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Dynamic common correlated effects of pandemic uncertainty on environmental quality: fresh insights from East-Asia and Pacific countries

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Abstract

It is well known that pandemic-related uncertainty affects various macroeconomic indicators, including environmental quality. Due to pandemic outbreaks, the reduction in economic activities affects the environmental quality in many economies. The study explores the impact of pandemic uncertainty on environmental quality in East-Asia and Pacific countries. Most past research use only CO_2 emissions, which is an inappropriate measurement of environmental quality. Besides CO_2 emissions, we have utilized other pollutants like N_2O and CH_4 emissions along with ecological footprint. The traditional econometric approaches ignore cross-sectional dependence and heterogeneity and give biased outcomes. Hence, we have employed a new method, "Dynamic Common Correlated Effects (DCCE)," which can excellently deal with the problems mentioned above. The short-run and long-run DCCE estimations show a negative and significant influence of pandemic uncertainty on ecological footprint, CO_2 and CH_4 emissions in whole and lower-income group of East-Asia and Pacific region. Moreover, pandemic uncertainty has a negative relationship with all indicators of environmental quality in higher-income economies. The study provides a unique opportunity to examine how pandemic uncertainty through anthropogenic activities affects environmental quality and serves as a significant resource for policymakers in planning and estimating the effectiveness of environmental quality measures. It is necessary to carry out sustainable environmental policies in East-Asia and Pacific region according to the vulnerabilities and resilience to global pandemic uncertainty.

Keywords Pandemic uncertainty · Environmental quality · GHG emissions · Ecological footprint · Cross-sectional dependence

Introduction

Six major epidemic and pandemic outbreaks have swept the world since last few decades, namely SARS[1] in 2003, Avian flu in 2003–2009, Swine flu in 2009–2010, MERS[2] in 2012, Ebola (2014–2016), and the Zika virus in 2015–2016 (Rahman et al., 2013; Ahukaemere et al., 2019; Lokhandwala & Gautam, 2020). The novel coronavirus (COVID-19) is said to have sparked more comprehensive debate and uncertainty than the above-mentioned pandemics. The main concerns for the current COVID-19 pandemic include global transmission, frequent emergence, incremental effect in susceptible or vulnerable groups, infection and mortality to health officials, and a significant number of deaths (Babaranti,

[1] Severe acute respiratory syndrome.

[2] Middle East respiratory syndrome.

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2019; Kong and He, 2020). In recent times, the countries have implemented lockdown policies and even blocked or limited several activities such as trades, airlines, transportations, and educational institutes to control COVID-19. Argumentatively, each country's oil consumption has been significantly reduced due to the closure of local transportation and regular social events, which leads to abatement in greenhouse gas (GHG) emissions (Bekun et al., 2021a, b, c, d; Balsalobre-Lorente et al. 2019). Poor environmental quality is responsible for the deaths of 4.6 million people per year. More specifically, lousy air quality has been linked to 25% from obstructive lung disease, 26% of deaths from respiratory infections, and about 17% from stroke and ischemic heart disease (WHO, 2020).

Epidemics and pandemics have been associated with historically low greenhouse gas emissions, even during the industrial revolution (Wang and Hou, 2020; Jakovljević et al., 2021). The plague epidemic spread in Europe in the fourteenth century and the smallpox epidemic that the Spanish invaders transferred to Latin America in the sixteenth century, leaving slight effects on carbon dioxide levels in the atmosphere. It is also evident from the analysis of the small bubbles trapped in the old ice core (Bastos et al., 2020). Continuous urbanization and manufacturing practices have led to rising air pollution in recent decades (Nathaniel et al. 2021; Agboola et al. 2021). However, the pandemics have caused numerous sudden changes in consumption and production, working conditions, social interactions, travel patterns, and many other aspects, which have resulted in improved environmental quality by minimizing ecological footprint (EF) and GHG emissions (Zambrano-Monserrate & Ruano, 2020).

A significant aspect of the current COVID-19 is the widespread usage of germicides to combat viral transmissions. Among these substances, chlorine is widely utilized as the most cost-effective method of preventing viral transmission (García-Ávila et al. 2020). Concerns have also been raised about the increased plastic pollution caused by the usage of personal protective equipments (PPEs), for example gloves and face masks (Abbasi et al. 2020). There is a need for more sustainable substitutes, such as bio-based plastic products (Silva et al. 2020). The usage of PPEs is causing plastic contamination, particularly in aquatic situations. Plastic contamination in water and sea habitats is easily consumed by bigger organisms such as fish, penetrating the food chain and possibly causing chronic health issues in people (Zambrano-Monserrate & Ruano, 2020).

There are 38 countries in East-Asia and Pacific (EAP) region. Due to trade openness, industrial output in EAP countries is growing, resulting in increased energy consumption and natural resources, which leads to increased pollution (Bekun et al., 2021). The EAP region was chosen for this study since it is one of the world's highest emitting regions. EAP countries emit 6.5 metric tons of CO_2 per capita, compared to the 4.7 metric tons of world average (World Bank, 2019). This region includes the world's top emitters, including China (first), Japan (fifth), South Korea (eighth), Indonesia (tenth), and Australia (sixteenth). China accounts for 28% of world CO_2 emissions, with Japan accounting for 3%, Indonesia accounting for 2%, and Australia and South Korea accounting for 1% each (World Bank, 2019). This region also has the world's most polluting countries in terms of EF, including China (first), Japan (fifth), Indonesia (seventh), South Korea (tenth), and Vietnam (seventeenth) (Global Footprint Network, 2019). EAP countries have a 3.8 global hectares (gha) of per capita EF, compared to the world's average of 2.8 gha (Global Footprint Network, 2019). The first case of the COVID-19 pandemic was discovered in December 2019 in China. Thailand, South Korea, Taiwan, Japan, and Vietnam were the first EAP nations to report COVID-19 cases following China. Following then, the COVID-19 expanded to the majority of EAP countries and other regions of the world. As of 12 December 2021, there are 17.8 million confirmed COVID-19 cases in the EAP region.[3] The EAP region was on the front lines during the battle against the SARS in 2003, and it was also mobilized during the pandemics of H1N1 (2009) and MERS (2012). Dengue fever has become a battleground in Southeast Asia. In recent times, the EAP countries have been suppressing the COVID-19 pandemic using various means such as vaccination programs and public awareness.

The international society is deeply concerned about environmental sustainability in the light of the pandemics (Gherheș et al., 2021). The EAP countries have opposed increased constraints on health and environmental preservation and now face an urgency to address this unexpected problem. The governments of developing countries and academics have known from the present COVID-19 and are planning a transition to a more resilient and greener environment. The major goal of these reforms is to gather timely, classified, and high-quality data analysis that will assist governments in developing effective and equitable measures and policies (Chiat et al., 2020; Li et al., 2021; Quan et al., 2021; Myllyvirta (2020).

