



Asymmetric impact of pandemics-related uncertainty on CO₂ emissions: evidence from top-10 polluted countries

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Abstract

The recent COVID-19 pandemic has been a major shock, affecting various macroeconomic indicators, including the environmental quality. The question of how the pandemics-related uncertainty will affect the environment is of paramount importance. The study analyzes the asymmetric impact of pandemic uncertainty on CO₂ emissions in top-10 polluted economies (China, USA, India, Russia, Germany, Japan, Iran, South Korea, Indonesia, and Saudi Arabia). Taking panel data from 1996 to 2018, a unique technique, 'Quantile-on-Quantile (QQ)', is employed. CO₂ emissions are used as an indicator of environmental quality. The outcomes define how the quantiles of pandemic uncertainty impact the quantiles of carbon emissions asymmetrically by providing an effective paradigm for comprehending the overall dependence framework. The outcomes reveal that pandemic uncertainty promotes environmental quality by lowering CO₂ emissions in our sample countries at various quantiles. However, Japan shows mixed findings. The effect of PUN on CO₂ is substantially larger in India, Germany, and South Korea and lower in Russia and Saudi Arabia. Furthermore, the magnitude of asymmetry in the pandemic uncertainty-CO₂ emissions association differs by economy, emphasizing that government must pay particular caution and prudence when adopting pandemics-related uncertainty and environmental quality policies.

Keywords CO₂ emissions · Pandemic uncertainty · Quantile estimation

1 Introduction

Over the previous several decades, six major pandemics have brushed the world: SARS in 2003, Swine flu in 2009–10, Avian flu in 2003–09, Middle East Respiratory

Syndrome (MERS) in 2012, Ebola (2014–2016), and the Zika virus in 2015–16. The recent coronavirus (COVID-19) is claimed to have created more controversy and confusion with compare to past pandemics. Global transmissions, frequent emergence, gradual effect on sensitive population groups, infections and mortalities among health-care personnel, and a large number of deaths are the key concerns for the current COVID-19 pandemic (Tian, An, Chen, & Tian 2021). To control COVID-19, countries have recently enacted lockdown rules and even restricted activities such as transportation, airlines, trades, and education (Chowdhuri et al. 2020; Pal et al. 2021a; Saha et al. 2021). Moreover, oil consumption of each country has been dramatically decreased due to the shutdown of local transport and social activities, resulting in a reduction in carbon dioxide emissions (CO₂) (Khan, Saxena, & Shukla 2021). Every year, 4.6 million people die as a result of poor environmental quality (ENQ). In addition, poor air quality has been associated with 25% of fatalities from obstructive pulmonary diseases, 26% of deaths from respiratory

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problems, and around 16% deaths from coronary heart disease and stroke (WHO 2020).

During the industrial revolution, pandemics were linked with historically low CO₂ (Gherheş et al. 2021). For example, during 14th and 16th centuries, the plague outbreak spread in the European region and the smallpox that Spanish occupiers brought to Latin American countries had minor effects on the levels of CO₂. This situation is also confirmed by the microscopic examination of the tiny fizzes retained in the oldest ice core samples (Bastos et al. 2020). In recent decades, increased air pollution has been caused by continuous urbanization and industry practices (Anser et al. 2021). However, pandemics and pandemic uncertainty (PUN) have triggered various abrupt changes in production and consumption, social connections, working conditions, travel patterns, and a variety of other factors, resulting in enhanced ENQ by reducing CO₂ (Nguyen, Hoang, Ölçer, & Huynh 2021).

The examination of the PUN-CO₂ nexus involves a number of fundamental problems. Does the PUN degrade or improve ENQ in most polluted nations? Is there an asymmetrical relationship between PUN and CO₂? How do PUN and CO₂ trends differ by country along with data distributional points? What are the government measurements of using PUN as a CO₂ mitigation tool? An analysis of the past studies reveals that these are obstacles that seem to have gained less attention, and to the best of our knowledge, there is no existing literature that addresses the concerns indicated above. The contribution of this study to earlier research can be described in three modes: First, numerous studies on the relationship between pandemics and CO₂ have been undertaken. However, the research on the link between PUN and CO₂ using top-polluted economies is scarce. Although some studies have looked into the impact of pandemics on the environment (Tian et al. 2021), no empirical studies have been conducted to determine if there is a link between pandemic uncertainties and CO₂. The PUN is the source of various societal transformations, but its effect on the environment is unknown. The perception how excessive behavioral disturbances caused by PUN impact environment will give critical knowledge regarding its connection with ENQ. According to our understanding, it is a first study to use the unique World Pandemic Uncertainty Index (WPUI) developed by Ahir et al. (2018) to regress the effects of PUN on CO₂ in the top ten polluted countries¹ of the world. Rather than taking the aggregate or overall uncertainty created by all economic, political, and social circumstances, simply the uncertainty caused by health pandemics is used. As a result, distinguishing the influence of PUN on CO₂ from aggregate

uncertainty may have significant policy implications for economic recovery after pandemics like COVID-19. The majority of past research relied on panel data methodologies, ignoring the fact that some countries have no indication of this type of relationship on their own. However, this work employs the Quantile-on-Quantile (QQ) method to provide world yet country-specific insight into the PUN-ENQ nexus. The QQ approach can analyze the time-series dependency in every nation one-by-one. The PUN-environment nexus has a number of properties that build it challenging to assess using traditional econometric methods (such as OLS and quantile regression). Traditional parameter estimates are susceptible to outliers and may allow little room for heterogeneous slopes (Shahzad et al. 2020). As a result, assessing the impact of PUN on CO₂ needs a strong econometric technique, like QQ, which can consider heterogeneous slopes and resilient to outliers. Furthermore, earlier studies estimated individual parameters (negative, positive, or indifferent) over their corresponding entire data distributions. On the other contrary, this research argues that distinct signs (inverse or positive) can be gained at various quantiles for the distribution of data.

The environmental impact of PUN may be different when the economy is in a recession versus when it is booming. In the same way, the environmental effects of higher levels of PUN may vary from those of low ones. As a result, we suggest the asymmetric PUN- CO₂ nexus because dispersion features cause economic variables to follow asymmetric or non-linear trends (Xu et al. 2021). We may also identify major causalities (co-movements) of both PUN and CO₂ at distinct data distribution quantiles (i. e., tops, tails, and median). As a result, we anticipate that study's findings will provide a thorough depiction of the essential PUN-ENQ nexus, which would be unachievable using typical econometric approaches. Because the PUN-GHG nexus changes significantly, the single-country technique of our study can give critical country-specific ramifications for governments and policymakers making political and economic judgments at various levels of pandemics-related uncertainty and pollution. Finally, this work will open up avenues for additional research into the PUN-CO₂ association and its consequences for other countries. It will be extremely valuable to policymakers in formulating and projecting the effects of pandemics-related uncertainty and air pollution control strategies.

The rest of the research is outlined as follows: Sect. 2 gives the empirical review of related studies. Section 3 presents the data and method. The outcomes of the research are presented in Sect. 4. The last section finalizes the study with a few policy implications.

¹ China, the USA, India, Russia, Japan, Germany, Iran, South Korea, Saudi Arabia, and Indonesia.

