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

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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

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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 growth and pollution (Ulucak and Bilgili 2018). The pairwise relation between health and economic growth is also studied by early studies (Apergis et al., 2018a, b; Shahzad et al. 2020). However, recent studies identified the link between environmental deterioration and health. Their focus was mainly on the impact of CO₂ emissions on health care expenditures (Khan et al. 2016). Most of the studies used aggregate-level-health-care-expenditures as their dependent variable. Their focus was either on determinants of health care expenditures, including pollution (Apergis et al., 2018a, b) or elasticities of health care

expenditures (Murthy and Okunade 2016). However, few studies used different proxies for public and private health expenditures (Alimi et al. 2019).

As compared to EKC, earlier literature paid less attention to the relationship between health, pollution, and even less to how health expenditure (public and private) is related to pollution (CO₂ emissions). This study aims to fill this gap by employing data from 36 Asian countries. Many of the countries in Asia are vulnerable to increased burden related to weak health care systems. Moreover, fragile infrastructure, lack of political will to invest in welfare systems, climate vulnerabilities, and the vast numbers of populations in Asia's continent make it a provocative case to examine. At the same time, energy consumption trends in Asian economies are critical to the environment (Murshed et al., b).

Specifically, this study is innovative from three aspects: (i) it did not use aggregate health expenditures like previous studies; instead, it used separate proxies for public and private health expenditures; (ii) this study used CO₂ emissions as a dependent variable and employed EKC framework to analyze the nexus between pollution, health expenditure, and economic growth; on the other hand, most of the earlier studies used health expenditures as dependent variable; (iii) we employed quantile regression to analyze the relationship between health and CO₂ emission for a different level of CO₂ emissions. The remaining part of this paper is organized as follows: (a) "Literature review" section, which is about literature review that covers the most relevant and useful literature in this area, (b) "Methodology" section describes data and methodology adopted for this study, (c) "Estimation output" section presents the empirical results of study, (d) "Further interpretations and discussions" section provides a discussion on findings, and (e) "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 Saidi (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 Odusanya 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 Khanalazadeh (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 to 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 decrease 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 Okunade 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, CO₂, 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 mono oxide and carbon dioxide emissions along with income per capita were found significant. Findings in previous literature show that the positive role of CO₂ emissions in health expenditures is more than the negative effect of renewable energy (Badulescu et al. 2019). The health expenditures and CO₂ emissions might be associated negatively or positively; it depends on GDP (Moosa and Pham 2019).

The nexus of trade openness, CO₂, 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 CO₂ 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 Odusanya 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 CO₂ emissions. For instance, Blázquez-Fernández et al. (2019) revealed a positive relationship between health expenditures and CO₂ emissions. A similar result was found by Yazdi and Khanalizadeh (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 sulfur¹ and nitrogen emissions, water waste from industry, and PM 10 and 2.5. 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 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 CO₂ emissions and 36 individual countries' per capita health expenditures.

¹ SO₂ is emitted majorly from vehicles and Nitrous Oxide from industrial process.

Table 1 Summary of empirical findings on climate change and health expenditures

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 bi-direction between 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 Khanalizadeh (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; SO2 and NO are insignificant; Y, CO, and CO2 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		

Table 1 (continued)

Authors	Country	Period	Estimation Technique	Major Findings
Ullah et al. (2019b)	China	1990–2017	Johansen co-integration, DOLS 2SLS, 3SLS, Granger Causality	In LR, 1% increase in CO ₂ decreases life exp. by 0.14 and increases infant mortality rate by 0.19 %. CO ₂ and Population increase HE, Trade, and Industrial production do not affect HE. Uni-directional causality runs from CO ₂ to HE. Bi-directional causality between Trade and HE and Population growth and HE.
Metu et al. (2017)	Nigeria	1990–2015	ARDL	In LR; Total GHG affects negatively HE, while all other variables are positive and significant. In SR; GHG is again negative, Population density and infant mortality contribute positively.
Yahaya et al. (2016)	125 Developing countries	1995–2012	OLS, DOLS	In LR, CO ₂ , CO, SO ₂ , NO, GDPPC, all contribute positively. After GDP, CO ₂ and CO have the highest impact on HE. In SR, all variables show the same significance and sign except SO ₂ and NO.
Abdullah et al. (2016)	Malaysia		ARDL	In LR, CO ₂ , CO, SO ₂ , NO, and GDPPC affect positively HE. In SR, CO ₂ , SO ₂ shows positive while MR and FR show negative signs.
Khan et al. (2019)	58 Belt and Road Initiative Countries	1995–2016	GMM, FMOLS	CO ₂ is positively associated with HE, GDP, and negatively with FDI and RE in LR.
Zaman and Abd-el Moemen (2017)	14 Latin American and Caribbean countries	1980–2013	FE, RE, 2SLS	Electricity, permanent cropland and HE increase CO ₂ . High technology exports reduce CO ₂ .
Apergis et al. (2018b)	50 U.S state-level data	1996–2009	Quintile Regression	Income increases health expenditures; CO ₂ increases health expenditures.
Murthy and Okunade (2016)	USA	1960–2012	ARDL Bound test	USA health care system is a necessity with income elasticity found to be 0.92
Khandelwal (2015)	India	1971–2011	ARDL, VECM	In LR, HE is significantly affected by GDP, Fiscal deficit, and Energy In SR, the only GDP has a relation with HE
Xing et al. (2019)	33 countries with high GDP	1995–2015	FE	GHG and Pm10 are negatively associated with Life expectancy after a certain level of pollution emission scale.
Xu et al. (2019)	China 30 provinces	2005–2016	Quantile regression	Waste and Gas have a positive effect on HE in high and medium-income regions and a negative in the low-income region. Income has a positive effect across all five quintiles.
Usman et al. (2019)	13 emerging economies	1994–2017	CUP-FM, CUP-BC	CO ₂ and index have a positive effect on govt. HE, but negative on private HE, GDP has a positive effect on both govt. and private HE. The aging population increases HE; secondary education decreases private HE.

LR long run, *SR* short run, *HE* health expenditures, *CO₂* carbon dioxide emissions, *SO₂* sulfur dioxide, *NO* nitrous oxide, *CO* carbon mono oxide, *WW* water waste, *GHG* greenhouse gases, *FE* fixed effect, *RE* random effect, *CUP-FM* continuously updated-fully modified, *CUP-BC* continuously updated-bias-corrected, *GDPPC* gross domestic product per capita, *EKC* environmental Kuznets curve

Methodology

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.

$$CO_2_PC_{it} = f(GDP_PC_{it}, GDP_PC_{it}^2) \quad (1)$$

$$CO_2_PC_{it} = f(GDP_PC_{it}, GDP_PC_{it}^2, Electricity\ Fossil_{it}) \quad (2)$$

$$CO_2_PC_{it} = f(GDP_PC_{it}, GDP_PC_{it}^2, Electricity\ Fossil_{it}, Government\ Health\ Expenditures_PC_{it}, Private\ Health\ Expenditures_PC_{it}) \quad (3)$$

Table 2 The panel variables

Data	Definition
Per capita CO ₂ emissions (CO ₂ _PC)	Tonnes CO ₂ /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) <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/>

where CO₂_PC, GDP_PC, and GDP_PC² represent per capita CO₂ emissions, per capita income, and squared per capita income of *i*th section of the panel at time *t*, respectively. Later, the EKC function in Eq. (2) includes electricity production from fossil sources. In Eq. (3), the EKC function employs additionally the variables of per capita government health expenditures, and per capita private health expenditures of *i*th section of panel data at time *t*. If the EKC hypothesis is true, there will be a positive sign of per capita income together with the negative 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 3 Asian countries

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

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.

$$\Delta Y_{it} = \varphi_i Y_{it-1} + v_{it} \quad (4)$$

$$H_0 : \varphi_i = \varphi_0 = 0 \text{ for all } i, \text{ whereas } H_A : \varphi_i = \varphi_A \neq \varphi_0. \quad (5)$$

$$H_0 : \varphi_i = \varphi_0 = 0 \text{ for all } i, \text{ as } H_A : \varphi_i \neq \varphi_0. \quad (6)$$