The rigorous investigation of pandemic uncertainty and environmental quality is crucial in this context. The study of the pandemic-environment nexus in the EAP countries has some typical value. We should investigate the current state of research in chosen nations, which is crucial for limiting the dissemination of the current COVID-19 and developing a more environmentally resilient and greener world (Mohsin et al., 2021; Mimmi, 2021). This study

[3] See worldometer COVID-19 dashboard on https://www.worldometers.info/coronavirus/.

supports to the current knowledge in these ways. (i) Many studies have analyzed the factors that determine the quality of environment. Some researchers have also looked into the pandemics-environmental quality nexus. There has been no empirical study on whether there is a connection between pandemic-related uncertainty and environmental quality. The pandemic uncertainty is the cause of the range of changes in society, but its impact on environmental quality is unclear. Understanding how extreme disruptions in behavior due to pandemic uncertainty affect air pollution will provide vital information about its relationship with environmental quality. It also has important consequences for a country's ability to meet environmental control targets in a more realistic institutional framework. (ii) As we know, this is the first research that utilizes the novel World Pandemic Uncertainty Index (WPUI) of Ahir et al. (2018) to analyze the pandemic uncertainty-environmental quality nexus. Instead of considering overall or aggregate uncertainty generated by all economic, social, and political events, only uncertainty associated with health pandemics is utilized to determine its influence on environmental quality. So, separating the impact of pandemic uncertainty on environmental quality from overall uncertainty may have substantial policy consequences for recovering economically after health-related pandemics such as COVID-19. Few studies have used the impact of WPUI on different macroeconomic variables, such as Demiessie (2020) for economic stability, Fang et al. (2020) for exports, and Ho and Gan (2021) for FDI. As we know, no research has looked into the effects of pandemic uncertainty on environmental quality using WPUI. (iii) Previous studies used a single proxy like CO_2 emissions to measure environmental quality, which is an inadequate tool to apprehend environmental consequences. We use more inclusive environmental proxies to resolve environmental challenges and obtain robust outcomes. This study considers four environmental indicators, in which three are GHG emissions (CO_2, N_2O, and CH_4), and the fourth is EF. (iv) In past studies, multiple panel data approaches such as GMM, AMG, and random and fixed effects are applied. However, these traditional approaches ignored heterogeneity and cross-sectional dependence (CSD) and provided biased outcomes. On the other hand, a novel method, "dynamic common correlated effects (DCCE)," is applied in this research, which can deal with different econometric issues like CSD and heterogeneity. (v) The consideration of EAP economies is relevant to policymakers, researchers, and governments as these countries account for one-fourth of the global population and is accountable for higher levels of emissions than non-EAP countries. (vi) In the last, the outcomes of this study will give valuable suggestions, which would pave the way for future studies on pandemic-environmental quality nexus and its consequences in EAP economies.

Literature review

Since climate change is a critical issue in many economies of the world, many studies investigating the factors that influence GHG emissions have emerged. However, past empirical works have ignored the role of pandemic uncertainty, which is closely linked to environmental quality.

Zscheischler et al. (2017) observed that people adopted new habits that may accompany them even after the pandemic recedes, such as reducing food waste due to limited stock and reducing travel which had reduced CO_2 emissions in the air. NASA's earth observatory discovered that N_2O concentrations in Central and Eastern China were 10 to 30% smaller in early 2020 than in same periods in 2019. Anser et al. (2021) explored the role of policy uncertainty and geopolitical risk in EF for selected emerging economies. After applying dynamic OLS, fully modified OLS, and augmented mean group estimators, it was found that policy uncertainty and non-renewable energy escalated the EF, while geopolitical risk and the renewable energy plunged the EF.

Different studies reported the reduction in N_2O levels in different countries during COVID-19, which could be helpful for people to get fresh air. For example, according to Myllyvirta (2020), CO_2 and N_2O emissions during COVID-19 have been minimized in China by 29% and 24%, respectively. Watts and Kommenda (2020) have also found a similar effect in different regions due to industrial closure and temporary reductions in GHG emissions. Muhammad et al. (2020) assessed the effects of the COVID-19 on the natural atmosphere by analyzing the data published by the ESA[4] and NASA,[5] which demonstrated that the air quality of Italy, Wuhan, Spain, and the USA has improved up to 30%. Similarly, Menut et al. (2020) also observed the negative impact of the pandemic on N_2O emission and particulate matter (PM) concentrations in Western Europe. In other study, Tobias et al. (2020) realized a decrease in pollution in the times of COVID-19 in Spain; however, substantial disparities were found among the pollutants. The highest reduction was found in N_2O and black carbon, while a less reduction occurred in PM10.[6]

Zambrano-Monserrate et al. (2020) found a direct relationship between COVID-19 measurements and the environmental quality. It was also seen that contingency measures reduced noise pollution and provided cleaner beaches. In another study, Tahir and Batool (2020) observed that the COVID-19 reduced 0.3% of CO_2 emissions due to the closure of the aviation sector and transportation. Severo et al. (2021) analyzed the pandemic-environmental

[4] European Space Agency.

[5] National Aeronautics and Space Administration.

[6] The particulate matter with a diameter of 10 μm or less.

awareness-social responsibility nexus in Portugal and Brazil. The outcomes of structural equation modeling revealed that the COVID-19 pandemic was a crucial vector for the change of people's behavior, which resulted in social responsibility and environmental sustainability. Tian et al. (2021) found that CO_2 emissions decreased due to COVID-19 in Canada while COVID-19 had an insignificant impact on SO_2 emissions. Moreover, an increase in the ozone level has also been reported. Similarly, Gherheș et al. (2021) also observed the improvement in environment in the times ofe COVID-19 in various economies.

On the other hand, some empirical research found detrimental impacts of pandemic outbreaks on environmental quality. For instance, Cheval et al. (2020) affirmed that not all the environmental consequences were positive. Pandemic outbreaks harmed the environment by increasing the volume of non-recyclable garbage, producing enormous amounts of biological waste due to lower levels of exports of agricultural products and fish, and challenges to maintain and monitor natural ecosystems. Zuo (2020) has examined the effect of COVID-19 on medical waste pollution amid the peak of COVID-19 in China. It was realized that due to increased medical activities, about 240 tons of hospital waste was generated daily, which was 600% greater than the normal value. According to Robert (2020), plastic-based face masks were another source of environmental degradation because these masks caused waste pollution and marine pollution and could not get lost in nature. Zambrano-Monserrate and Ruano (2020) discovered several negative secondary effects of COVID-19 on environmental quality, such as a decrease in recycling and an increase in waste, impeding the pollution problems of physical spaces, where the highest disposal and a decrease in recycling are adverse effects.

Besides pandemics, many empirical studies used other factors as a determinant of environmental quality. Lin (2017) observed a direct or positive association between GDP per capita and pollution. Mrabet and Alsamara (2017) analyzed the trade-pollution nexus by utilizing CO_2 emissions and EF in Qatar for the years 1980 to 2012. After utilizing the ARDL method, it was observed that openness was positively correlated with both CO_2 emissions and EF. Uddin et al. (2017) found the relationship between growth, openness, and EF by using DOLS methodology and observed a positive impact of economic growth and inverse impact of trade openness on EF. In another work, Dogan and Turkekul (2016) examined the relationship between energy usage, trade openness, and GDP on CO_2 in the USA for the years 1960–2010. It was observed that energy use was positively while trade openness was inversely correlated with CO_2 .

To summarize, the current literature has given a wealth of information on the effects of different pandemic outbreaks like SARS, MERS-Cov, Ebola, and COVID-19 on environmental quality. Not a single study has examined the effect of pandemic uncertainty on environment. The previous studies found that pandemic uncertainty has a critical effect on economic growth (Song & Zhou, 2020), the stock market (Sharif et al. 2020), investment (Sharma et al., 2020), and energy consumption (Qin et al., 2020), but the impact of pandemic uncertainty on environment has been ignored. In this case, this study will pave the gap in empirical literature by checking the aforementioned relationship.