2 Literature review

Because climate change is the most pressing matter in many countries worldwide, a plethora of literature about the determinants that affect ENQ has been developed (e.g., Dogan and Turkekul 2016; Shahbaz et al. 2018; Ali et al. 2020). Previous empirical studies, however, have neglected the significance of PUN, which is intimately related to environmental sustainability.

Zscheischler et al. (2017) found that people acquired new practices that could stick with them even after the end of the epidemic, such as bio-waste reduction owing to low stock and limiting transportation, which curtailed the GHG in the atmosphere. Earth Observatory report of NASA found that N₂O concentration in Eastern and Central China was 10 to 20% lower in early 2020 than they were at a similar period in 2019. Anser et al. (2021) evaluated the impact of geopolitical risk and policy uncertainties on the ecological footprint. The results of fully modified OLS, dynamic OLS, and AMG estimators revealed that the non-renewable energy consumption and policy uncertainties increased the ecological footprint, while the renewable energy and geopolitical risk decreased it. Brzezinski (2021) evaluated the impact of six past pandemics, i.e., H3N2 (Flu), MERS, SARS, Ebola, H1N1 (Swine Flu), and Zika on CO₂ emissions for 174 countries. The results showed that the previous pandemics reduced CO₂ emissions by 3.4 to 3.7%.

Many studies reported a minimization in GHG in various economies during COVID-19, which could help people obtain more fresh air (Tobias et al. 2020; Menut et al. 2020; Khan et al. 2021; Pal et al. 2022, and Chowdhri et al. 2022). According to Myllyvirta (2020), N₂O and CO₂ emissions levels in China have been curtailed by 24% and 28%, respectively. Watts & Kommenda (2020) discovered the same impact in many regions as a result of the industrial shutdown and a temporary decrease in GHG. In another research, Muhammad et al. (2020) evaluated the Covid-19-environment nexus by utilizing the data set obtained from ESA² and NASA.³ It was demonstrated that during COVID-19, the atmosphere of Wuhan, Italy, the USA, and Spain bettered up to 30%. In another study, Menut et al. (2020) also found an inverse effect of the pandemic outbreak on Particulate Matter (PM) and N₂O concentrations in the countries of Western Europe. Tobias et al. (2020) discovered a betterment in ENQ during the period of COVID-19 in Barcelona (Spain); however significant variances were detected among the contaminants. The largest declines were reported in black carbon and N₂O emissions, with PM10⁴ having the smallest

decline. Tian et al. (2021) discovered that COVID-19 reduced CO₂ emissions in Canada while having no effect on SO₂ emissions. Furthermore, a rise in ozone levels has also been noted. Khan et al. (2021) analyzed the influence of lockdown during COVID-19 on the heavy metal concentrations in River Gomti (India). The quantities of heavy metals (Cd, As, Fe, Cr, Pb, and Mn) were clearly reduced. Moreover, the heavy metal pollution index (HPI) was also reduced. Yazdani et al. (2021) anatomized the influence of the COVID-19 on the ENQ in Tehran (Iran) and realized that COVID-19 positively affected ENQ. For India, Chakraborty et al. (2021), Pal et al. (2021b), Pal et al. (2022), and Chowdhri et al. (2022) explored the impact of COVID-19 lockdown on ENQ and temperature level. The studies found that due to lockdown period, the level of temperature and pollutants have significantly decreased. Similarly, Cheval et al. (2020), Hartono et al. (2021), and Gherheş et al. (2021) also found the better ENQ due to the COVID-19 pandemic.

On the contrary, some empirical studies have discovered that pandemic outbreaks have detrimental impacts on ENQ (Robert 2020; Cheval et al. 2020; Zuo 2020). Cheval et al. (2020), for example, stated that all environmental implications were not beneficial. Pandemic outbreaks affected the ENQ by enhancing the non-recyclable waste, generating massive volumes of organic wastes due to low levels of agricultural and seafood exports, and posing difficulty in maintaining and monitoring natural ecosystems. Various studies observed the economic policy uncertainty-pollution nexus in G7 countries for the year 1997–2015. It was realized that economic policy uncertainty increased pollution. Zuo (2020) investigated the influence of COVID-19 on biomedical waste in China during the pandemic's peak. It was discovered that due to increasing health activities, around 245 tons of hospital waste were produced every day, which was 600% more than the normal amount. According to the studies of Robert (2020) the uses of personal protective equipments (PPEs) and plastic-based face masks during COVID-19 were the main sources of environmental deterioration because these items produced waste and marine pollution and could not be destroyed in nature.

In conclusion, the current literature provides a plethora of knowledge on the consequences of several pandemics on ENQ, such as Ebola, SARS, MERS-Cov, and Covid-19. There hasn't been a single study that looks at the influence of PUN on GHG. Previous research has revealed that PUN has a significant impact on economic growth (Salisu, Gupta, and Demirer, 2020; Song & Zhou 2020), investment (Sharma et al. 2020), energy consumption (Qin et al. 2020), and the stock market (Sharif, Aloui, and Yarovaya, 2020),

² European Space Agency.

³ National Aeronautics and Space Administration.

⁴ The particulate matter having diameter of 10 µm or less.

but the impact of PUN on GHG has been overlooked. In this situation, by examining the aforementioned relationship, our study will fill a gap in the empirical literature.

3 Data and its description

The data set consists of two variables. Pandemic uncertainty (PUN) is treated as an independent variable. Our dependent variable is carbon dioxide emission (CO₂), which represents the proxy of ENQ. We explore the association between PUN and CO₂ for the top-10 polluted countries.⁵ According to the data availability, the study period covers from 1996 to 2018. The data for CO₂ is acquired from the website of World Bank (<https://databank.worldbank.org/>) while the data for PUN is obtained from (<https://worlduncertaintyindex.com/>) formulated by Ahir et al. (2018). The nomenclature for the abbreviations and symbols practiced in this research is provided in Table 1.

In our study, CO₂ is used as ENQ proxy since it accounts for a considerable portion of overall GHG emissions, along with CH₄ and N₂O. CO₂ is primarily caused by energy consumption, industrial production, and transportation (Xu et al. 2021). CO₂ as a proxy for ENQ is used in various empirical studies like Dogan and Turkekul (2016), Myllyvirta (2020), Tian et al. (2021), and Brzezinski (2021). To assess the influence of PUN on ENQ, the World Pandemic Uncertainty Index (WPUI) is utilized, which is acquired from the World Uncertainty Index (WUI) of Ahir et al. (2018). According to theoretical foundation and meaning, the WPUI differs from the WUI. Although both indices have been created for 143 economies worldwide since 1996, the WUI analyses overall uncertainties (economic, political, and social uncertainty), whereas the WPUI calculates the uncertainty related to pandemics (Ahir et al. 2018; WPUI 2020; WUI 2020). The WPUI counts the number of times the word “uncertainty” appears in official Economist Intelligence Unit (EIU) reports about pandemics (Ahir et al. 2018; WPUI, 2020).

The WPUI specifically measures the uncertainties’ levels produced by various global pandemics like Avian flu, SARS, Ebola, and recent COVID-19. There is no previous study which has used PUN as an indicator of ENQ. However various studies used COVID-19 as a determinant of ENQ (Tobias et al. 2020; Menut et al. 2020; Khan et al. 2021; Pal et al. 2022, Chowdhri et al. 2022). The WPUI trend from 1996Q1 to 2021Q3 is depicted in Fig. 1. The trend line demonstrates that WPUI changes

over time and reaches its peak in 2021Q1 owing to the COVID-19.

