** We, the authors, verify that all authors have seen and approved the final version of the manuscript being submitted. We warrant that the article is the authors' original work, has not received prior publication, and is not under consideration for publication elsewhere.

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