Data and methodology

To analyze the pandemic uncertainty-environmental quality nexus in EAP economies, we use three GHG emissions (CO_2, N_2O, and CH_4) along with EF. The main motivation for selecting these pollutants as environmental proxies is that they have a huge proportion of total GHG emissions. CO_2 accounts for the greatest proportion of GHG emissions, accompanied by CH_4 and N_2O. The main causes of CO_2 emissions are consumption of energy, industrial output, and transportation (Bilgili et al., 2016). N_2O is generated during agricultural activities (Chen et al., 2021; Miao et al., 2022; Aneja et al., 2019). CH_4 is generated during extracting and transporting coal, oil, and natural gas (Yusuf et al. 2020). The EF is considered one of the key indicators of the environment that indicate the biological and ecological capabilities of an economy (Destek et al., 2018). World Pandemic Uncertainty Index (WPUI), trade openness, GDP per capita, population density, and energy consumption are our independent variables.

Pandemic uncertainty is estimated through the World Pandemic Uncertainty Index (WPUI) on the basis of the World Uncertainty Index (WUI) of Ahir et al. (2018) to analyze the impact of pandemic uncertainty on environmental quality. The WPUI is different from the WUI in terms of theoretical ground and meaning. Although both indices were produced for 143 countries worldwide from 1996, the WUI assesses aggregate uncertainty or political and economic uncertainty, while the WPUI estimates the uncertainty associated with pandemics. The WPUI measures the frequency of the word "uncertainty" related to only pandemics in the official reports of the Economist Intelligence Unit (EIU) (Ahir et al. 2018). Specifically, the WPUI assesses the level of uncertainty created by worldwide pandemics like Swine flu, Avian flu, Ebola, SARS, and COVID-19. In Fig. 1, the trend of WPUI is shown during the 1996Q1–2021Q3 period. The trend line shows that WPUI varies with different periods and reaches its highest value in 2021Q1 due to the COVID-19 pandemic outbreak.

Out of 38 EAP countries, 30 are chosen according to the data availability. With the exception of WPUI, data for the variables after 2018 is not available as of August 2021. As a result, a panel data set from 1996 to 2018 is employed for the study. The

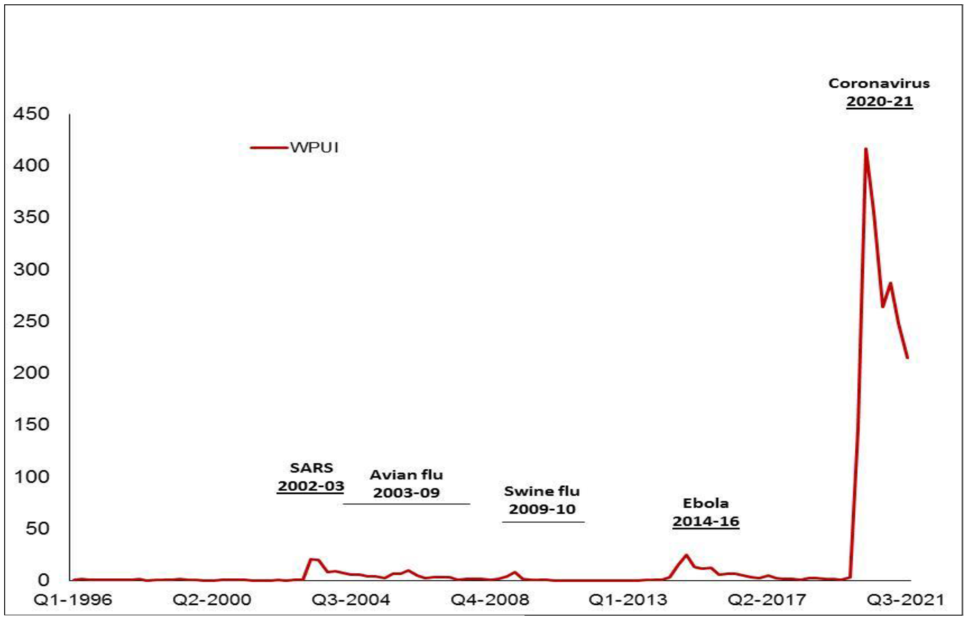

Fig. 1 Pandemics and uncertainty (1996Q1–2021Q3). Source: Author's own calculation based on WPUI (2020) and Ahir (2018). WPUI is the simple average of WPUI of 143 countries

Table 1 The nomenclature of the symbols and the abbreviations

Symbols or abbreviations	Explanation	Symbols or abbreviations	Explanation
EAP	East-Asia and Pacific Countries	WUI	World Uncertainty Index
DCCE	Dynamic common correlated effects	WPUI	World Pandemic Uncertainty Index
CIPS-test	Cross-sectional Im, Pesaran, and Shin test	PUN	Pandemic uncertainty
CSD	Cross-sectional dependence	$\overline{\Delta}$	Homogeneity test
PMG	Pooled mean group	TO	Trade openness
MG	Mean group	ENC	Energy consumption
CCE	Common correlated effects	GDP	GDP per capita
GMM	Generalized method of moments	POD	Population density
EAP-Overall	Overall East-Asia and Pacific economies	X_{it}	Set of independent variables
EAP-LIG	Lower-income group of East-Asia and Pacific countries	P_T	Lag of cross-sectional averages
EAP-HIG	Higher-income group of East-Asia and Pacific countries	$\overline{\Delta}_{\mathrm{adj}}$	Bias-adjusted version of homogeneity test

World Bank has classified countries into four income groups: low-income, lower-middle-income, upper-middle-income, and high-income economies. For our research, we split EAP countries into three categories based on the work of Farooq et al. (2020). We have placed all EAP economies, hereafter called the Overall-EAP group (EAP-Overall), in the first group. The second group contains both lower-middle-income and low-income EAP economies, henceforth referred to as lower-income EAP group (EAP-LIG). High-income and upper-middle-income EAP economies, hereinafter termed as higher-income EAP group (EAP-HIG), have been included in the third group (see Table 11). The nomenclature for the abbreviations and symbols used in this research is listed in Table 1.

For panel data estimation in previous studies, multiple approaches such as GMM, AMG, and random and fixed effects models are applied. However, these traditional approaches overlook the issues of cross-sectional dependence (CSD) and heterogeneity by assuming homogeneity and cross-sectional independence in data. In present times, there is now a greater need to concentrate on the above-mentioned issues.

The whole procedure of panel data estimation involves various steps like checking CSD among cross-sectional units and unit root tests which direct us to follow the concerned methodology, cointegration test to see the association between dependent and independent variables, checking slope homogeneity/heterogeneity of the coefficients, and then move toward the suitable estimation methodology.

Cross-sectional dependence tests

There are several reasons for cross-sectional dependence (CSD), such as similar economic or social networks as well as space effects, unobserved factors, and so forth (Chudik & Pesaran, 2015). It is claimed that without addressing this CSD, panel data provides inconsistent and biased estimators (Meo et al. 2020). We can use different tests to verify the existence of CSD, like the LM test, scaled LM test, CD test, and bias-adjusted scaled LM test.