4 Econometric method

4.1 Quantile cointegration (QC) test

QQ is built on a bivariate framework, which may result in endogeneity problems due to omitted variables. Because of the exclusion of additional control variables, the error term is connected with the independent variable, which may produce an endogeneity problem. To address this issue, the quantile cointegration (QC) test introduced by Xiao (2009) is used to better understand the nature of cointegration among variables.

If $\beta(\tau)$ denotes the constant vector, then the cointegration model’s special version is expressed as follows:

$$Y_t = \alpha + \beta' Z_t + \sum_{j=-k}^k \Delta Z_{t-j}' \Pi_j + \mu_t \quad (1)$$

Here, Y_t represents time series. After including the quadratic factor of the explanatory variable in the cointegration equation, it can be expressed as follows:

$$Q_\tau^Y(Y_t/I_t^Y, I_t^Z) = \alpha(\tau) + \beta(\tau)' Z_t + \gamma(\tau)' Z_t^2 + \sum_{j=-k}^k \Delta Z_{t-j}' \Pi_j + \sum_{j=-k}^k \Delta Z_{t-j}' \Gamma_j F_u^{-1}(\tau) \quad (2)$$

Here, $\beta(\tau)$ represents a drift term. $F_u^{-1}(\tau)$ indicates the error terms for different conditional distribution quantiles. The time series data consists of past information, denoted by I_t^Y . Suppose $F_y(\cdot/I_t^Y)$ is the conditional distribution function of Y_t given I_t^Y . Hence, $Q_\tau^Y(\cdot/I_t^Y)$ is the τ^{th} quantile for $F_y(\cdot/I_t^Y)$. $H_0: \beta(\pi) = \beta$ is supposed to be the null hypothesis for the QC test. We can obtain the cointegration coefficients from Eq. (2). Our null hypothesis $\hat{V}_n(\tau) = [\hat{\beta}(\tau) - \beta]$ is also expressed as the supremum rule “ $\text{Sup}_\tau |V_n'(\tau)|$ ” for the absolute value of difference, which is utilized as a statistical value for QC test in this research across all quantile-based distribution. The critical values for these supremum norm values are acquired by using the 1000-Monte Carlo simulation.

4.2 Quantile-on-quantile approach

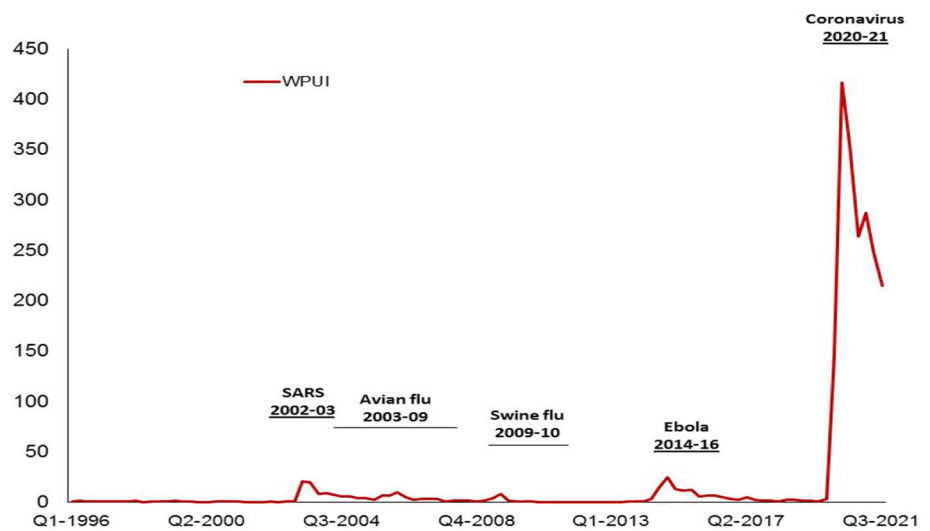
The current work explores the relationship between PUN and ENQ for a specific country using Quantile-on-Quantile

⁵ China, the USA, India, Russia, Japan, Germany, Iran, South Korea, Saudi Arabia, and Indonesia.

Table 1 The nomenclature of the abbreviations and symbols

Symbols or abbreviations	Description	Symbols or abbreviations	Description
CO ₂	Carbon dioxide emissions	h	Bandwidth parameter
PUN	Pandemic uncertainty	WPUI	World pandemic uncertainty index
GHG	Greenhouse gas emissions	WUI	World uncertainty index
ENQ	Environmental quality	ρ_ϕ	quantile loss function
QC	Quantile cointegration	ADF	Augmented Dickey-Fuller
QR	Quantile regression	τ	τ^{th} quantile of pandemic uncertainty
QQ	Quantile-on-Quantile Estimation	kt	kiloton
J-B	Jarque–Bera test	μ_t^θ	Quantile error term
I_t^Y	Past information of time-series data	$\text{Sup}_\tau V_n(\tau) $	Supremum norm value of α and δ (coefficients)

Fig. 1 Pandemics and uncertainty (1996Q1–2021Q3)
 Source: Author’s own calculation based on WPUI (2020) and Ahir (2018). The World Pandemic Uncertainty Index (WPUI) is the simple average of WPUI of 143 countries



(QQ) proposed by Sim and Zhou (2015). This technique analyzes the influence of quantiles of the independent variable (PUN) on the quantiles of dependent variable (CO₂). This unique method combines nonparametric method and quantile regression (QR). The traditional QR model investigates the impacts of PUN on various CO₂ quantiles. The QQ technique, on the other hand, incorporates these traditional methods to describe the relationship between quantiles of both PUN and CO₂. In comparison to other previously employed approaches, such as Ordinary Least Squares (OLS) and QR, the QQ technique aids in gaining a clearer understanding of the relationship between the variables under examination. The QQ technique is used in this research to explore the impact of different quantiles of PUN on various quantiles of CO₂.

Following the empirical studies of Khan et al. (2021) and Anser et al. (2021), we can apply the below non-parametric quantile regression equation to develop our model in its initial version.

$$CO_{2t} = \gamma^\theta(PUN_t) + \mu_t^\theta \tag{3}$$

where, PUN_t and CO_{2t} are pandemic uncertainty and carbon dioxide emissions in time t, respectively. θ explains the θ^{th} quantile for the CO₂ distribution. As we know nothing about the linkage between PUN and CO₂, the load element $\alpha^\theta(\cdot)$ is considered an unknown term. The quantile error is represented by μ_t^θ with θ^{th} quantile.