Under homogeneity, φ_i are identical across members (cross-sections) as explained by Breitung (2000) and Levine et al., (2002). Under heterogeneity assumption, φ_i are not identical across members as are given in Maddala and Wu, 1999 and Im et al., 2003. Y_{it} is found stationary through homogeneous unit root tests if $\varphi_i = \varphi_A \neq \varphi_0$ and again Y_{it} is found stationary through heterogeneous unit root tests if $\varphi_i \neq \varphi_0$. Eq. (7) exhibits the panel regression.

$$Y_{it} = \alpha_i + X'_{it} B_i + \eta_{it} \quad (7)$$

where Y , α , X , and I denote $k \times 1$ column vector, $k \times 1$ vector of constants, $k \times n$ matrix of the independent variable(s), $n \times 1$ is slope vector, and η_{it} is $k \times 1$ the residual term vector, respectively. If the residual term η_{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 $B_i \neq B_0$). Equation (4) explores the cointegration test conducted through Eq. (8) by following Kao et al. (1999) and Pedroni (1999).

$$\eta_{it} = \gamma \eta_{it-1} + u_{it} \quad (8)$$

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

$$H_0 : \gamma_i = \gamma_0 = 1 \text{ for all } i; H_A : \gamma_i = \gamma_A < 1 \neq \gamma_0. \quad (9)$$

$$H_0 : \gamma_i = \gamma_0 = 1 \text{ for all } i; H_A : \gamma_i < 1 \neq \gamma_0 \quad (10)$$

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 Ω is decomposed (Kao et al. 1999).

$$\Omega = \sum_{j=-\infty}^{\infty} E(\Psi_{ij} \Psi'_{io}) = \begin{bmatrix} \Omega_{\mu} & \Omega_{\mu\epsilon} \\ \Omega_{\epsilon\mu} & \Omega_{\epsilon} \end{bmatrix} \quad (11)$$

where $\Psi_{it} = (\mu_{it}, \epsilon'_{it})'$. The symmetric covariance matrix is depicted in Eq. (12)

$$\Pi = \sum_{j=0}^{\infty} E(\Psi_{ij} \Psi'_{io}) = \begin{bmatrix} \Pi_{\mu} & \Pi_{\mu\epsilon} \\ \Pi_{\epsilon\mu} & \Pi_{\epsilon} \end{bmatrix} \quad (12)$$

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).

$$\hat{B}_{OLS} = \left(\sum_{i=1}^N \sum_{t=1}^T (X_{it} - \bar{X}_i)^2 \right)^{-1} \left(\sum_{i=1}^N \sum_{t=1}^T (X_{it} - \bar{X}_i) (Y_{it} - \bar{Y}_i) \right) \quad (13)$$

$$\hat{B}_{FMOLS} = \left(\sum_{i=1}^N \sum_{t=1}^T (X_{it} - \bar{X}_i)^2 \right)^{-1} \left(\sum_{i=1}^N \sum_{t=1}^T (X_{it} - \bar{X}_i) (\hat{Y}_{it}^* - T \hat{\Pi}_{\epsilon\mu}^*) \right) \quad (14)$$

where $\hat{Y}_{it}^* = Y_{it} - \hat{\Omega}_{\mu\epsilon}^{-1} \hat{\Omega}_{\epsilon} \epsilon_{it}$ and $\hat{\Pi}_{\epsilon\mu}^* = \hat{\Pi}_{\epsilon\mu} - \hat{\Pi}_{\epsilon}^{-1} \hat{\Pi}_{\mu\epsilon}$

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).

$$E[Z_i' u_i] = 0 \quad (15)$$

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).

$$W_N = [Z_i' Z_i]^{-1} = [Z' Z]^{-1} \quad (17)$$

$$\hat{\beta}_{2SLS} = [X' Z(W)^{-1} Z' X]^{-1} X' Z(W)^{-1} Z' y \quad (18)$$

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

$$Y_i = \begin{pmatrix} \Delta X'_{i1} & \text{dummies} & m_{i1} & m_{i2} & 0 & 0 & 0 & \cdots & 0 & \cdots & 0 \\ \Delta X'_{i2} & \text{dummies} & 0 & 0 & m_{i1} & m_{i2} & m_{i3} & \cdots & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ \Delta X'_{i7} & \text{dummies} & 0 & 0 & 0 & 0 & 0 & \cdots & m_{i1} & \cdots & m_{i7} \end{pmatrix} \quad (19)$$

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 quantities, 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 Yilmaz 2020; Xu and Lin 2020). Hence traditionally, the linear regression model is expressed as the linear regression model equation as follows:

$$z_i = \alpha_0 + \alpha_1 y_{i1} + \dots + \alpha_p y_{ip} \quad i = 1, \dots, n \quad (20)$$

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 τ th quantile can be written as below:

$$Q_\tau(z_i) = \alpha_0(\tau) + \alpha_1(\tau)y_{i1} + \dots + \alpha_p(\tau)y_{ip} \quad i = 1, \dots, n \quad (21)$$

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).

$$Q_\tau z_{it}(\tau | z_{i,t-1}, x_{it}) = \zeta_i + \gamma(\tau)z_{i,t-1} + x_{it}^T \beta(\tau), \quad i = 1, \dots, n, t = 1, \dots, T_i \quad (22)$$

where z_{it} is the estimated output, $z_{i,t-1}$ is the lag of the z_{it} , x_{it} depicts the exogenous variables, and $\zeta = (\zeta_1, \dots, \zeta_N)'$ denotes the $N \times 1$ vector of intercepts. The effects of the covariates ($z_{i,t-1}, x_{it}$) are allowed to depend upon the quantile, τ , 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; Ditzén 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.

Fig. 1 Methodological framework

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	CO ₂ _PC	GDP_PC	GDP_PC ²	Electricity_Fossil	Gov_Health_Expend	Priv_Health_Expend
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	30033.00	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

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		0.0000
Pasaran-Yamagata Adj. Delta	15.525		0.0000

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 relationship 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 CO_2 emissions. At initial per capita income levels (GDP_PC), as income increases, the CO_2_PC level increases as well. At later stages, as countries improve their per capita incomes (GDP_PC^2), an increase in GDP_PC^2 causes CO_2_PC to diminish. Eventually, there exists 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 CO_2_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_PC^2 obtained from FMOLS, GMM, QREG (25), QREG (50), and QREG (75) are $-1.88\text{E-}06$, $-1.37\text{E-}06$, $-7.43\text{E-}06$, $-$

Table 7 Westerlund (2007) ECM panel cointegration tests

Statistic ^a	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

^a Gt and Ga represent group mean statistics, whereas Pt and Pa denote panel statistics as indicated in Westerlund (2007)

$1.15\text{E-}05$, and $-1.00\text{E-}05$, respectively. As expected hypothetically, the squared GDP_PC influences CO_2_PC emissions 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 CO_2_PC emissions. According to panel FMOLS, GMM and QREG estimations, the electricity generation based on fossil sources has a significant positive effect on carbon emissions. The estimated coefficients 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 expenditures decreases per capita carbon emissions by 0.60 units while a unit increase in the per capita private health expenditures lowers per capita carbon emissions by 2.73 units. Although an increase in both government and private health

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
CO_2_PC	58.1400	0.0000	CO_2_PC	-3.3115	0.9995
GDP_PC	78.6599	0.0000	GDP_PC	-1.9466	0.9742
GDP^2_PC	75.5128	0.0000	GDP^2_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 8 Westerlund (2007) ECM panel cointegration tests

Statistic ^a	Value	Z value	P value	Robust P value ^b
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

^a Gt and Ga represent group mean statistics as Pt and Pa denote panel statistics as explained in Westerlund (2007)

^b Robust P value through bootstrap with 500 replications

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 quantile (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

Table 9 Westerlund (2007) ECM panel cointegration tests

Statistic ^a	Value	Z value	P value	Robust P value ^b
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	0.018

^a Gt and Ga represent group mean statistics as Pt and Pa denote panel statistics in Westerlund (2007)

^b Robust P value through bootstrap with 1000 replications

Table 10 Panel cointegration test (Westerlund 2005, 2007)

	Statistic	P value
Variance Ratio (VR) ^a	− 2.0971	0.0180

Ho: No cointegration

Ha: Some panels are cointegrated

^a VR test for no cointegration by testing for the presence of a unit root in the residuals.