The widely used Breusch and Pagan (1980) LM test can be represented as follows:

$$LM_{BP} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{1}$$

Here, $\hat{\rho}_{ij}^2$ indicates the the pairwise correlation coefficients. LM test is adequate for small cross-sections (N) and comparatively large time period (T). This test cannot perform well when the average pairwise correlation's mean value approaches zero (Pesaran, 2004). To deal with this issue, Pesaran (2004) introduced the scaled version for the LM test.

$$\textit{Scaled}\ \text{LM Test} = \sqrt{\left(\frac{1}{N(N-1)}\right)} \left[\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\hat{\rho}_{ij}^2 - 1\right)\right] \tag{2}$$

According to Pesaran (2004), one of the major drawbacks of the scaled LM test is that it reveals significant size distortions when $N > T$. Later on, Pesaran (2004) introduced the CD test, which can be utilized in both cases of $T < N$ or $N < T$.

$$\text{CD} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \left[\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}\right] \tag{3}$$

The CD test encompasses several structural breaks of slope coefficients and gives resilient outcomes in the situation of heterogenouspanel data.

After that, the CD test is modified by Baltagi et al. (2012) by applying the mean of the LM statistics and variance.

$$\text{LM}_{adj} = \sqrt{\left(\frac{2T}{N(N-1)}\right)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \frac{(T-k)\hat{\rho}_{ij}^2 - \mu_{Tij}}{\sqrt{v_{Tij}^2}} \tag{4}$$

Here, μ_{Tij} and v^2_{Tij} indicate the accurate mean and variance of $(T-k)\hat{\rho}_{ij}$ illustrated by Baltagi et al. (2012).

CIPS-test (second-generation panel cointegration test)

The conventional cointegration tests of Levin et al. (2002) and Im et al. (2003) are based on the first-generation unit root test, which assumes CSD and homogeneity. These traditional tests give inadequate outcomes when the data is suffered from heterogeneity and/or CSD. To cover this drawback, Pesaran (2007) developed CIPS-test which is a second-generation unit root test. This test gives more robust results due to its ability to control both heterogeneity and CSD.

Westerlund panel cointegration test

The traditional unit root tests such as Pedroni (1999) give biased findings as they overlook some crucial issues like CSD, heteroscedasticity, and autocorrelation (Meo et al., 2020). In contrast, Westerlund (2007) develops a second-generation test for cointegration, which can deal with all the above-mentioned problems and provide more authentic outcomes even in the situation of structural breaks and/or small size of data (Persyn & Westerlund, 2008). The panel-based statistics of this test (Panel-Ʈ and Panel-α) estimate the error-correction terms for the overall panel, whereas the mean or average-based statistics (Group-Ʈ and Group-α) compute the weighted-sums of the error-correction terms. Using the error-correction mechanism, these statistics verify the long-run association among the integrated variables for the individual cross-sections as well as the entire panel. The significant values of two panel-based tests verify the concept that the overall panel is cointegrated, whiles the other two group-mean based tests validate the hypothesis that at least a single cross-sectional unit is cointegrated.

Heterogeneity/slope homogeneity test

For the estimation of panel data, a heterogeneity or slope homogeneity test is utilized to identify the heterogeneity/homogeneity in the panel data. It compares the null hypothesis of homogeneous slope coefficient against the alternative hypothesis of heterogeneous slope coefficient. Primarily, Swamy (1970) initiated a heterogeneity test that required a fixed amount of cross-section (N) in relation to time (T). Later on, the new heterogeneity test was presented by Pesaran and Yamagata (2008), which is adequate in the case of $T, N \rightarrow \infty$. It assumes a normal distribution of error terms. Equation (3) can be utilized to get the standard dispersion statistic for the heterogeneity test ($\overline{\Delta}$):

$$\overline{\Delta} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - k}{\sqrt{2k}}\right) \tag{5}$$

Based on a null hypothesis of $\sqrt{N/T} \rightarrow \infty$ and $(T, N) \rightarrow \infty$, the heterogeneity test ($\overline{\Delta}$) includes asymptotically normal and standard distribution. Pesaran and Yamagata (2008) also consider the following bias-adjusted form of the heterogeneity test.

$$\overline{\Delta}_{adj} = \sqrt{N}\left(\frac{N^{-1}\tilde{S} - E(\overline{z}_{it})}{\sqrt{\mathrm{var}(\overline{z}_{it})}}\right) \tag{6}$$

Here, the mean and variance are represented by $E(\overline{z}_{it}) = k$ and $\mathrm{var}(\overline{z}_{it}) = 2k(T-k-1)/T+1$, respectively. The bias-adjusted version of the heterogeneity test ($\overline{\Delta}_{adj}$) follows the crucial assumption that the error term is cross-sectionally and serially independent. The heterogeneity test is useful for determining whether long-run cross-section coefficients are homogenous or heterogeneous. For heterogeneous panel data, the presumption of slope homogeneity causes biased outcomes (Meo et al., 2020).

Dynamic common correlated effects estimation

The study uses panel data analysis due to its many superior attributes. Panel data merges the time-series observations and horizontal-cross-section and also allow analysis with more observations. Panel data take into consideration more sample variations and degree of freedom compared to time series models (Meo et al., 2020). Dynamic panel data have an advantage over the static models as it can analyze both short-run and long-run results (Sadorsky, 2014). On the contrary, panel data has some disadvantages if we are not able to consider heterogeneity and CSD. The prior studies tremendously used the estimation methods that are not able to consider the cross-sectional effect and they have only entertained the homogenous slopes (Meo et al., 2020). Many well-known statistical techniques are commonly used in the literature related to homogenous slope for time series as well as the panel data, i.e., OLS, random and fixed effects models, and GMM, which show a higher degree of homogeneity as intercept changes between cross-sectional units. There is no other opinion that this assumption is wrong and directed to misleading results (Ditzen, 2019).

To this end, Chudik and Pesaran (2015) developed the dynamic common correlated effects (DCCE) estimation method that has the ability to tackle the aforementioned problems of CSD and heterogeneity. Basically, this estimation technique supports common correlated effect (CCE) estimation, mean group (MG) model, and pooled mean group (PMG) modeln. Although PMG treats the intercepts, short-run coefficients, and adjustment speed as heterogeneous factors among cross-sections, it applies a condition that slope coefficients across countries should be homogeneous in the long run (Ditzen, 2019). So, PMG is not capable of tackling the problem of CSD among countries (Chudik and Pesaran 2015). Although the CCE technique is persistent to (structural) breaks and serial correlations, it is inappropriate for the models of dynamic nature because it does not consider a dependent variable as purely exogenous (Ditzen, 2019).

The DCCE approach, on the other hand, can consider different critical issues that other conventional methodologies cannot tackle. (i) This technique solves the issues of heterogeneity and CSD by extracting averages and lags of cross-sectional units. (ii) This technique addresses the problem of parameter heterogeneity by using the properties of MG estimation. (iii) It estimates dynamic common correlated effects by presuming that the regression variables may all be described by a single factor. (iv) It is resilient to endogenous regression coefficients in static and dynamic panel data modeland enhances the small sample qualities of the estimation irrespective of the fact that the regressors in the model are weakly or strictly exogenous or endogenous. The application of instrumental variables is similarly resilient to CSD and slope heterogeneity. The ivreg2 command introduced by Baum et al. (2007) allows DCCE estimation to tackle instrumental variable regression. (v) This method is applicable in small data size by applying the Jackknife[7] correction command (Chudik & Pesaran, 2015). (vi) It produces reliable results whether there are structural breaks or uneven panel data (Ditzen, 2019).