In the vicinity of PUN $^\tau$, we use following regression to explore Eq. 3 as:

$$\alpha^\theta(PUN_t) \approx \alpha^\theta(PUN^\tau) + \alpha^{\theta'}(PUN^\tau)(PUN_t - PUN^\tau) \tag{4}$$

In Eq. (4), the derivative of $\alpha^\theta(PUN_t)$ in terms of PUN_t is denoted by $\alpha^{\theta'}$, which is called partial effect or partial derivative. $\alpha^\theta(PUN^\tau)$ and $\alpha^{\theta'}(PUN^\tau)$ are called the functions of θ and τ . $\alpha^{\theta'}(PUN^\tau)$ is explained by $\alpha_1(\theta, \tau)$ while $\alpha^\theta(PUN^\tau)$ is shown by $\alpha_0(\theta, \tau)$. As a consequence, the modified version of Eq. 4 can be written as:

$$\alpha^\theta(PUN_t) \approx \alpha_0(\theta, \tau) + \alpha_1(\theta, \tau)(PUN_t - PUN^\tau) \tag{5}$$

The following Eq. 6 for the QQ technique is obtained by putting the values of Eqs. 5 into Eq. 3.

$$CO_{2t} = \frac{\alpha_0(\theta, \tau) + \alpha_1(\theta, \tau) (PUN_t - PUN^\tau)}{(*)} + u_t^\theta \quad (6)$$

The functional framework of the QQ method is depicted in Eq. 6. It shows the relationship between θ^{th} PUN quantiles and τ^{th} CO₂ quantiles. The part (*) expresses the θ^{th} conditional quantile of the dependent variable (CO₂). The relationship between PUN and CO₂ is indicated by the parameters α_0 and α_1 , which are dual-indexed by θ and τ . The values of α_1 and α_0 can be changed on the basis of the quantiles of our variables. By connecting their respective distributions, Eq. 6 establishes the general structure of dependence between PUN and CO₂.

Although QQ is known as a bivariate methodology that cannot incorporate extra variables into the model in addition to PUN, it surpasses other typical time-series approaches. It estimates the association between the independent variable (PUN) and dependent variable (CO₂) at the higher and lower quantiles, producing more detailed and reliable results than other traditional approaches. (Shahzad et al. 2020).

The choice of bandwidth (h) is critical in the QQ model. We have used bandwidth in the following minimization equation, which indicates the influence of PUN on CO₂.

$$Min_{\delta_0, \delta_1} \sum_{t=1}^n \rho_\phi [CO_{2t} - \delta_0 - \delta_1(PUN_t - PUN^\tau)] L \left[\frac{M_n(PUN_t) - \tau}{h} \right] \quad (7)$$

where, ρ_ϕ shows the quantile-based loss function. L(.) implies the Gaussian function, which serves as a weight standard for the estimation strength by assigning different weights to data in the PUN neighborhood. The Gaussian kernel’s weighting parameters are negatively linked to the gap between the values of the distribution function that relates to the quantile of PUN_t and the empirical distribution function of PUN_t. h and I show the bandwidth parameter and the usual indicator function, respectively.

A kernel regression’s bandwidth is called a smoothing indicator as it decreases bias and variation in the outcomes. A high bandwidth produces skewed estimations, whereas a small bandwidth produces higher variance values (Sim and Zhou 2015). Finding a middle ground between variance and bias is vital. Consequently, we select 5% (h=0.05) as bandwidth, according to the studies of Sim and Zhou (2015) and Shahbaz et al. (2018).⁶

⁶ A number of various values of bandwidth have also been tested, but the estimates are qualitatively the same.

4.3 Robustness of QQ method

The QQ model can generate the standard QR estimation by authorizing precise estimates for different explanatory variable quantiles. For this investigation, the QR regression can assess the influence of the θ^{th} quantile of PUN on CO₂, whereas quantile-based PUN parameters can only be indexed by θ . In contrast to the QR method, the QQ technique examines the influence of the θ^{th} quantile of PUN on the τ^{th} quantile of CO₂ through indexing the quantile-based parameters by both θ and τ , giving in the more disintegrating data.

As a consequence, the parameters of QR can be calculated by obtaining the simple average of the QQ parameters along τ . The slope of the coefficient for the QR model is indicated by $\gamma_1(\theta)$, which calculates the effect of PUN on distinct GHG quantiles, can be written as follows:

$$\gamma_1(\theta) \equiv \bar{\alpha}_1 = \frac{1}{s} \sum_{\tau} \hat{\alpha}_1(\theta, \tau) \quad (8)$$

where, $\tau = [0.05, 0.10, \dots, 0.95]$ and s indicates the number of quantiles (s=19).

In this scenario, we can test the robustness of QQ regression by matching the estimated QR coefficients to the τ -averaged estimates of QQ.

5 Estimations and discussion

Now, we present the preliminary and key findings of this research and full discussion of the findings.

5.1 Preliminary results

Table 2 illustrates a descriptive statistics of PUN and GHG in different countries in our sample.

* and ** indicate the level of significance at 1% and 5%, respectively.

With a mean value of PUN (9.51) ranging from 0.01 to 227.67, China has the highest value for pandemic uncertainty. Indonesia places second with a mean value of PUN (6.86), ranging from 0.00 to 104.12. South Korea is third, accompanied by Japan, Saudi Arabia, and India. China is extremely polluted, with an average CO₂ level of (5,754,676.87) kt spanning from 2,585,790.43 to 10,381,826.76. The United States is placed second, with a mean CO₂ of (5,357,918.87) kt fluctuating from 4,820,876.70 to 5,788,726.75. India and Russia are ranked third and fourth, with mean CO₂ levels of 1,546,990 and 1,330,406.78 kt, respectively.

The especially significant Jarque–Bera test results demonstrate that PUN and CO₂ do not have normal data distributions in our chosen economies, with the exception

Table 2 Descriptive statistics for pandemic uncertainty (PUN) and CO₂

Variable	Mean	Maximum	Minimum	Std. Dev	J-B Stats	ADF (Level)	ADF(Δ)
<i>Panel A: Pandemic Uncertainty (PUN)</i>							
China	9.51	227.67	0.01	31.41	3,473.22*	-1.48	-4.33*
USA	0.72	13.78	0.00	2.52	850.08*	-1.97	-5.80*
India	2.32	65.05	0.00	10.53	2,715.74*	-1.76	-5.82*
Russia	0.71	15.73	0.00	2.68	1,097.87*	-1.68	-5.05*
Japan	4.02	115.88	0.00	18.51	2,900.06*	-1.38	-5.87*
Germany	0.28	20.21	0.00	2.18	2,743.67*	-1.54	-5.62*
Iran	0.28	18.71	0.00	2.09	17,338.90*	-0.93	-6.78*
South Korea	4.19	108.76	0.00	15.03	3,657.06*	-2.76*	-5.56**
Saudi Arabia	3.52	119.60	0.00	15.57	55.40*	-1.49	-4.62*
Indonesia	6.86	104.12	0.00	19.58	12.81	-1.71	-4.82**
<i>Panel B: CO₂ Emissions (kt)</i>							
China	5,754,676.87	10,381,826.76	2,585,790.43	2,892,261.20	12.56*	-1.72	-5.65*
USA	5,357,918.87	5,788,726.75	4,820,876.70	292,487.86	18.06*	-5.36*	-6.25*
India	1,546,990	1,666,860	1,418,510	68,524.78	15.08*	-1.98	-3.97*
Russia	1,330,406.78	2,407,672.45	658,189.46	543,189.90	10.10*	-1.82	-4.15*
Japan	1,191,551.10	1,262,394.78	1,098,439.96	47,205.56	9.17*	-2.09	-5.75*
Germany	795,133.05	902,750.87	709,540.87	52,022.65	5.90*	-1.90	-3.75**
Iran	516,625.87	630,870.72	365,676.90	80,013.76	2.39*	-1.91	-3.75**
South Korea	476,432.76	629,290.65	280,240.76	121,975.75	2.36*	-1.68	-4.48*
Saudi Arabia	386,495.54	583,110.76	234,480.75	99,261.76	1.70*	-1.67	-4.47*
Indonesia	374,211.98	561,140.87	214,930.86	123,345.87	4.40*	-4.32*	-6.75*