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 11 Panel FMOLS, GMM, and quantile regression outputs following Eq. (1)

Dependent variable: CO ₂ -PC	Coefficient	Std. error	t-stat	Prob.
Panel FMOLS ^{a,b,c,d,e,f,g}				
GDP_PC	0.340558	0.039497	8.622437	0.0000
GDP_PC ^b	− 1.88E-06	7.06E-07	− 2.670099	0.0077
Panel GMM ^{a,b,h,i}				
GDP_PC	0.284117	8.31E-05	3418.667	0.0000
GDP_PC ^b	− 1.37E-06	8.27E-10	− 1653.708	0.0000
Panel quantile regression (0.25) ^{a,b,j,k}				
GDP_PC	0.530069	0.026371	20.10048	0.0000
GDP_PC ^b	− 7.43E-06	6.80E-07	− 10.91799	0.0000
Panel quantile regression (0.50) ^{a,b,j,k}				
GDP_PC	0.760386	0.022561	33.70431	0.0000
GDP_PC ^b	− 1.15E-05	9.28E-07	− 12.33841	0.0000
Panel quantile regression (0.75) ^{a,b,j,k}				
GDP_PC	1.041590	0.040445	25.75333	0.0000
GDP_PC ^b	− 1.00E-05	6.40E-07	− 15.63943	0.0000

^a Cross-sections included: 36^b Total panel (balanced) observations: 936^c Panel method: Pooled estimation^d Cointegrating equation deterministic: C^e Additional regressors deterministic: @TREND^f Coefficient covariance computed using the sandwich method (heterogeneous variance structure)^g Long-run covariance estimates (Bartlett kernel, Newey-West fixed)^h Instrument specification: @DYN (CO₂_PC,-2) GDP_PCⁱ Constant added to the instrument list^j Huber heterogeneous standard errors and covariance^k Sparsity method: Kernel (Epanechnikov) using residuals

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

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

Dependent variable: CO ₂ -PC	Coefficient	Std. error	t-stat	Prob.
Panel FMOLS ^{a,b,c,d,e,f,g}				
GDP_PC	0.294130	0.035630	8.255118	0.0000
GDP_PC ^b	− 1.22E-06	5.49E-07	− 2.225666	0.0263
Electricity_Fossil	24.88699	3.768459	6.604022	0.0000
Panel GMM ^{a,b,h,i}				
GDP_PC	0.295856	0.000532	555.8879	0.0000
GDP_PC ^b	− 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) ^{a,b,j,k}				
GDP_PC	0.481137	0.031865	15.09914	0.0000
GDP_PC ^b	− 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) ^{a,b,j,k}				
GDP_PC	0.687465	0.035834	19.18451	0.0000
GDP_PC ^b	− 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) ^{a,b,j,k}				
GDP_PC	0.623495	0.102264	6.096909	0.0000
GDP_PC ^b	− 3.87E-06	1.54E-06	− 2.516744	0.0120
Electricity_Fossil	33.47263	4.375306	7.650354	0.0000

^a Cross-sections included: 36^b Total panel (balanced) observations: 792^c Panel method: Pooled estimation^d Cointegrating equation deterministic: C^e Additional regressors deterministic: @TREND^f Coefficient covariance computed using the sandwich method (heterogeneous variance structure)^g Long-run covariance estimates (Bartlett kernel, Newey-West fixed^h Instrument specification: @DYN (CO2_PC,-2) GDP_PCⁱ Constant added to the instrument list^j Huber heterogeneous standard errors and covariance^k 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 13 Panel FMOLS, GMM, and quantile regression outputs following Eq. (3)

Dependent variable: CO ₂ -PC	Coefficient	Std. error	t-stat	Prob.
Panel FMOLS ^{a,b,c,d,e,f,g}				
GDP_PC	0.719818	0.045065	15.97303	0.0000
GDP_PC ^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 ^{a,b,h,i}				
CO ₂ _PC(-1)	0.809282	0.001465	552.5077	0.0000
GDP_PC	0.152405	0.001493	102.0645	0.0000
GDP_PC ^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) ^{a,b,j,k}				
GDP_PC	0.600204	0.084088	7.137765	0.0000
GDP_PC ^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) ^{a,b,j,k}				
GDP_PC	0.949234	0.059301	16.00703	0.0000
GDP_PC ^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) ^{a,b,j,k}				
GDP_PC	1.272247	0.158397	8.031999	0.0000
GDP_PC ^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

^a Cross-sections included: 36^b Total panel (balanced) observations: 573^c Panel method: Pooled estimation^d Cointegrating equation deterministic: C^e Additional regressors deterministic: @TREND^f Coefficient covariance computed using the sandwich method (heterogeneous variance structure)^g Long-run covariance estimates (Bartlett kernel, Newey-West fixed)^h Instrument specification: @DYN (CO₂_PC, -2) GDP_PCⁱ Constant added to the instrument list^j Huber heterogeneous standard errors and covariance^k 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)

Fig. 2 Graphical expression of the relationship between independent variables and CO₂ “+” represents the positive impact, and “-” denotes the negative impact

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 telemedicine 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.

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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.

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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.

References

- Abbas J (2020) The impact of coronavirus (SARS-COV2) epidemic on individuals mental health: the protective measures of Pakistan in managing and sustaining transmissible disease. *Psychiatr Danub* 32(3–4):472–477. <https://doi.org/10.24869/psyd.2020.472>
- Abbasi KR, Abbas J, Tufail M (2021) Revisiting electricity consumption, price, and real GDP: A modified sectoral level analysis from Pakistan. *Energy Policy* 149:112087. <https://doi.org/10.1016/j.enpol.2020.112087>
- Abbasi KR, Hussain K, Abbas J, Adedoyin FF et al (2020) Analyzing the role of industrial sector's electricity consumption, prices, and GDP: a modified empirical evidence from Pakistan. *AIMS Energy* 9(1):29–49. <https://doi.org/10.3934/energy.2021003>
- Abdullah H, Azam M, Zakariya SK (2016) The impact of environmental quality on public health expenditure in Malaysia. *Asia Pacific Journal of Advanced Business and Social Studies* 2:365–379