On the basis of the aforementioned specifications, the DCCE equation can be stated as below:

$$Y_{it} = \alpha_i Y_{it-1} + \delta_i X_{it} + \sum_{p=0}^{p_T} \gamma_{xip} \overline{X}_{t-p} + \sum_{p=0}^{p_T} \gamma_{yip} \overline{Y}_{t-p} + \mu_{it} \tag{7}$$

where t and i depict time and cross-sectional dimensions, respectively. The dependent variable is represented by Y_{it}, while Y_{it-1} is its lag, which is treated here as an independent variable. X_{it} denotes the set of other explanatory variables. The unobserved common factors of the regression are represented by γ_{xip} and γ_{yip}. P_T and μ_{it} denote the lag of cross-sectional average and the residual term, respectively.

Model specification

The empirical models of our study are based on the works of Muhammad et al. (2020) and Cheval et al. (2020), who acknowledge the contribution of pandemics while analyzing environmental quality. Other significant variables that can affect environmental quality, like trade openness, energy consumption, per capita GDP, and population density, have been included in models in addition to pandemic uncertainty for the prevention of omitted variable bias.

The basic model of DCCE, which is defined in Eq. (7), can be further extended into the four models by adding the variables of our models. Four proxies of environmental quality are utilized here as dependent variables in these models, following the previous works of Mrabet and Alsamara (2017) and Uddin et al. (2017).

[7] In STATA, the jackknife command is used to estimate robust standard error and variance. This command is also beneficial for small data size.

Table 2 List of variables with their description and sources

Variables	Description	Unit of measurement	Sources
LNPUN	Log of pandemic uncertainty	World Pandemic Uncertainty Index (WPUI) (country level, four-quarter average)	World Pandemic Uncertainty Index (WPUI)
$LNCO_2$	Log of CO_2 emissions	Metric tons per capita	World Bank
LNEF	Log of ecological footprint	Global hectares (gha)	Global Footprint Network
$LNCH_4$	Log of methane emissions	kt of CO_2 equivalent	World Bank
LNN_2O	Log of nitrous oxide emissions	Thousands metric tons of CO_2 equivalent	World Bank
LNPOD	Log of population density	People per square km of land area	World Bank
LNENC	Log of energy consumption	Thousand metric tons of oil equivalent	World Bank
LNTO	Log of trade openness	Exports plus imports divided by GDP (constant 2010 US$)	World Bank
LNGDP	Log of GDP per capita	Constant 2010 US$	World Bank

The World Pandemic Uncertainty Index (WPUI) shows the frequency of the word "uncertainty" related to health pandemics in the Economist Intelligence Unit (EIU) country reports (Ahir et al. 2018; WPUI, 2020). On the other hand, the World Uncertainty Index (WUI) is built on counting the word "uncertainty" related to all economic events (such as terrorist attacks, wars, financial crises, debt crises, health outbreaks, trade tensions, Brexit, and the United States presidential elections) in the EIU country reports and thus considered aggregate uncertainty (Ahir et al., 2018).

$$LNCO_{2it} = \alpha_i LNCO_{2it-1} + \delta_i X_{it} + \sum_{p=0}^{PT} \gamma_{xip} \overline{X}_{t-p} + \sum_{p=0}^{PT} \gamma_{yip} \overline{Y}_{t-p} + \mu_{it}$$

(Model A)

$$LNN_2O_{it} = \alpha_i LNN_2O_{it-1} + \delta_i X_{it} + \sum_{p=0}^{PT} \gamma_{xip} \overline{X}_{t-p} + \sum_{p=0}^{PT} \gamma_{yip} \overline{Y}_{t-p} + e_{it}$$

(Model B)

$$LNCH_4 = \alpha_i LNCH_{4it-1} + \delta_i X_{it} + \sum_{p=0}^{PT} \gamma_{xip} \overline{X}_{t-p} + \sum_{p=0}^{PT} \gamma_{yip} \overline{Y}_{t-p} + \varepsilon_{it}$$

(Model C)

$$LNEF_{it} = \alpha_i LNEF_{it-1} + \delta_i X_{it} + \sum_{p=0}^{PT} \gamma_{xip} \overline{X}_{t-p} + \sum_{p=0}^{PT} \gamma_{yip} \overline{Y}_{t-p} + v_{it}$$

(Model D)

$LNCO_2$, LNN_2O, $LNCH_4$, and LNEF are dependent variables, in which $LNCO_2$, LNN_2O, and $LNCH_4$ represent GHG emissions, log of carbon dioxide, log of nitrous oxide, and log of methane, respectively. LNEF represents the log of ecological footprint. The set of independent variables, pandemic uncertainty, GDP per capita, trade openness, energy consumption, and population density (all are taken in the log), is denoted by X_{it}. μ_{it}, e_{it}, ε_{it}, and v_{it} show the residual terms.

Based on previous studies and theoretical background, we have selected different independent variables that affect environmental quality. These variables are selected due to their relevant importance. Pandemic uncertainty (PUN) is our core variable which affects environmental quality. The majority of studies believe that pandemic uncertainty improves environmental quality (Myllyvirta, 2020). Trade openness is another major variable which affects environmental quality positively (Wang et al., 2013) or negatively (Lin, 2017). Energy consumption is another important determinant of environmental quality (Bekun et al., 2019). It has a commonly negative association with environmental quality through the scale effect (Bekun et al., 2021). Population density affects environmental quality through the depletion of natural resources (Han & Sun, 2019).

A detailed variables description of our models and data sources are given in Table 2.

Results and discussion

The descriptive statistics of our variables is given in Table 3, which summarizes the significant characteristics of the data. PUN, POD, ENC, GDP, TO, CO_2, EF, N_2O, and CH_4 represent pandemic uncertainty, population density, consumption of energy, GDP per capita, trade openness, CO_2 emissions, ecological footprint, nitrous oxide emissions, and methane emissions, respectively.

To verify the existence of CSD among countries, we have applied various tests, as demonstrated in Table 4. The findings verify the existence of CSD between countries. The values of these CSD tests are not only helpful to decide the appropriate method but also essential to choose the application of the CIPS-test that is most appropriate in the situation of CSD Table 5.

Table 5 indicates the outcome of the unit root tests of second-generation, commonly called the CIPS-test. All of the variables are found stationary at their levels and first differences, and no one is stationary at the second difference. The outcomes of the test confirm that LNTO and $LNCO_2$ are stationary at the first difference, while the rest of the variables are found stationary at level.