*indicate the level of significance at 1% and 5%, respectively.

of Indonesia for PUN. The non-normal distribution aspect of our data permits us to use the QQ method, which delivers robust results in such kinds of data (Xu et al. 2021). According to the ADF test, most of the variables are non-stationary at the level but become stationary at their first differences. We use stationary series through transformation of PUN and CO₂ into their first difference, as proposed by Shahzad et al. (2020).⁷

Table 3 demonstrates that the correlation coefficients of the variables (pun and co₂) are strongly correlated across all selected countries. Both china and russia show the largest correlation value of (-0.84), followed by germany (-0.79), saudi arabia (-0.76), and south korea (-0.75). With the exception of turkey, pun and co₂ are found to be adversely related in all countries.

5.2 Main Results

Table 4 displays the outcomes of the QC test for each selected economy. τ indicates the τ^{th} quantiles of PUN. The stability of parameters is described by the coefficients of supremum norm (α and δ) taken from Eq. (3).

⁷ kiloton.

Table 3 Correlation between pandemic uncertainty (PUN) and CO₂

Country	Correlation	t-Statistics	p-value
China	-0.84	-10.72*	0.00
USA	-0.68	-8.61*	0.00
India	-0.67	-7.82*	0.00
Russia	-0.84	-11.29*	0.00
Japan	-0.73	-7.43*	0.00
Germany	-0.79	-25.31*	0.00
Iran	-0.52	-2.80*	0.00
South Korea	-0.75	-4.06*	0.00
Saudi Arabia	-0.76	-5.34*	0.00
Indonesia	-0.73	-4.16*	0.00

**Indicates the level of significance at 1%

The results of the QC test indicate that the long-run linkage between PUN and CO₂ changes along with the quantile-based distribution of data for each nation. At all levels of significance, α and δ (coefficients) have larger supremum norm estimates compared to critical bounds, demonstrating a vigorous asymmetric long-run connection between PUN and CO₂ in all the countries. Figure 2 depicts

the slope estimations for the top ten polluted economies, illustrating the relationship among the θ^{th} quantile of PUN and the τ^{th} quantiles of CO₂ for various values of θ and τ .

For **China** and **USA**, a vigorous and inverse linkage between PUN and CO₂ exists between the large numbers of quantiles of both variables. It explains that PUN upgrades ENQ in these countries at different levels of PUN and CO₂. The outcomes align with the empirical study of Myllyvirta (2020), who observed that COVID-19 reduced CO₂ in China. However, such negative linkage becomes insignificant among the regions, which integrates the low quantiles of PUN (0.05–0.30) with the total quantiles of CO₂ in the USA. This relationship turns into a strong positive association among the areas, which connects the middle quantiles of PUN with all CO₂ quantiles in both countries. This pattern recommends that pandemic-related uncertainty in China and USA deteriorates ENQ during moderate levels of PUN. In **Iran**, the negative effect of PUN on CO₂ is dominant. The strong negative linkage between PUN and CO₂ is present in the area, which joins the lower-middle to upper-middle quantiles of PUN (0.45–0.80) with all the quantiles of CO₂ (0.05–0.95). This explicitly strong inverse association in periods of healthy growth of PUN implies that the PUN improves the ENQ by minimizing the amount of CO₂ during moderate levels of PUN. The study

is consistent with the outcomes of Yazdani et al. (2021), who observed the same outcomes in Iran that COVID-19 improved ENQ. However, this relation becomes strong and positive between the small zones, which merge the low quantiles of PUN (0.05–0.20) with entire CO₂ quantiles. It shows that CO₂ is significantly enhanced when pandemic-related uncertainty is low. Moreover, the PUN-CO₂ relationship becomes weak and negative among the zones, which unite the mid–low and high quantiles of PUN (0.25–0.35 & 0.85–0.95) with all quantiles of CO₂.

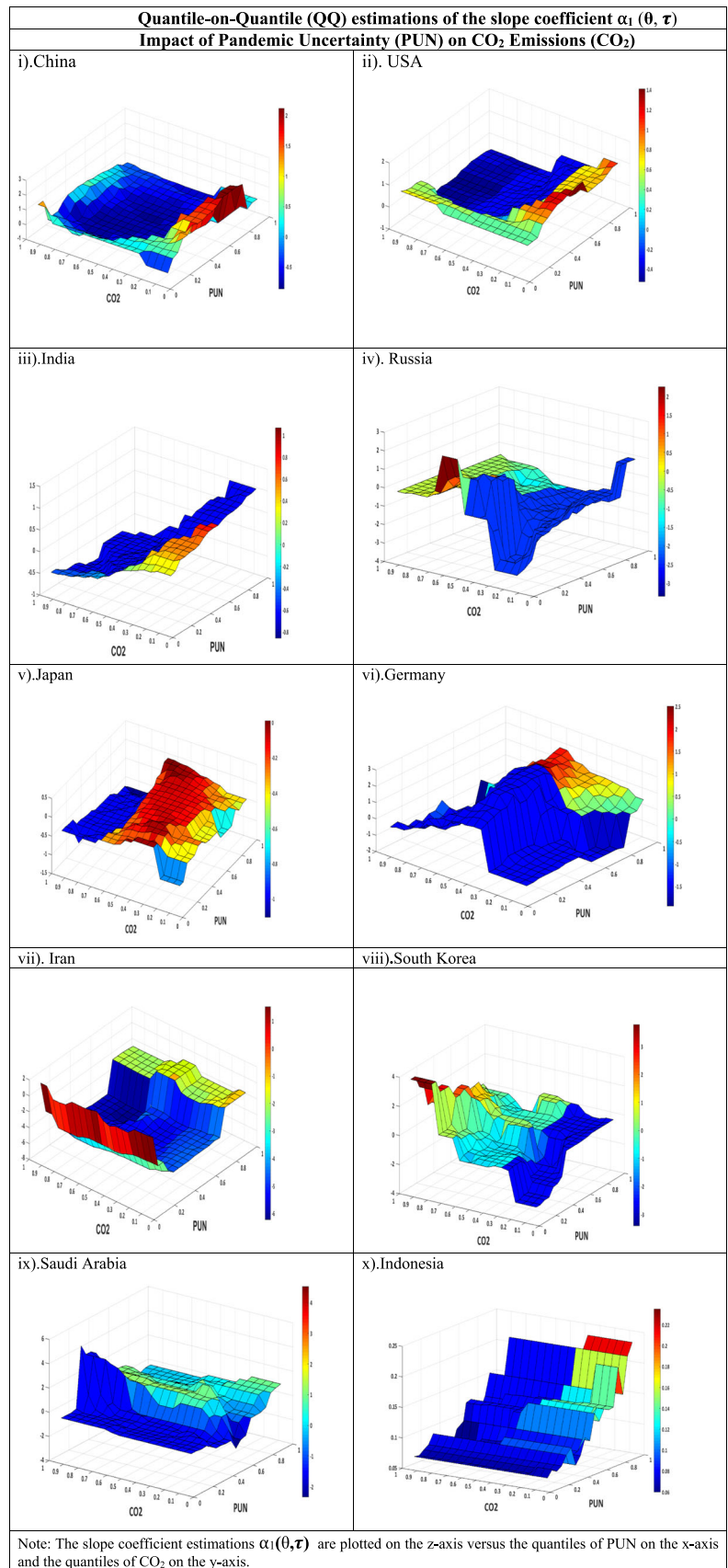
In **Indonesia**, a substantial proportion of quantiles of PUN and CO₂ show an inverse association with each other. A strong negative association is found among the areas, which join the low to upper-middle quantiles of PUN (0.05–0.65) with overall CO₂ quantiles (0.05–0.95). According to the findings, PUN seems to be a cause of improved environment by reducing CO₂, particularly during periods of healthy PUN. The low to medium–low quantiles of CO₂ exhibit a feeble inverse relation with the moderate–high quantiles of PUN (0.70–0.90). Hartono et al. (2021) also observed the same findings about Indonesia that COVID-19 pandemic increased ENQ. Furthermore, the top quantiles of PUN (0.90–0.95) are positively and strongly linked with bottom quantiles of CO₂ (0.05–0.15), indicating that PUN deteriorates ENQ when