- Agamuthu P, Khidzir KM, Hamid FS (2009) Drivers of sustainable waste management in Asia. *Waste Manag Res* 27(7):625–633. <https://doi.org/10.1177/0734242X09103191>
- Ahmad M, Akram W, Ikram M, Ahmad A et al (2020) Estimating dynamic interactive linkages among urban agglomeration, economic performance, carbon emissions, and health expenditures across developmental disparities. *Sustainable Production and Consumption* 26:239–255. <https://doi.org/10.1016/j.spc.2020.10.006>
- Ahmad M, Rehman A, Shah SAA, Solangi YA, Chandio AA, Jabeen G (2021) Stylized heterogeneous dynamic links among healthcare expenditures, land urbanization, and CO₂ emissions across economic development levels. *Sci Total Environ* 753(2021):142228. <https://doi.org/10.1016/j.scitotenv.2020.142228>
- Ahmed S, Ahmed K, Ismail M (2020) Predictive analysis of CO₂ emissions and the role of environmental technology, energy use and economic output: evidence from emerging economies. *Air Qual Atmos Health* 13:1035–1044. <https://doi.org/10.1007/s11869-020-00855-1>
- Aldieri L, Vinci CP (2020) Climate change and knowledge spillovers for cleaner production: new insights. *J Clean Prod* 271:122729. <https://doi.org/10.1016/j.jclepro.2020.122729>
- Alimi OY, Ajide KB, Isola WA (2019) Environmental quality and health expenditure in ECOWAS. *Environ Dev Sustain* 22(6):5105–5127. <https://doi.org/10.1007/s10668-019-00416-2>
- Amri F (2018) Carbon dioxide emissions, total factor productivity, ICT, trade, financial development, and energy consumption: testing environmental Kuznets curve hypothesis for Tunisia. *Environ Sci Pollut Res* 25:33691–33701. <https://doi.org/10.1007/s11356-018-3331-1>
- Apergis N, Ben Jebli M, Ben Youssef S (2018a) Does renewable energy consumption and health expenditures decrease carbon dioxide emissions? Evidence for sub-Saharan Africa countries. *Renew Energy* 127:1011–1016. <https://doi.org/10.1016/j.renene.2018.05.043>
- Apergis N, Bhattacharya M, Hadhri W (2020) Health care expenditure and environmental pollution: a cross-country comparison across different income groups. *Environ Sci Pollut Res* 27:8142–8156. <https://doi.org/10.1007/s11356-019-07457-0>
- Apergis N, Gupta R, Lau CKM, Mukherjee Z (2018b) U.S. state-level carbon dioxide emissions: does it affect health care expenditure? *Renew Sust Energy Rev* 91:521–530. <https://doi.org/10.1016/j.rser.2018.03.035>
- Araïn H, Sharif A, Akbar B, Younis Md Y (2020) Dynamic connection between inward foreign direct investment, renewable energy, economic growth and carbon emission in China: evidence from partial and multiple wavelet coherence. *Environ Sci Pollut Res* 27:40456–40474. <https://doi.org/10.1007/s11356-020-08836-8>
- Arellano M, Bond S (1991) Some test of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev Econ Stud* 58:277–297. <https://doi.org/10.2307/2297968>
- Atuahene SA, Yusheng K, Bentum-Micah G (2020) Health expenditure, CO₂ emissions, and economic growth: China vs. India. *Preprints*: 2020090384. <https://doi.org/10.20944/preprints202009.0384.v1>
- Badulescu D, Simut R, Badulescu A, Badulescu AV (2019) The relative effects of economic growth, environmental pollution and non-communicable diseases on health expenditures in European Union countries. *Int J Environ Res Public Health* 16(24):1–19. <https://doi.org/10.3390/ijerph16245115>
- Barkat K, Sbïa R, Maouchi Y (2019) Empirical evidence on the long and short run determinants of health expenditure in the Arab world. *Quarterly Review of Economics and Finance* 73:78–87. <https://doi.org/10.1016/j.qref.2018.11.009>
- Basher SA, Mohsin M (2004) PPP tests in cointegrated panels: evidence from Asian developing countries. *Appl Econ Lett* 11(3):163–166. <https://doi.org/10.1080/1350485042000203788>
- Belaïd F, Youssef AB, Lazaric N (2020) Scrutinizing the direct rebound effect for French households using quantile regression and data from an original survey. *Ecol Econ* 176:106755. <https://doi.org/10.1016/j.ecolecon.2020.106755>
- Bibi F, Jamil M (2020) Testing environment Kuznets curve (EKC) hypothesis in different regions. *Environ Sci Pollut Res* 28:13581–13594. <https://doi.org/10.1007/s11356-020-11516-2>
- Bilgili F, Koçak E, Bulut Ü, Kuşkaya S (2017) Can biomass energy be an efficient policy tool for sustainable development? *Renew Sust Energy Rev* 71:830–845. <https://doi.org/10.1016/j.rser.2016.12.109>
- Bilgili F, Kuskaya S, Ünü F, Gencoğlu P (2019b) Does waste energy usage mitigate the CO₂ emissions? A time-frequency domain analysis. *Environ Sci Pollut Res* 27:5056–5507. <https://doi.org/10.1007/s11356-019-07253-w>
- Bilgili F, Ulucak R (2018) Is there deterministic, stochastic and/or club convergence in ecological footprint indicator among G20 countries? *Environ Sci Pollut Res* 25:1–16. <https://doi.org/10.1007/s11356-018-3457-1>
- Bilgili F, Koçak E, Bulut Ü (2016) The dynamic impact of renewable energy consumption on CO₂ emissions: A revisited Environmental Kuznets Curve approach. *Renew Sust Energy Rev* 54:838–845. <https://doi.org/10.1016/j.rser.2015.10.080>
- Bilgili F, Muğaloğlu E, Kuşkaya S, Bağlıtaş HH, Gençoğlu P (2019a) Most up-to-date methodologic approaches. In *Environmental Kuznets Curve (EKC)* (pp. 115–139). Elsevier. <https://doi.org/10.1016/b978-0-12-816797-7.00010-2>
- Blanchard OJ (1987) Comment. *J Bus Econ Stat* 5:449–451. <https://doi.org/10.1080/07350015.1987.10509611>
- Blázquez-Fernández C, Cantarero-Prieto D, Pascual-Sáez M (2019) On the nexus of air pollution and health expenditures: new empirical evidence. *Gac Sanit* 33(4):389–394. <https://doi.org/10.1016/j.gaceta.2018.01.006>
- Breitung J, Das S (2005) Panel unit root tests under cross-sectional dependence. *Statistica Neerlandica* 59:414–433. <https://doi.org/10.1111/j.1467-9574.2005.00299.x>
- Breusch TS, Pagan AR (1979) A simple test for heteroskedasticity and random coefficient variation. *Econometrica* 47(5):1287–1294. <https://doi.org/10.2307/1911963>
- Breitung J (2000) The local power of some unit root tests for panel data. In B. H. Baltagi (Ed.), *Advances in Econometrics. Nonstationary Panels, Panel Cointegration, and Dynamic Panels* 15:161–177. Emerald Group Publishing Limited. [https://doi.org/10.1016/S0731-9053\(00\)15006-6](https://doi.org/10.1016/S0731-9053(00)15006-6)
- Broek-Altenburg EM, Atherly AJ (2020) The relation between selective contracting and healthcare expenditures in private health insurance plans in the United States. *Health Policy* 124(2):174–182. <https://doi.org/10.1016/j.healthpol.2019.12.008>
- Burns S, Garcha S, Sobalova R, Kim C et al (2013) Heart health risk awareness and knowledge translation in young South Asians. *Can J Cardiol* 29(10):413. <https://doi.org/10.1016/j.cjca.2013.07.765>
- Burns TJ (2016) Department of sociology, Humboldt State University globalization, the environment, and infant mortality: A Cross-national study Author (s): Andrew K Jorgenson and Thomas J Burns Source. *Humboldt Journal of Social Relations* 28(1):7–52
- Bustamante AV, Shimoga SV (2018) Comparing the income elasticity of health spending in middle-income and high-income countries: the role of financial protection. *Int J Health Policy Manag* 7(3):255–263. <https://doi.org/10.15171/IJHPM.2017.83>
- Cameron AC, Trivedi PK (2005) *Microeconometrics: methods and applications*. Cambridge University Press. <http://cameron.econ.ucdavis.edu/mmabook/mma.html>
- Carmichael B, Coën A (2020) Real estate as a common risk factor in the financial sector: international evidence. *Financ Res Lett* 32:101172. <https://doi.org/10.1016/j.frl.2019.04.029>
- Chaabouni S, Saidi K (2017) The dynamic links between carbon dioxide (CO₂) emissions, health spending and GDP growth: A case study for 51 countries. *Environ Res* 158:137–144. <https://doi.org/10.1016/j.envres.2017.05.041>