Table 3 Descriptive statistics of variables

	PUN	POD	ENC	GDP	TO	CO_2	EF	N_2O	CH_4
Mean	3.17	197.15	1,234,397	7246.17	0.75	5.39	57,886,498	13,535.26	37,837.57
Median	1.09	64.18	12,017.61	2746.83	0.69	2.61	22,253,592	4478.44	12,691.30
Minimum	0.00	2.86	1210.80	339.14	0.08	0.08	1,245,639	71.75	945.68
Maximum	20.06	2012.10	37,712,280	72,444.08	4.44	44.64	389,000,000	369,900.3	912,858
Skewness	2.49	2.68	4.89	2.65	2.08	2.14	1.97	6.08	5.78
Std. dev	4.71	356.37	6,041,469	10,000.18	0.41	7.51	72,409,720	29,192.30	68,507.20
Kurtosis	9.76	9.77	25.36	11.79	13.54	7.35	6.96	54.86	57.20
Observations	1081	1081	1081	1081	1081	1081	1081	1081	1081

Table 4 Results of CSD tests

Variables	CD test		Scaled LM test		Bias-adjusted scaled LM	
	Statistic	Probability	Statistic	Probability	Statistic	Probability
LNPUN	16.02	0.00*	80.17	0.00*	78.29	0.00*
LNPOD	143.57	0.00*	531.52	0.00*	530.64	0.00*
LNENC	70.44	0.01*	141.25	0.00*	140.39	0.00*
LNGDP	27.69	0.02**	104.02	0.00*	102.12	0.00*
LNTO	60.76	0.00*	269.48	0.00*	267.63	0.00*
$LNCO_2$	31.76	0.00*	129.48	0.00*	128.63	0.00*
LNEF	80.99	0.00*	220.57	0.00*	219.67	0.00*
LNN_2O	27.85	0.00*	130.30	0.00*	129.21	0.00*
$LNCH_4$	80.71	0.00*	221.23	0.00*	220.16	0.00*

*Level of significance at 1%

**Level of significance at 5%

Table 5 Result of CIPS unit root test

	b	First difference
LNPUN	−2.89*	−5.16*
LNPOD	−2.57*	−5.18*
LNENC	−2.95*	−5.46*
LNGDP	−2.21*	−4.02*
LNTO	−1.91	−5.66*
$LNCO_2$	−1.79	−5.22*
LNEF	−2.95*	−4.50*
LNN_2O	−3.05*	−5.10*
$LNCH_4$	−2.90*	−5.20*

*Level of significance at 1%

**Level of significance at 5%

Table 6 gives the findings of the Westerlund (2007) test. The values of all test statistics are determined to be significant. The null hypothesis for the absence of cointegration is refused, and the alternate hypothesis is accepted, confirming a long-run relationship among the variables.

The result of the heterogeneity test is given in Table 7. The null hypothesises of the models state that slope coefficients are not heterogeneous (homogenous), while the alternate hypothesises show heterogeneity (no homogeneity). In each of our four models, the *t*-statistics of the heterogeneity test ($\overline{\Delta}$) along its bias-adjusted form ($\overline{\Delta}_{adj}$) give adequate indications to refuse the null hypothesises and approve the alternate hypothesises that explain the presence of cross-country heterogeneity in all models.

Tables 8 and 9 show the outcomes of DCCE estimation in which the explanatory variables of all the models demonstrate significant associations with the lags of their explained variables ($L.LNCO_2$, $L.LNCH_4$, and $L.LNN_2O$). The short-and long-run DCCE estimations indicate a significant and negative influence of pandemic uncertainty on CO_2, CH_4, and EF in the overall EAP group of countries (EAP-Overall) and a lower-income group of EAP countries (EAP-LIG). It demonstrates that pandemic uncertainty reduces pollution in these countries in terms of CO_2, N_2O, and EF. The finding is in line with the work of Lokhandwala and Gautam (2020), who also observed that environmental quality improved during pandemics. Limited social freedom or social distance policies resulted in lower energy consumption and industrial output, lowering environmental quality. Social distancing and the reduction of various activities like tourism business, manufacturing, railway, and road transportation are anticipated to boost biodiversity and the

Table 6 Result of Westerlund cointegration test

H_0: no cointegration	Model A		Model B		Model C		Model D	
	Stat	Robust *p*-value	Stat	Robust *p*-value	Stat	Robust *p*-value	Stat	Robust *p*-value
Group-Ʈ	−3.10*	0.00	−3.62*	0.00	−3.85	0.00	−4.22*	0.00
Group-α	−3.08*	0.01	−3.33*	0.00	−3.39*	0.00	−4.28*	0.00
Panel-Ʈ	−7.40*	0.00	−5.81*	0.00	−8.14*	0.00	−3.58**	0.02
Panel-α	−3.30*	0.00	−3.71**	0.02	−3.32*	0.00	−3.94*	0.00

*Level of significance at 1%

**Level of significance at 5%

Table 7 Results of heterogeneity test

	$\bar{\Delta}$	$\bar{\Delta}_{adj}$
Model A	4.97*	5.85*
Model B	6.17*	7.18*
Model C	6.43*	7.82*
Model D	5.40*	6.11*

*Level of significance at 1%

regenerating capacity of the fishing ground (marine habitats) and forest reserves. Reduced pollution levels may help nature to repair itself and allow people to breathe cleaner air than before. Our findings are consistent with those of Myllyvirta (2020), who says that due to industrial closure and a temporary halt in air pollutants, CO_2 and nitrogen dioxide (NO_2) levels have been lowered by 25% and 30%, respectively. Cadotte (2020) reports similar effects, claiming that $PM_{2.5}$ levels in South Korea were lowered by 54% during the shutdown compared to the same time the prior year.

Moreover, pandemic uncertainty (PUN) has a negative relationship with all proxies of the environment in the higher-income EAP group (EAP-HIG). The potential explanation for the reductions in environmental indicators in these countries is the reduction of various activities like road transportation, industrial output, educational, and other activities due to pandemic uncertainties. From an anthropocentric standpoint, pandemic uncertainty may result in a more sustainable future, such as shorter supply chains or enhanced resilience of the socio-ecological systems, resulting in better environmental quality. PUN is positively and significantly interlinked with N_2O in EAP-Overall and EAP-LIG. It demonstrates that pandemic uncertainty increases pollution in terms of N_2O in Overall-EAP and EAP-LIG. Most EAP economies (particularly those with lower incomes) rely on the agriculture sector, which is the primary source of N_2O (Aneja et al., 2019). According to Duan et al. (2021), the services and manufacturing sectors are more affected by pandemic outbreaks than the agriculture sector. The possible reason for a positive association between PUN and N_2O is that the economies of EAP countries concentrate more on agriculture than other sectors in response to PUN. So, due to the dominance of the agriculture sector in these EAP countries, N_2O increases due to pandemic-related uncertainty.

In our analysis, we discovered that the effect of pandemic uncertainty on environmental quality is reported to be larger in the EAP-LIG compared to EAP-HIG. This condition is also consistent with the works of Ahir et al. (2018), who found that pandemic-related uncertainty was higher in poor nations due to its powerful link to market volatility as well as economic and social uncertainty. The short- and long-run DCCE outcomes show a significant and positive linkage of per capita GDP with all proxies of environment, with the exception of model B, in which GDP is inversely and significantly interlinked with N_2O in EAP-LIG and EAP-Overall. However, in model B, GDP is positively associated with N_2O in EAP-HIG. The direct link between GDP and the indicators of the environment (EF, CO_2, and CH_4) is aligned with the work of Jebli and Youssef (2015). As already mentioned, the positive effect of GDP on environmental indicators is due to the scale effect, which causes the deterioration of the environment due to the consumption of energy and economic activity (industrial production, transport, and disforestation). Because countries prioritize growth over environmental quality, the environment worsens when per capita GDP rises due to increased economic activities, i.e., energy consumption, deforestation, transportation, and industrial production (Bekun & Agboola, 2019). However, for EAP-Overall and EAP-LIG, GDP and N_2O have a significant and negative association in both the long run and short run. One of the potential causes of this negative association is that N_2O is generally produced during agricultural activities.[8] When the people's income in these countries increases, they use advanced methods in cultivation, which lead to a reduction in N_2O. The negative impact of GDP on N_2O is supported by the findings of Bilgili et al. (2016).