Table 4 Results of quantile cointegration (QC) test (PUN and CO₂)

Countries	Coefficients	Sup _{τ} V _n (τ)	CV1	CV5	CV10
China PUN vs. CO ₂	α	68,590.87	58,350.36	57,319.27	54,881.72
	δ	2455.69	1497.21	1437.47	1431.10
USA PUN vs. CO ₂	α	8319.21	5281.23	3138.08	2534.30
	δ	176.63	105.46	52.83	39.36
India PUN vs. CO ₂	α	9381.06	7205.07	5907.70	2624.08
	δ	252.60	166.45	129.58	99.15
Russia PUN vs. CO ₂	α	1243.78	938.70	544.09	206.70
	δ	785.80	587.91	499.90	379.73
Japan PUN vs. CO ₂	α	8754.56	6711.19	4771.15	1476.89
	δ	398.16	202.68	103.07	99.18
Germany PUN vs. CO ₂	α	7118.35	3493.13	3085.18	2228.30
	δ	607.41	302.86	217.17	119.13
Iran PUN vs. CO ₂	α	539.45	326.35	295.70	238.57
	δ	287.90	197.84	126.73	99.37
South Korea PUN vs. CO ₂	α	6238.61	5680.90	4688.50	3788.70
	δ	3270.90	2695.77	2186.70	1858.41
Saudi Arabia PUN vs. CO ₂	α	1836.73	1541.76	1040.74	999.83
	δ	946.77	687.60	491.75	346.88
Indonesia PUN vs. CO ₂	α	3932.98	3767.24	249.58	203.95
	δ	161.78	158.84	48.09	47.76

The t-statistics for QC are computed using an evenly spaced grid of 19 quantiles (0.05–0.95). The parameters’ supremum norm estimations, as well as the critical values at the 1%, 5%, and 10% levels, are also provided, marked by CV1, CV5, and CV10, respectively.

Fig. 2 Quantile-on-Quantile (QQ) estimations of the slope coefficient $\alpha_1(\theta, \tau)$ Impact of Pandemic Uncertainty (PUN) on CO₂ Emissions (CO₂)



there is a shallow level of pandemic-related uncertainty. For **India**, a vigorous but inverse association is found among the segments, which join the mid to high quantiles of PUN (0.50–0.95) with lower-middle to top quantiles of CO₂ (0.40–0.95). It indicates that PUN improves ENQ by mitigating CO₂ during rising PUN and CO₂. The results align with Khan et al. (2021), who also found a positive pandemic-ENQ association for India. Moreover, a positive relationship is also detected among the localities, which unite the lower quantiles of both PUN and CO₂ (0.05–0.40). This direct association between PUN and CO₂ suggests that pandemic-related uncertainty deteriorates ENQ during periods of low PUN and CO₂.

In **Russia and South Korea**, the negative impact prevails among the substantial quantiles of both PUN and CO₂. A negative and strong correlation between the quantiles of both the variables is found, which connects all the quantiles of PUN with lower to medium quantiles of CO₂ (0.05–0.50) in Russia and low to lower-middle quantiles of CO₂ in South Korea (0.05–0.40). This very apparent negative association shows that PUN causes a marked decline in CO₂ in Russia and South Korea for the duration of lower PUN. A weak negative PUN-CO₂ correlation is also detected among the localities that integrate entire quantiles of PUN with moderate to higher CO₂ quantiles (0.55–0.95) in Russia and lower-middle to high CO₂ quantiles (0.45–0.95) in South Korea, implying that PUN has an insignificant or weak correlation with CO₂ during the periods of rising CO₂. The dominance of the positive influence of PUN on ENQ is persistent with the works of Khan et al. (2021) and Anser et al. (2021).

In **Saudi Arabia**, the localities that unite the lower to mid quantiles of PUN (0.05–0.50) with the linkage across the overall CO₂ quantiles imply a powerful and negative association between PUN and CO₂. This very apparent inverse relationship shows that PUN produces a marked decline in CO₂ during periods of low to moderate PUN. A weak negative PUN-CO₂ correlation is also detected among the localities that join the medium to top quantiles of PUN (0.50–0.95) with all CO₂ quantiles, implying that PUN possesses an insignificant linkage with CO₂ in the rising times of PUN. In **Germany**, the inverse effect prevails among the substantial quantiles of both PUN and CO₂. It shows that PUN increases ENQ in these countries at different levels of PUN and CO₂. However, this negative link turns into a positive among the regions, which unites the upper-middle to top quantiles of PUN (0.70–0.95) with medium-low to medium quantiles of CO₂ (0.30–0.50). It implies that pandemic-related uncertainty degrades ENQ when PUN levels are high and CO₂ levels are low.

Contrary to the above results, **Japan** shows a mixed linkage between PUN and CO₂. There is a strong positive relation between the sections connecting the overall PUN

quantiles and the bottom to moderate CO₂ quantiles (0.05–0.60). The finding suggests that when pollution rises from the bottom to the top, the pandemic-related uncertainty harms the environment by increasing CO₂. The positive pandemic-CO₂ emissions association complies with the study of Zand & Heir (2021). However, a highly negative linkage between PUN and CO₂ is also found in places where the overall PUN quantiles are combined with the medium-high CO₂ quantiles (0.65–0.95). It displays that PUN is reducing pollution in Japan during high CO₂ levels. The negative PUN-CO₂ relation is also confirmed by the previous empirical works of Watts & Kommenda (2020) and Muhammad et al. (2020).

The results shown in Fig. 2 are summarised in Table 5, which shows the linkage among various quantiles of PUN and CO₂ for our economies. A strong negative correlation between PUN and CO₂ is predominant in all economies except Japan, which shows a mixed relationship between PUN and CO₂.

The QQ estimations can be matched to the QR estimations to check if they are equivalent. Figure 3 verifies the preceding conclusions of the QQ method. The graphs illustrate that for all sample economies, the average QQ estimations of the slope coefficients follow the same trend as the QR estimates.