- Chaabouni S, Zghidi N, Mbarek MB (2016) On the causal dynamics between CO2 emissions, health expenditures and economic growth. *Sustain Cities Soc* 22:184–191. <https://doi.org/10.1016/j.scs.2016.02.001>
- Charfeddine L, Kahia M (2019) Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: a panel vector autoregressive (PVAR) analysis. *Renew Energy* 139:198–213. <https://doi.org/10.1016/j.renene.2019.01.010>
- Cheikh NB, Zaied YB, Chevallier J (2020) On the nonlinear relationship between energy use and CO2 emissions within an EKC framework: Evidence from panel smooth transition regression in the MENA region. *Res Int Bus Financ* 55:101331. <https://doi.org/10.1016/j.ribaf.2020.101331>
- Chen H, Zhang X, Wu R, Cai T (2020) Revisiting the environmental Kuznets curve for city-level CO2 emissions: based on corrected NPP-VIIRS nighttime light data in China. *J Clean Prod* 268: 121575. <https://doi.org/10.1016/j.jclepro.2020.121575>
- Chin B, Rani M, Bonu S (2017) South Asia, Health Systems of. In: Quah SR (ed) *International Encyclopedia of Public Health* (2nd ed., pp. 1–9). Elsevier Inc. <https://doi.org/10.1016/B978-0-12-803678-5.00422-7>
- Dahiya B (2012) Cities in Asia, 2012: Demographics, economics, poverty, environment and governance. *Cities* 29:S44–S61. <https://doi.org/10.1016/j.cities.2012.06.013>
- Dawar I, Dutta A, Bouri E, Saeed T (2021) Crude oil prices and clean energy stock indices: Lagged and asymmetric effects with quantile regression. *Renew Energy* 163:288–299. <https://doi.org/10.1016/j.renene.2020.08.162>
- De Costa A, Diwan V (2007) Where is the public health sector?. Public and private sector healthcare provision in Madhya Pradesh. *India Health Policy* 84(2–3):269–276. <https://doi.org/10.1016/j.healthpol.2007.04.004>
- Destek MA, Sinha A (2020) Renewable, non-renewable energy consumption, economic growth, trade openness and ecological footprint: Evidence from organisation for economic Co-operation and development countries. *J Clean Prod* 242:118537. <https://doi.org/10.1016/j.jclepro.2019.118537>
- Dieleman JL, Templin T, Sadat N, Reidy P, Chapin A, Foreman K, Haakenstad A, Evans T, Murray CJL, Kurowski C (2016) National spending on health by source for 184 countries between 2013 and 2040. *Lancet* 387(10037):2521–2535
- Dinda S (2004) Environmental Kuznets Curve hypothesis: a survey. *Ecol Econ* 49(4):431–455. <https://doi.org/10.1016/j.ecolecon.2004.02.011>
- Ditzen J and Bersvendsen T (2021). *XTHST: Stata module to test slope homogeneity in large panels*, "Statistical Software Components S458714, Boston College Department of Economics. <http://fmwww.bc.edu/repec/bocode/x/xthst ado>
- Dogan E, Inglesi-Lotz R (2020) The impact of economic structure to the environmental Kuznets curve (EKC) hypothesis: evidence from European countries. *Environ Sci Pollut Res* 27:12717–12724. <https://doi.org/10.1007/s11356-020-07878-2>
- Dogan E, Seker F (2016) The influence of real output, renewable and non-renewable energy, trade and financial development on carbon emissions in the top renewable energy countries. *Renew Sust Energ Rev* 60:1074–1085. <https://doi.org/10.1016/j.rser.2016.02.006>
- Dye S (2020) Quantile Regression, <https://towardsdatascience.com/quantile-regression-f2343c4a03> (Accessed 07.07.2020).
- Erdoğan S, Yıldırım DÇ, Gedikli A (2019) The Relationship Between CO2 Emissions and Health Indicators. *Econ Lett* 6:28–39
- Evans J, Wickstead R, Hanman K, Steeves S (2016) Universal health coverage in countries across East and Southeast Asia – Associations Between Health Expenditure and Service Provision. *Value Health* 19(7):A820–A821. <https://doi.org/10.1016/j.jval.2016.08.621>
- Fan VY, Savedoff WD (2014) The health financing transition: a conceptual framework and empirical evidence. *Soc Sci Med* 105:112–121. <https://doi.org/10.1016/j.socscimed.2014.01.014>
- Farooq MU, Shahzad U, Sarwar S, Zaijun L (2019) The impact of carbon emission and forest activities on health outcomes: Empirical evidence from China. *Environ Sci Pollut Res* 26(13):12894–12906. <https://doi.org/10.1007/s11356-019-04779-x>
- Fitzpatrick AL, Steinman LE, Tu SP, Ly KA, Ton TGN, Yip MP, Sin MK (2010) Using photovoice to understand cardiovascular health awareness in Asian elders. *Health Promot Pract* 13(1):48–54. <https://doi.org/10.1177/1524839910364381>
- Galvao AF, Montes-Rojas GV (2010) Penalized quantile regression for dynamic panel data. *Journal of Statistical Planning and Inference* 140:3476–3497. <https://doi.org/10.1016/j.jspi.2010.05.008>
- Gangadharan L, Valenzuela MR (2001) Interrelationships between income, health and the environment: extending the Environmental Kuznets Curve hypothesis. *Ecol Econ* 36(3):513–531. [https://doi.org/10.1016/S0921-8009\(00\)00250-0](https://doi.org/10.1016/S0921-8009(00)00250-0)
- GBP International (2020) How can EU companies meet growing demand for medical technology in Asia?, <https://gbp-international.com/blog/2019/12/18/medical-technology-in-asia/> (Accessed: 6 Sep. 2020).
- Gerdtham U-G, Jönsson B (2000) International comparisons of health expenditure: theory, data and econometric analysis. *Handb Health Econ, Part A*: 11–53. [https://doi.org/10.1016/S1574-0064\(00\)80160-2](https://doi.org/10.1016/S1574-0064(00)80160-2)
- Ghorashi N, Alavi Rad A (2017) CO2 Emissions, Health Expenditures and Economic Growth in Iran: Application of Dynamic Simultaneous Equation Models. *Journal of Community Health Research* 6(2):109–116 <https://www.sid.ir/en/journal/ViewPaper.aspx?id=571184>
- Golan A (2017) Foundations of info-metrics: modeling, inference, and imperfect information. In *Foundations of Info-Metrics: Modeling, Inference, and Imperfect Information*. Oxford University Press. <https://doi.org/10.1093/oso/9780199349524.001.0001>
- Grossman GM, Krueger AB (1995) Economic growth and the environment. *Q J Econ* 110(2):353–377. <https://doi.org/10.2307/2118443>
- Grossman GM, Krueger AB (1991) Environmental impacts of a North American free trade agreement. *National Bureau of Economic Research Working Paper Series* 3914(3914):1–57. <https://doi.org/10.3386/w3914>
- Gupta R, Pandey R, Misra A et al (2012) High prevalence and low awareness, treatment and control of hypertension in Asian Indian women. *J Hum Hypertens* 26:585–593. <https://doi.org/10.1038/jhh.2011.79>
- Hadri K (2000) Testing for stationarity in heterogeneous panel data. *Econ J* 3:148–161 <https://www.jstor.org/stable/23114886>
- Halicioglu F (2009) An econometric study of CO2 emissions, energy consumption, income and foreign trade in Turkey. *Energy Policy* 37(3):1156–1164. <https://doi.org/10.1016/j.enpol.2008.11.012>
- Halkos GE, Paizanos EA (2013) The effect of government expenditure on the environment: an empirical investigation. *Ecol Econ* 91:48–56. <https://doi.org/10.1016/j.ecolecon.2013.04.002>
- Hansen LP (1982) Large sample properties of generalized method of moments estimators. *Econometrica* 50(4):1029–1054. <https://doi.org/10.2307/1912775>
- He Y, Lin B (2019) Investigating environmental Kuznets curve from an energy intensity perspective: Empirical evidence from China. *J Clean Prod* 234:1013–1022. <https://doi.org/10.1016/j.jclepro.2019.06.121>
- Henningsen A, Henningsen G (2019) Analysis of panel data using R. *Panel Data Econometrics*:345–396. <https://doi.org/10.1016/B978-0-12-814367-4.00012-5>
- Ibukun CO, Osinubi TT (2020) Environmental quality, economic growth, and health expenditure: empirical evidence from a panel of African countries. *African Journal of Economic Review* 8(2)