All four environmental indicators are inversely and significantly connected with trade openness (TO) in EAP-Overall and EAP-HIG, demonstrating that TO has a favorable impact on the quality of environment. The outcome is in line with Destek et al. (2018) and Onifade et al. (2021). The scale effect relates to an enhancement in economic activities due to TO, including deforestation, transportation, energy use, and industrialization, causing environmental deterioration (Antweiler et al., 2001). On the contrary, when people's income increases, they

[8] See Aneja et al. (2019).

Table 8 DCCE estimation (EAP-Overall)

Short-run Estimates		Model A ($LNCO_2$)	Model B (LNN_2O)	Model C ($LNCH_4$)	Model D (LNEF)
	Regressors	Coefficients	Coefficients	Coefficients	Coefficients
	D.LNPUN	−0.170* (0.01)	0.085 (0.12)	−0.140* (0.01)	−0.120* (0.00)
	D.LNGDP	0.345** (0.03)	−0.153** (0.02)	0.324* (0.01)	0.285** (0.02)
	D.LNTO	−0.300* (0.01)	−0.246* (0.00)	−0.350 (0.14)	−0.222** (0.03)
	D.LNENC	0.265** (0.03)	0.166** (0.02)	0.240* (0.00)	0.350 (0.11)
	D.LNPOD	0.745* (0.01)	0.210 (0.11)	0.345* (0.01)	1.145* (0.00)
Long-run Estimates	L.$LNCO_2$	−0.550** (0.04)	—	—	
	L.LNN_2O	—	−0.500* (0.00)	—	
	L.$LNCH_4$	—	—	−0.420* (0.01)	
	L.LNEF	—	—	—	−0.60* (0,01)
	LNPUN	−0.164* (0.00)	0.065** (0.04)	−0.130* (0.01)	−0.109* (0.00)
	LNGDP	0.320* (0.01)	−0.160** (0.03)	0.315** (0.02)	0.268*** (0.07)
	LNTO	−0.280** (0.02)	−0.260* (0.01)	−0.185* (0.00)	−0.209* (0.00)
	LNENC	0.245** (0.02)	0.150** (0.02)	0.235* (0.00)	0.400 (0.14)
	LNPOD	0.765* (0.01)	0.260 (0.15)	0.365* (0.01)	1.135* (0.00)

*Level of significance at 1%

**Level of significance at 5%

***Level of significance at 10%

Numbers in parenthesis are probability values.

demand a healthy environment to enhance their standard of living, known as the technique or technology effect. Dirty production techniques are being interchanged with environmentally friendly/cleaner production or the services sector, carrying out a composition effect that improves environmental quality. TO can enhance environmental quality when the technique effect overcomes the scale effect and composition effect (Antweiler et al., 2001). The Pollution Halo Hypothesis also supports this negative trade openness-GHG emissions nexus by stating that overseas enterprises transfer cleaner and more advanced technologies to the host economies resulting in a reduction of pollution (Wang et al., 2013). However, in EAP-LIG, TO is positively related to GHG emissions and EF, indicating that environmental quality is deteriorating. This observation is in compliance with the study of Lin (2017). The positive impact of TO on environmental indicators in EAP-LIG is aligning with the pollution haven hypothesis (PHH), which asserts that developing economies have lax environment legislations, which leads to deterioration of the environment in these economies as a result of excessive industrialization due to trade openness (Baek & Koo, 2009).

All environmental indicators are positively and significantly linked to energy consumption (ENC) in the short run and long run, which shows that extensive ENC worsens environmental quality. This outcome supports the results of Dogan and Turkekul (2016). It is true that EAP economies are emphasizing on conventional energies, which emit a greater amount of emissions due to higher human activities and industrialization. Moreover, it also damages the ecological capacities of these countries (Farooq et al., 2020). However, in EAP-Overall countries, ENC is positively but insignificantly linked with EF in long run and short-run. In all groups of EAP, population density (POD) has a significant and positive linkage with CO_2, CH_4,

Table 9 DCCE estimation (EAP-HIG and EAP-LIG)

		Higher-income EAP group (EAP-HIG)				Lower-income EAP group (EAP-LIG)			
		Model A ($LNCO_2$)	Model B (LNN_2O)	Model C ($LNCH_4$)	Model D (LNEF)	Model A ($LNCO_2$)	Model B (LNN_2O)	Model C ($LNCH_4$)	Model D (LNEF)
	Regressors	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients	Coefficients
Short-run estimates	D.LNPUN	−0.100* (0.01)	−0.055** (0.03)	−0.080* (0.01)	−0.080* (0.00)	−0.150* (0.00)	0.070*** (0.06)	−0.115* (0.00)	−0.105* (0.00)
	D.LNGDP	0.370** (0.02)	0.125 (0.13)	0.360* (0.01)	0.292** (0.02)	0.300** (0.03)	−0.120** (0.02)	0.273* (0.01)	0.240** (0.02)
	D.LNTO	−0.320* (0.01)	−0.290* (0.00)	−0.255 (0.13)	−0.245** (0.03)	0.200* (0.01)	0.150* (0.00)	0.215 (0.15)	0.200** (0.02)
	D.LNENC	0.260** (0.02)	0.120** (0.02)	0.283* (0.00)	0.340 (0.11)	0.205** (0.02)	0.126** (0.02)	0.226* (0.00)	0.300 (0.11)
	D.LNPOD	0.940** (0.04)	0.221 (0.17)	0.468* (0.01)	1.585* (0.00)	0.635* (0.01)	0.285 (0.12)	0.311* (0.01)	0.875* (0.00)
Long-run estimates	$L.LNCO_2$	−0.850** (0.02)	—	—	—	−0.800** (0.04)	—	—	—
	$L.LNN_2O$	—	−0.800* (0.01)	—	—	—	−0.750* (0.01)	—	—
	$L.LNCH_4$	—	—	−0.720* (0.00)	—	—	—	−0.651* (0.00)	—
	L.LNEF	—	—	—	−0.700* (0.01)	—	—	—	−0.600* (0.01)
	LNPUN	−0.090* (0.00)	−0.058** (0.03)	−0.075* (0.00)	−0.085* (0.00)	−0.143* (0.00)	0.065** (0.04)	−0.107* (0.00)	−0.092* (0.00)
	LNGDP	0.359* (0.01)	0.200** (0.02)	0.348** (0.02)	0.284** (0.03)	0.285* (0.01)	−0.135* (0.01)	0.255** (0.02)	0.227** (0.03)
	LNTO	−0.305** (0.02)	−0.275* (0.00)	−0.209* (0.00)	−0.227* (0.00)	0.190** (0.02)	0.160* (0.00)	0.177* (0.00)	0.188* (0.01)
	LNENC	0.280* (0.01)	0.130* (0.01)	0.268* (0.00)	0.150** (0.04)	0.188** (0.02)	0.115* (0.01)	0.218* (0.00)	0.090*** (0.06)
	LNPOD	0.950** (0.04)	0.230 (0.14)	0.485* (0.00)	1.550* (0.00)	0.640* (0.00)	0.249 (0.15)	0.315* (0.01)	0.850** (0.02)

*Level of significance at 1%

**Level of significance at 5%

***Level of significance at 10%

Numbers in parenthesis are probability values.

and EF, while insignificantly linked with N_2O. It demonstrates that a population burden will decrease environmental quality in terms of environmental indicators except for N_2O. This result is consistent with the works of Bekun et al., (2021).