Figure 3 depicts the heterogeneity of PUN and CO₂ in the sample countries. The sizes of coefficients show that the effect of PUN on CO₂ is substantially larger in India, Germany, and South Korea and lower in Russia and Saudi Arabia.

5.3 Discussion of results

Overall, the results express a positive correlation between PUN and ENQ in the majority of the sample economies. Our study's empirical findings support our hypothesis, as do other studies such as Anser et al. (2021), which suggest that pandemics have a favorable impact on ENQ. The discovery of substantial and negative PUN coefficients provides support to earlier policy pronouncements relating to the COP21 energy day, emphasizing the importance of reducing GHG emissions. Our findings can be compared to early estimates of how the COVID-19 pandemic affected CO₂, as well as stringent regulations enacted by governments in reaction to the pandemic.⁸ Estimates based on near-real-time monitoring data compiled by the Carbon Monitor initiatives (<https://carbonmonitor.org/>) reveal that global emissions fell by 6.2% in 2020, with significant country-specific heterogeneity (Liu et al. 2020). The findings are also endorsed by the empirical works of Watts and Kommenda (2020) and Muhammad et al. (2020). The

⁸ See Brzezinski (2021), Tian et al. (2021), and Gherheş et al. (2021)

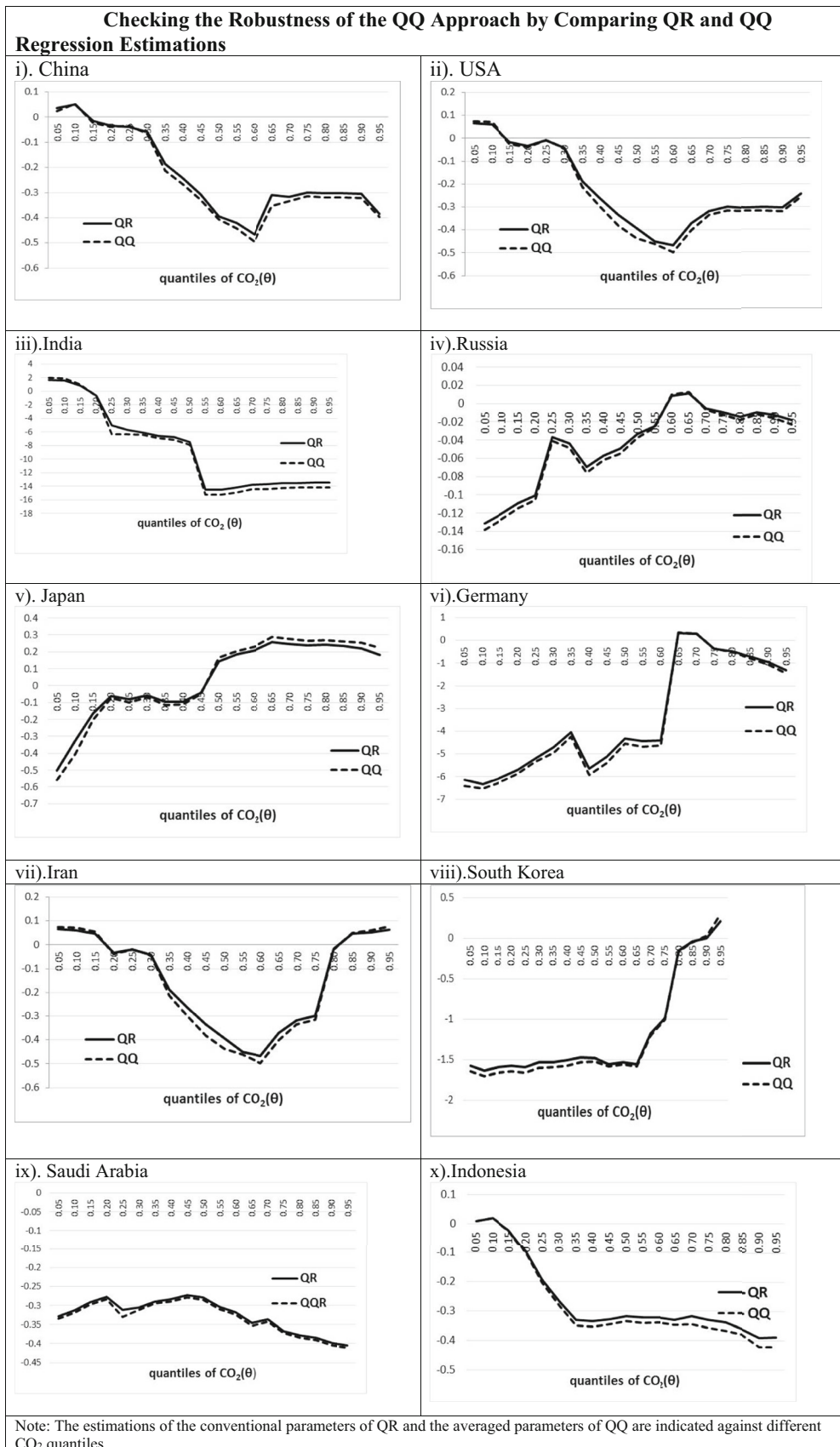
Table 5 Summary of Findings (Association b/w Various Quantiles of PUN and CO₂)

Countries	Quantiles of PUN	Quantiles of CO ₂	Association b/w quantiles	Dominant association
China	Significant number of quantiles	Significant number of quantiles	Strong and negative	Strong and negative
	Middle quantiles	Overall quantiles	Strong and positive	
USA	Significant number of quantiles	Significant number of quantiles	Strong and negative	Strong and negative
	Middle quantiles	Overall quantiles	Strong and positive	
	Lower quantiles	Entire quantiles	Weak and negative	
India	Middle to high quantiles	Lower-middle to top quantiles	Strong and negative	Strong and negative
	Lower quantiles	Lower quantiles	Strong and positive	
Russia	Entire quantiles	Lower to middle quantiles	Strong and negative	Strong and negative
	Entire quantiles	Middle to top quantiles	Weak and negative	
	Entire quantiles	Top quantiles	Strong and positive	
Japan	Overall quantiles	Lower to upper-middle quantiles	Strong and positive	Mixed
	Overall quantiles	Upper-middle to higher quantiles	Strong and negative	
Germany	A significant number of quantiles	A significant number of quantiles	Strong and negative	Strong and negative
	Upper-middle to top quantiles	Lower-middle to moderate quantiles	Weak and negative	
Iran	Lower-middle to upper-middle quantiles	Overall quantiles	Strong and negative	Strong and negative
	Lower quantiles	Entire quantiles	Strong and positive	
	Lower-middle quantiles	Entire quantiles	Weak and negative	
South Korea	Entire quantiles	Low to lower-mid quantiles	Strong and negative	Strong and negative
	Entire quantiles	medium–low to higher quantiles	Weak and negative	
Saudi Arabia	Medium to top quantiles	Entire quantiles	Strong and negative	Strong and negative
	Medium–high to high quantiles	Entire quantiles	Weak and negative	
Indonesia	Low to upper-middle quantiles	Entire quantiles	Strong and negative	Strong and negative
	Medium–high quantiles	Lower to lower-middle quantiles	Weak and negative	
	Top quantiles	Bottom quantiles	Strong and positive	

findings are partially consonant with those of Khan et al. (2021) for India, Hartono et al. (2021) for Indonesia, and similarly Myllyvirta (2020) for China, who contend that PUN improves ENQ. The findings also support the theory that pandemic-related CO₂ reductions are caused by a contraction in economic activities, which is either caused by the health crisis themselves or by government interventions that restrict industrial and human activities in order to combat the pandemic.