- IEA (2020) CO₂ Emissions From Fuel Combustion 2020 Edition Database Documentation. http://wds.iea.org/wds/pdf/Worldco2_Documentation.pdf.
- Im KS, Pesaran MH, Shin Y (2003) Testing for unit roots in heterogeneous panels. *J Econ* 115(1):53–74. [https://doi.org/10.1016/S0304-4076\(03\)00092-7](https://doi.org/10.1016/S0304-4076(03)00092-7)
- Imbens GW (1997) One-Step Estimators for Over-Identified Generalized Method of Moments Models. *Rev Econ Stud* 64(3):359. <https://doi.org/10.2307/2971718>
- Inglesi-Lotz R, Dogan E (2018) The role of renewable versus non-renewable energy to the level of CO₂ emissions a panel analysis of Sub-Saharan Africa's big 10 electricity generators. *Renew Energy* 123:36–43. <https://doi.org/10.1016/j.renene.2018.02.041>
- Isik C, Ongan S, Özdemir D (2019) The economic growth/development and environmental degradation: evidence from the US state-level EKC hypothesis. *Environ Sci Pollut Res* 26:30772–30781. <https://doi.org/10.1007/s11356-019-06276-7>
- Javed SA, Liu S, Mahmoudi A, Nawaz M (2019) Patients' satisfaction and public and private sectors' health care service quality in Pakistan: Application of grey decision analysis approaches. *Int J Health Plann Manag* 34(1):e168–e182. <https://doi.org/10.1002/hpm.2629>
- Jayanthakumaran K, Verma R, Liu Y (2012) CO₂ emissions, energy consumption, trade and income: a comparative analysis of China and India. *Energy Policy* 42:450–460. <https://doi.org/10.1016/j.enpol.2011.12.010>
- John OO, Nduka EC (2009) Quantile regression analysis as a robust alternative to ordinary least squares. *Scientia Africana* 8(2):61–65. <https://doi.org/10.14419/ijasp.v3i2.4686>
- Johnston J (1984) *Econometric Methods*, 3rd edn. McGraw-Hill, New York, p 249
- Juhl T, Lugovskyy O (2014) A test for slope heterogeneity in fixed effects models, econometric reviews. *Aust Econ Rev* 33(8):906–935. <https://doi.org/10.1080/07474938.2013.806708>
- Kao C, Chiang M-H, Chen B (1999) International R&D spillovers: An application of estimation and inference in panel cointegration. *Oxf Bull Econ Stat* 61:693–711. <https://doi.org/10.1111/1468-0084.0610s1691>
- Kao C, Chiang M-H (1997) On the estimation and inference of a cointegrated regression in panel data. *SSRN Electron J*:1–24. <https://doi.org/10.2139/ssrn.2379>
- Katchova A (2013) Quantile regression example, https://docs.google.com/file/d/0BwogTI8d6EEi_TjJpSGxLSzBmaXc/edit. (Accessed 08.09.2020).
- Katircioglu S, Katircioglu S, Saqib N (2020) Does higher education system moderate energy consumption and climate change nexus? Evidence from a small island. *Air Qual Atmos Health* 13:153–160. <https://doi.org/10.1007/s11869-019-00778-6>
- Kennedy P (1998) *A Guide to Econometrics*, 4th edn. MIT Press, Cambridge, p 190
- Khan A, Hussain J, Bano S, Chenggang Y (2020a) The repercussions of foreign direct investment, renewable energy and health expenditure on environmental decay? An econometric analysis of BandRI countries. *J Environ Plan Manag* 63(11):1965–1986. <https://doi.org/10.1080/09640568.2019.1692796>
- Khan SAR, Sharif A, Golpîra H, Anil Kumar A (2019) A green ideology in Asian emerging economies: From environmental policy and sustainable development. *Sustain Dev* 27:1063–1075. <https://doi.org/10.1002/sd.1958>
- Khan SAR, Zaman K, Zhang Y (2016) The relationship between energy-resource depletion, climate change, health resources and the environmental Kuznets curve: Evidence from the panel of selected developed countries. *Renew Sust Energ Rev* 62:468–477. <https://doi.org/10.1016/j.rser.2016.04.061>
- Khan SAR, Zhang Y, Kumar A, Zavadskas E, Streimikiene D (2020b) Measuring the impact of renewable energy, public health expenditure, logistics, and environmental performance on sustainable economic growth. *Sustain Dev* 28:833–843. <https://doi.org/10.1002/sd.2034>
- Khandelwal V (2015) Impact of Energy Consumption, GDP and Fiscal Deficit on Public Health Expenditure in India: An ARDL Bounds Testing Approach. *Energy Procedia* 75:2658–2664. <https://doi.org/10.1016/j.egypro.2015.07.652>
- Koenker R, Bassett G (1978) Regression quantiles. *Econometrica* 46(1):33–50. <https://doi.org/10.2307/1913643>
- Koenker R, Hallock KF (2001) Quantile regression. *J Econ Perspect* 15(4):143–156. <https://doi.org/10.1257/jep.15.4.143>
- Koc S, Bulus GC (2020) Testing validity of the EKC hypothesis in South Korea: role of renewable energy and trade openness. *Environ Sci Pollut Res* 27:29043–29054. <https://doi.org/10.1007/s11356-020-09172-7>
- Kosherbayeva L, Kalmakhanov S, Hailey D, Pazilov S, et al (2020) Rethinking priorities in hospital management: a case from Central Asia. In *Health Policy and Technology* 9(3): 391–396. Elsevier B.V. <https://doi.org/10.1016/j.hlpt.2020.06.002>
- Kuşkaya S, Bilgili F (2020) The wind energy-greenhouse gas nexus: The wavelet-partial wavelet coherence model approach. *J Clean Prod* 245:118872. <https://doi.org/10.1016/j.jclepro.2019.118872>
- Levine A, Lin CF, Chu CS (2002) Unit root tests in panel data: asymptotic and finite-sample properties. *J Econ* 108:1–24. [https://doi.org/10.1016/S0304-4076\(01\)00098-7](https://doi.org/10.1016/S0304-4076(01)00098-7)
- Li ZZ, Li RYM, Malik MY, Murshed M, Khan Z, Umar M (2021) Determinants of carbon emission in China: How good is green investment? *Sustainable Production and Consumption* 27:392–401. <https://doi.org/10.1016/j.spc.2020.11.008>
- Machado JAF, Silva JMCS (2019) Quantiles via moments. *J Econom* 213(1):145–173. <https://doi.org/10.1016/j.jeconom.2019.04.009>
- Maddala GS, Wu S (1999) A comparative study of unit root tests with panel data and a new simple test. *Oxf Bull Econ Stat* 61:631–652. <https://doi.org/10.1111/1468-0084.0610s1631>
- Metu AG, Kalu C, Ezenekwe U, Olisaemeka D (2017) Does greenhouse gas emission have any relevance to per capita health expenditure? *Empirical Evidence from Nigeria. African Journal of Sustainable Development* 7(3):17–36
- Moosa N, Pham HNA (2019) The effect of environmental degradation on the financing of healthcare. *Emerg Mark Financ Trade* 55(2):237–250. <https://doi.org/10.1080/1540496X.2018.1439375>
- Morgan R, Ensor T, Walter H (2016) Performance of private sector health care: implications for universal health coverage. *Lancet* 388(10044):606–612. [https://doi.org/10.1016/S0140-6736\(16\)00343-3](https://doi.org/10.1016/S0140-6736(16)00343-3)
- Mubeen R, Han D, Abbas J, Hussain I (2020) The effects of market competition, capital structure, and CEO duality on firm performance: A mediation analysis by incorporating the GMM model technique. *Sustainability* 12(8):3480. <https://doi.org/10.3390/su12083480>
- Murshed M, Alam R, Ansarin A (2021) The environmental Kuznets curve hypothesis for Bangladesh: the importance of natural gas, liquefied petroleum gas, and hydropower consumption. *Environ Sci Pollut Res* 28:17208–17227. <https://doi.org/10.1007/s11356-020-11976-6>
- Murshed M, Ali SY, Banerjee S (2020a) Consumption of liquefied petroleum gas and the EKC hypothesis in South Asia: evidence from cross-sectionally dependent heterogeneous panel data with structural breaks. *Energy, Ecology and Environment*. <https://doi.org/10.1007/s40974-020-00185-z>
- Murshed M, Dao NTT (2020) Revisiting the CO₂ emission-induced EKC hypothesis in South Asia: The role of export quality improvement. *GeoJournal*. <https://doi.org/10.1007/s10708-020-10270-9>
- Murshed M, Mahmood H, Alkhateeb TTY, Banerjee S (2020b) Calibrating the impacts of regional trade integration and renewable energy transition on the sustainability of international inbound

- tourism demand in south Asia. *Sustainability* 12(20):8341. <https://doi.org/10.3390/su12208341>
- Murthy VNR, Okunade AA (2016) Determinants of U.S. health expenditure: evidence from autoregressive distributed lag (ARDL) approach to cointegration. *Econ Model* 59:67–73. <https://doi.org/10.1016/j.econmod.2016.07.001>
- Narayan PK, Narayan S (2008) Does environmental quality influence health expenditures? Empirical evidence from a panel of selected OECD countries. *Ecol Econ* 65(2):367–374. <https://doi.org/10.1016/j.ecolecon.2007.07.005>
- Ngoc UN, Schnitzer H (2009) Sustainable solutions for solid waste management in Southeast Asian countries. *Waste Manag* 29(6):1982–1995. <https://doi.org/10.1016/j.wasman.2008.08.031>
- Oduşunya A, Adegboyega SB, Kuku MA (2014) Environmental quality and health care spending in Nigeria. *Fountain Journal of Management and Social Science* 3(2):57–67
- Ong B, Lee TM, Li G, Chuen DLK (2015) Evaluating the potential of alternative cryptocurrencies. In: Chuen DLK (ed) *Handbook of Digital Currency: Bitcoin, Innovation, Financial Instruments, and Big Data* (pp. 81–135). Elsevier Inc. <https://doi.org/10.1016/B978-0-12-802117-0.00005-9>
- Osborne JW (2000) Prediction in multiple regression. *Pract Assess Res Eval* 7(2). <https://doi.org/10.7275/7j20-gg86>
- Özcan B, Öztürk I (2019) *Environmental Kuznets Curve: a manual*. (B. Özcan & I. Öztürk, Eds.) (First). Academic Press-Elsevier.
- Palma M, Tavakoli S, Brettschneider J, Nichols TE (2020) Quantifying uncertainty in brain-predicted age using scalar-on-image quantile regression. *NeuroImage* 219:116938. <https://doi.org/10.1016/j.neuroimage.2020.116938>
- Pata UK (2018) Renewable energy consumption, urbanization, financial development, income and CO2 emissions in Turkey: Testing EKC hypothesis with structural breaks. *J Clean Prod* 187(2018):770–779. <https://doi.org/10.1016/j.jclepro.2018.03.236>
- Pata UK, Caglar AE (2021) Investigating the EKC hypothesis with renewable energy consumption, human capital, globalization and trade openness for China: Evidence from augmented ARDL approach with a structural break. *Energy* 216:119220. <https://doi.org/10.1016/j.energy.2020.119220>
- Pedroni P (1999) Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxf Bull Econ Stat* 61:653–670. <https://doi.org/10.1111/1468-0084.0610s1653>
- Pedroni P (2001) Purchasing power parity tests in cointegrated panels. *Rev Econ Stat* 83(4):727–731. <https://doi.org/10.1162/003465301753237803>
- Peng Z, Wu Q, Li M (2020) Spatial characteristics and influencing factors of carbon emissions from energy consumption in china's transport sector: An empirical analysis based on provincial panel data. *Pol J Environ Stud* 29(1):217–232. <https://doi.org/10.15244/pjoes/102369>
- Pesaran MH (2004) General diagnostic test for cross section dependence in panels. *Working Paper* University of Cambridge & USC.
- Pesaran M, Yamagata T (2008) Testing slope homogeneity in large panels. *J Econ* 142(1):50–93. <https://doi.org/10.1016/j.jeconom.2007.05.010>
- Pontarollo N, Muñoz MR (2020) Land consumption and income in Ecuador: a case of an inverted environmental Kuznets curve. *Ecol Indic* 108:105699. <https://doi.org/10.1016/j.ecolind.2019.105699>
- Qureshi MI, Noor K, Amran R, Khalid Z (2015) The battle of health with environmental evils of Asian countries: promises to keep. *Environ Sci Pollut Res* 22(15):11708–11715. <https://doi.org/10.1007/s11356-015-4440-8>
- Radmehr R, Henneberry SR, Shayanmehr S (2021) Renewable energy consumption, CO2 emissions, and economic growth nexus: a simultaneity spatial modeling analysis of EU countries. *Struct Chang Econ Dyn* 57:13–27. <https://doi.org/10.1016/j.strueco.2021.01.006>
- Rasul G (2016) Managing the food, water, and energy nexus for achieving the sustainable development goals in South Asia. *Environmental Development* 18:14–25. <https://doi.org/10.1016/j.envdev.2015.12.001>
- Saida Z, Kais S (2018) Environmental pollution, health expenditure and economic growth and in the Sub-Saharan Africa countries: Panel ARDL approach. *Sustainable Cities and Society* 41: 833–840. <https://doi.org/10.1016/j.scs.2018.04.034>
- Salahuddin M, Gow J (2019) Effects of energy consumption and economic growth on environmental quality: evidence from Qatar. *Environ Sci Pollut Res* 26:18124–18142. <https://doi.org/10.1007/s11356-019-05188-w>
- Samet JM, Grambsch A, Ebi KL, Romieu I (2020) The potential impacts of climate variability and change on air pollution-related health effects in the United States. *Environ Health Perspect* 109:199–209. <https://doi.org/10.1289/ehp.109-1240667>
- Sengupta A, Nundy S (2005) The private health sector in India. *Br Med J* 331(7526):1157–1158. BMJ Publishing Group. <https://doi.org/10.1136/bmj.331.7526.1157>
- Shafiei S, Salim RA (2014) Non-renewable and renewable energy consumption and CO2 emissions in OECD countries: A comparative analysis. *Energy Policy* 66:547–556. <https://doi.org/10.1016/j.enpol.2013.10.064>
- Shahzad K, Jianqiu Z, Hashim M, Nazam M, Wang L (2020) Impact of using information and communication technology and renewable energy on health expenditure: A case study from Pakistan. *Energy* 204:117956. <https://doi.org/10.1016/j.energy.2020.117956>
- Shekdar AV (2009) Sustainable solid waste management: An integrated approach for Asian countries. *Waste Manag* 29(4):1438–1448. <https://doi.org/10.1016/j.wasman.2008.08.025>
- Shujah-ur-Rahman Chen S, Saleem N et al (2020) Potential influential economic indicators and environmental quality: insights from the MERCOSUR economies. *Air Qual Atmos Health* 13:751–762. <https://doi.org/10.1007/s11869-020-00833-7>
- Sileem HHM (2016) Health expenditure, climate changes and corruption in the MENA region: a granger causality approach. *Journal of African Development* 18(2):61–72. <https://ideas.repec.org/a/afe/journal/v18y2016i2p61-72.html>
- Sirin SM, Yilmaz BN (2020) Variable renewable energy technologies in the Turkish electricity market: Quantile regression analysis of the merit-order effect. *Energy Policy* 144:111660. <https://doi.org/10.1016/j.enpol.2020.111660>
- Smith E, Brugha R, Zwi A (2001) Working with private sector providers for better health care an introductory guide. www.lshtm.ac.uk
- Sood SP, Negash S, Mbarika VWA, Kifle M, et al (2007) Differences in public and private sector adoption of telemedicine: Indian case study for sectoral adoption - PubMed. *Studies in Health Technology and Informatics* 68. <https://pubmed.ncbi.nlm.nih.gov/17917199/>
- Soto M (2009) System GMM estimation with a small sample. *Working Papers* 395. Barcelona Graduate School of Economics. <https://ideas.repec.org/p/bge/wpaper/395.html>
- Stata ® 15 (2020) Timberlake Analytics, [www: http://www.timberlake-analytics.com/](http://www.timberlake-analytics.com/)
- Su Z, Wen J, Abbas J, McDonnell D, Cheshmehzangi A, Li X, Ahmad J, Šegalo S, Maestro D, Cai Y (2020) A race for a better understanding of COVID-19 vaccine non-adopters. *Brain, Behavior, & Immunity - Health* 9:100159. <https://doi.org/10.1016/j.bbih.2020.100159>
- Suki NM, Sharif A, Afshan S, Suki NM (2020) Revisiting the Environmental Kuznets Curve in Malaysia: The role of globalization in sustainable environment. *J Clean Prod* 264:121669. <https://doi.org/10.1016/j.jclepro.2020.121669>
- Suzuki T, Hotta J, Kuwabara T, Yamashina H, Ishikawa T, Tani Y, Ogasawara K (2020) Possibility of introducing telemedicine services in Asian and African countries. *Health Policy and Technology* 9(1):13–22. <https://doi.org/10.1016/j.hlpt.2020.01.006>