However, in Japan, we found a mixed relationship between PUN and ENQ in a substantial proportion of quantiles, which could be attributed to unique characteristics such as population, tendencies of growth, technological progress, and trade cycles. This is in line with the outcomes of Brzezinski (2021). Overall, current estimates of the impact of pandemic-related uncertainty on CO₂ are very similar to those derived from prior pandemics. The cumulative drop in GHG emissions connected with COVID-19 is anticipated to be short and will disappear in

2022 or 2023, whereas pandemic-related uncertainty is likely to have a somewhat bigger coverage than previous pandemics considered on an individual basis. It is also worth noting that our estimations are extremely close to those obtained for the impact of pandemics (i.e. COVID-19) on economic growth (Salisu et al. 2020; Song & Zhou 2020), investment (Sharma et al. 2020), energy use (Qin et al. 2020), and the stock market (Sharif et al. 2020). The variations in the PUN effect between sample economies may be expressed by our sample countries' varying economic circumstances. South Korea and China, for instance, stand out from the other sample economies in terms of population, technology, and growth tendencies. Overlooking such a type of heterogeneity in an economy may result in incorrect results. The slope coefficients of PUN and CO₂ differ among countries, indicating that the PUN-Environment link is not consistent across discrete lower and higher quantiles and related to the volumes and indications of



◀ **Fig. 3** Checking the Robustness of the QQ Approach by Comparing QR and QQ Regression Estimations

shocks and the specific stage of the economy that affects PUN.

6 Concluding remarks and policy implications

The study analyzes the asymmetric impact of PUN on ENQ in top-10 polluted economies. Taking panel data from 1996 to 2018, a unique technique 'QQ' is employed. CO₂ is used as an indicator of ENQ. The findings analyzed how the quantiles of PUN affect the CO₂ quantiles nonlinearly by providing an effective paradigm for comprehending the overall dependency framework. The outcomes reveal that PUN promotes ENQ by lowering CO₂ in our sample countries at various quantiles. However, Japan shows mixed findings. As a result, this study anticipates the evolution of the global environment during pandemics and proposes effective solutions to the environmental difficulties confronting the most polluted countries in the context of pandemics-related uncertainty.

The current worldwide pandemic crisis has clearly proved that the research related to uncertainty and environmental change diplomacy should rethink their strategic and integrated evolution to make up for even the most unexpected events. Pandemics like COVID-19 will generate substantial fluctuations in social and economic behaviors on a world scale, and our research has underlined the environmental components of the future policy implications of PUN. The repercussions of COVID-19 will have long-lasting effects on social gatherings, public areas, and workplaces, which will have a direct impact on economic transitions. As a consequence of the prospective trade-off impacts, governmental initiatives must strike an equilibrium between long-run economic growth and ENQ. Global warming is often regarded as a major risk factor, and pandemics like COVID-19 have demonstrated how overlooked threats can affect global security, economic stability, democratic governance, and hence environmental sustainability. If countries fail to implement the Paris Agreement's nationally determined contributions, the world's CO₂ mitigation activities will expense between 149.7 and 793.0 trillion US dollars by 2100 (WHO 2020). The COVID-19 challenge also jeopardizes current local government commitments to explore climate resilience and GHG mitigating measurements.

The 2030 Agenda includes a number of SDG targets to address poverty and ensure sustainable development by 2030. The COVID-19, we believe, will have an instant influence on the bulk of these goals, which are intimately tied to metropolitan areas and health. As a result, the Paris Agreement and the SDGs connected to the sustainability of the environment must be implemented in accordance with vulnerabilities and resistance to global PUN. Industrial and human activities that are harmful to environmental sustainability should be reduced. The governments should establish stringent environmental regulations to restrict the generation of GHG from industrial activities. Fines and levies should be placed on firms that damage the environment the most, and the income from these penalties should be used to fund public pollution-control activities.

National leaders and multilateral agencies are being urged to take action to halt the rising trend in global CO₂ and disconnect the linkage between CO₂ and growth. There are a growing number of new options for the development of cost-effective renewable energies' techniques. As people are isolated in their homes as a result of the present pandemic, typical everyday activities have certainly taken online, transforming face-to-face business meetings and classroom-based education becomes fully virtual. Hence, many educational institutes of the world have shifted to online learning, and businesses and organizations have turned to online meetings and remote working. Furthermore, there are reasons to expect that remote working, e-learning, teleconference, and other types of distance learning will be more popular as people grow more comfortable with these practices in the post-COVID-19 world. As long as people share the same planet, no one can be fully safe from the indirect consequences of such calamities in other regions of the world. In the meanwhile, no country is safe from the devastating implications of climate change until immediate concerted action is adopted.

International exchanges and collaboration are critical for resolving the crisis produced by pandemics such as COVID-19. Different countries actively respond to pandemics based on their own national circumstances. Developed and developing countries must share and exchange knowledge, learn from one another, and complement one another's advantages. Under-developed countries can use rich countries' technology advantages to assist scientists, policymakers, and health professionals in better understanding the changes in environmental conditions during pandemics. Countries can benefit from one another's expertise and resources in pandemics and environmental research in order to develop a stable and scientific research cooperation team capable of responding to pandemic concerns and promoting environmental sustainability. To encourage sustainable growth, policymakers should focus more on designing policies with multilateral

environmental restrictions while also focusing on R&D investment and implementing rigorous environmental regulations.

To summarize, we agree with Hale and Leduce (2020) that major and continuous changes in human activities that generate a rise in CO₂ may make it impossible to minimize pollution in the long run considerably. However, the lesson acquired from the COVID-19 pandemic can assist politicians and communities take suitable steps to reduce CO₂ in the long run. Utilizing the insights learned during the COVID-19 epidemic, there are chances to apply solutions to reduce pollution. We must recognize that this is not the first or last pandemic to which humans will be exposed as a result of undermining environmental and wildlife protection. To avoid future pandemics, a sustainable environment must be achieved, and the lessons learned from COVID-19 on GHG emissions should help guide this effort.

Finally, there are a few limitations to this study that will pave the path for future research in this field. We excluded many GHG emissions (such as N₂O, SO₂, and CH₄) and ecological footprints due to the missing data set. Future studies can use these indicators to see how the outcomes alter across various environmental indicators. Furthermore, the effect of other types of uncertainties, such as overall uncertainty, policy uncertainty and trade uncertainty, on CO₂ can be studied in future research. Another significant limitation of this investigation is the use of the QQ approach, which does not allow for the inclusion of extra control variables that affect the impact of PUN on ENQ. As a result, in the future study, our empirical model could be improved by using multivariate methodologies (such as Quantile ARDL) to better grasp the nexus with the more independent variables.

Author Contributions LC: conceptualization, data analysis, writing-original draft KC: writing-original draft, literature review HBS: writing-original draft Muhammad ZF: data analysis, proofreading.

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Data Availability Data set used in this study can be obtained through reasonable request to corresponding author.

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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