- Ullah I, Ali S, Shah MH, Yasim F, Rehman A, al-Ghazali BM (2019b) Linkages between trade, CO2 emissions and healthcare spending in China. *Int J Environ Res Public Health* 16(21). <https://doi.org/10.3390/ijerph16214298>
- Ullah I, Rehman A, Khan FU, Shah MH et al (2019a) Nexus between trade, CO2 emissions, renewable energy, and health expenditure in Pakistan. *Int J Health Plann Manag*:1–14. <https://doi.org/10.1002/hpm.2912>
- Ulucak R, Bilgili F (2018) A reinvestigation of EKC model by ecological footprint measurement for high, middle and low income countries. *J Clean Prod* 188:144–157. <https://doi.org/10.1016/j.jclepro.2018.03.191>
- UNECE (2012) *A preliminary reflection on the best practice in PPP in healthcare sector: a review of different PPP case studies and experiences*. A Preliminary Reflection on the Best Practice in PPP in Healthcare Sector: A Review of Different PPP Case Studies and Experiences. <https://www.unece.org/>
- UNEP (2020) Letter from the Executive Director UNEP in 2020. Retrieved from <https://wedocs.unep.org/bitstream/handle/20.500.11822/34917/AN2020.pdf>
- Usman M, Ma Z, Wasif Zafar M, Haseeb A, Ashraf RU (2019) Are air pollution, economic and non-economic factors associated with per capita health expenditures? Evidence from emerging economies. *Int J Environ Res Public Health* 16(11). <https://doi.org/10.3390/ijerph16111967>
- Wang C-M, Hsueh H-P, Li F, Wu C-F (2019a) Bootstrap ARDL on health expenditure, CO2 emissions, and GDP growth relationship for 18 OECD countries. *Front Public Health* 7:324. <https://doi.org/10.3389/fpubh.2019.00324>
- Wang Z, Asghar MM, Zaidi SAH, Wang B (2019b) Dynamic linkages among CO2 emissions, health expenditures, and economic growth: empirical evidence from Pakistan. *Environ Sci Pollut Res* 26: 15285–15299. <https://doi.org/10.1007/s11356-019-04876-x>
- Wenz SE (2018) What quantile regression does and doesn't do: A commentary on petscher & logan. *Child Dev* 90(4):1442–1452. <https://doi.org/10.1111/cdev.13141>
- WHO, World Health Organization (2020b) Preventing disease through healthy environments: a global assessment of the burden of disease from environmental risks, WHO. World Health Organization. Available at: http://www.who.int/quantifying_ehimpacts/publications/preventing-disease/en/ (Accessed: 6 July 2020).
- Windmeijer F (2005) A finite sample correction for the variance of linear efficient two-step GMM estimators. *J Econ* 126:25–51. <https://doi.org/10.1016/j.jeconom.2004.02.005>
- World Bank (2020) World Bank Development Indicators. <https://databank.worldbank.org/source/world-development-indicators#> (Accessed: 20 Aug. 2020)
- Wu CF, Li F, Hsueh HP, Wang C et al (2020b) A dynamic relationship between environmental degradation, healthcare expenditure and economic growth in wavelet analysis: Empirical evidence from Taiwan. *Int J Environ Res Public Health* 17(4). <https://doi.org/10.3390/ijerph17041386>
- Xing X, Wang J, Liu T, Liu H, Zhu Y (2019) How energy consumption and pollutant emissions affect the disparity of public health in countries with high fossil energy consumption. *Int J Environ Res Public Health* 16(23). <https://doi.org/10.3390/ijerph16234678>
- Xu B, Lin B (2020) Investigating drivers of CO2 emission in China's heavy industry: A quantile regression analysis. *Energy* 206:118159. <https://doi.org/10.1016/j.energy.2020.118159>
- Xu X, Xu Z, Chen L, Li C (2019) How does industrial waste gas emission affect health care expenditure in different regions of China : An application of Bayesian quantile regression. *Int J Environ Res Public Health* 16(2748):1–12. <https://doi.org/10.3390/ijerph16152748>
- Yahaya A, Nor NM, Habibullah MS, Ghani JA, Noor ZM (2016) How relevant is environmental quality to per capita health expenditures? Empirical evidence from panel of developing countries. *SpringerPlus* 5(1):925. <https://doi.org/10.1186/s40064-016-2505-x>
- Yazdi SK, Khanalizadeh B (2017) Air pollution, economic growth and health care expenditure. *Economic Research-Ekonomika Istrazivanja* 30(1):1181–1190. <https://doi.org/10.1080/1331677X.2017.1314823>
- Yazdi SK, Mastorakis N (2011) Renewable, CO2 emissions, trade openness, and economic growth in Iran. *Latest Trends in Energy, Environment and Development*:360–370
- Yoosefi Lebni J, Abbas J, Moradi F, Salahshoor MR, Chaboksavar F, Irandoost SF, Nezhaddadgar N, Ziapour A (2020) How the COVID-19 pandemic effected economic, social, political, and cultural factors: A lesson from Iran. *Int J Soc Psychiatry*:002076402093998. <https://doi.org/10.1177/0020764020939984>
- Yu Y, Zhang L, Zheng X (2016) On the nexus of environmental quality and public spending on health care in China: a panel cointegration analysis. *Economic and Political Studies* 4(3):319–331. <https://doi.org/10.1080/20954816.2016.1218670>
- Zaidi S, Saidi K (2018) Environmental pollution, health expenditure and economic growth in the Sub-Saharan Africa countries: Panel ARDL approach. *Sustain Cities Soc* 41:833–840. <https://doi.org/10.1016/j.scs.2018.04.034>
- Zaman K, Abd-el Moemen M (2017) The influence of electricity production, permanent cropland, high technology exports, and health expenditures on air pollution in Latin America and the Caribbean Countries. *Renew Sust Energy Rev* 76:1004–1010. <https://doi.org/10.1016/j.rser.2017.03.103>
- Zhao H, Cao X, Ma TA (2020) spatial econometric empirical research on the impact of industrial agglomeration on haze pollution in China. *Air Qual Atmos Health* 13:1305–1312. <https://doi.org/10.1007/s11869-020-00884-w>
- Zhou C, Wang S, Wang J (2019) Examining the influences of urbanization on carbon dioxide emissions in the Yangtze River Delta, China: Kuznets curve relationship. *Sci Total Environ* 675:472–482. <https://doi.org/10.1016/j.scitotenv.2019.04.269>

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