Conclusion and policy recommendations

The pandemic uncertainty is the cause of the range of changes in society, but its impact on environmental quality is unclear. The literature shows that there is no empirical study on whether there is a connection between pandemic-related uncertainty and environmental quality. In this research, we have observed the relationship between PUN and environmental quality in EAP economies. The traditional econometric approaches ignore CSD and heterogeneity and provide biased outcomes. So, we have employed a new method, "DCCE," which can excellently deal with the problems mentioned above. Most previous studies have relied solely on CO_2 emissions as a proxy for environmental quality. In addition to CO_2, we employed other GHG emissions such as CH_4 and N_2O as well as another significant indicator EF. The short- and long-run DCCE estimations show a significant and negative influence of PUN on CO_2, CH_4, and EF in EAP-Overall and EAP-LIG. Moreover, for EAP-HIG, PUN has a negative relationship with all environmental indicators. Pandemic-related uncertainty has curtailed movement and confined individuals mostly to their homes, reducing industrial and commercial energy use as well as waste generation. This fall in demand has resulted in considerable reductions in GHG emissions and ecological footprint, as well as a significant improvement in environmental quality. Our research has shown that pandemic-related uncertainty is closely related to environmentally sustainable behaviors. It is also possible that the uncertainty caused by the pandemic may increase consumer concerns about the environment, increasing their choice for green consumption and environmental sustainability in EAP countries. Overall, our research gives new insights into the potential for PUN to positively influence environmental quality concerns.

Our research has many implications for EAP countries. As a policy recommendation, EAP policymakers should pay more attention to environmental pollution and develop pandemic response strategies to reduce the ecological footprint and GHG emissions. We recommend that EAP economies learn from the COVID-19 outbreaks and focus on implementing long-term pollution management strategies. Our research findings give firms with insights into the brand building in the aftermath of the pandemic. Given the ongoing uncertainty surrounding the recent COVID-19, the dread of the coronavirus persists. Hence, we recommend that entrepreneurs develop or strengthen their brands' green image, as the findings of this study show that the fear of coronavirus will increase the people's faith in green product brands and further increase their willingness to pay more and even make sacrifices for environmental sustainability. For example, entrepreneurs can use numerous practices to enhance their green image, such as decreasing solid waste, conserving water and energy, and recycling and reusing durable service products. Second, governments in EAP economies can create effective public awareness initiatives that affect people's environmental concerns. The uncertainty surrounding the pandemic has compelled governments to enact stringent measures to limit the number of affected individuals and deaths. Such techniques, on the other hand, have a favorable impact on the atmosphere, lowering pollution and enhancing ecological quality. Understanding how extreme disruptions in behavior due to pandemic uncertainty affect air pollution will provide vital information about its relationship with environmental quality.

This global crisis has eloquently proved that uncertainty-related research, ecosystem services, and climate change diplomacy must reevaluate their integrated and strategic development to account for even the most unlikely events. Finally, pandemics such as COVID-19 will cause dramatic changes in economic and social behavior on a global scale, and our study has highlighted the environmental dimensions of the subsequent repercussions caused by the uncertainties of pandemic outbreaks. The aftermath of the COVID-19 pandemic will have long-term social impacts on workspaces, public places, and social gatherings, which indirectly/directly affects economic activities. As a result of the potential trade-off effects, governmental efforts across EAP countries are bound to establish a balance between sustained economic development and environmental sustainability. Climate change is frequently viewed as a global risk driver, and pandemic outbreaks such as COVID-19 have provided a good illustration of how underestimated dangers can jeopardize global security, democratic governance, economic stability, and thus environmental quality. If countries of the world fail to execute the nationally defined contributions adopted by the Paris Agreement, the world's carbon reduction efforts will cost between 149.8 and 792.0 trillion US$ until 2100 (WHO., 2020). The COVID-19 dilemma also threatens recent agreements made by local governments to pursue climate change adaptation and mitigation measures. The 2030 Agenda consists of various SDGs aimed at eradicating poverty and achieving sustainable development by 2030. We contend that the COVID-19 pandemic will have an immediate effect on the majority of these aims, which are directly related to urban regions and population health, but longer-term repercussions are also expected. So, it is needed to implement the Paris Agreement and the SDGs related to environmental sustainability according to vulnerabilities and resilience to global pandemic uncertainty.

As of 19 January 2022, only 3.92 billion (50.3%) of the world population is fully vaccinated against COVID-19 (WHO, 2022). Slower and delayed vaccination deployment has left low and middle-income economies vulnerable to COVID-19 variants and slower recovery from the epidemic. Most developing countries of the EAP region have not been able to procure enough viable vaccines to cover their entire population in comparison to wealthier countries. To properly defeat COVID-19, widespread vaccination will be required. Notably, this must occur not only across countries (taking equality features between developed and developing nations) but also importantly inside countries (considering equity dimensions between different groups of people and existing barriers to healthcare access). We must ensure that everyone has equitable access to vaccination. We must make certain that no one is left behind. Only then will EAP countries be able to recover and defeat this pandemic.

Trade openness policies, according to our findings, should be maintained since they enhance environmental quality in EAP-HIG and EAP-Overall, and they are also beneficial for gaining comparative advantages as well as composition effects. These economies can implement suitable policy frameworks to channel trade-induced technical advances and FDI inflows for a sustainable environment. As trade openness degrades the environment in EAP-LIG, rigorous environmental norms and regulations are required to ensure environmental sustainability. Those human and industrial activities that are harmful to ecological capability should be minimized. EAP economies should enact rigorous environment regulations to control emissions from industries. Fines should be levied on those industries that pollute the environment the most, and revenue from these fines can be utilized in public activities to control pollution. EAP-LIG should enact regulations to limit N_2O emissions in the agriculture sector through various means, like minimum usage of nitrogen fertilizers, less crop tillage, and the utilization of nitrification inhibitors.

It is found that energy consumption in EAP countries also increases pollution. Energy consumption through its composition effect is deemed as one of the main factors of environmental deterioration. Energy sector reforms are required, and EAP governments should prioritize renewable and nuclear energy above conventional energy sources. Various initiatives, such as energy performance, fuel-switching, material recycling, and renewable energy use, can help reduce industrial GHG emissions. EF and GHG emissions can be minimized by slowing deforestation, conserving forest carbon stocks, implementing sustainable forest management, and ecological diversity. EAP economies should invest in renewable energy sources, encourage effective and efficient consumption of energy, and upgrade outdated manufacturing techniques. Green and environmentally friendly energies like biomass, solar, wind, ocean/tidal, and other energy initiatives can be used to replace old climate-wrecking energy sources.

Finally, this study has some limitations that will point the way forward for future studies in this area. Due to the missing data set, we have excluded several GHG emissions such as sulfur hexafluoride, sulfur dioxide, perfluorocarbons, and hydrofluorocarbons. Future research can utilize these proxies to observe how the results change across different environmental indicators. To increase the generalizability of our outcomes, the replication of this research in other groups of economies is encouraged. Moreover, in future research, the impact of other kinds of uncertainties like overall uncertainty and trade uncertainty on environmental quality can also be assessed.

Appendix

Table 10

Table 10 EAP countries with environmental indicators and World Pandemic Uncertainty Index (WPUI)

Countries	CO_2 emissions (kiloton)	N_2O emissions (thousand metric tons of CO_2 equivalent)	CH_4 emissions (kiloton of CO_2 equivalent	Ecological footprint (million gha)	World Pandemic Uncertainty Index (WPUI)
China	989,3038	587,166.4	1752,290	5,352,997,272	21.9
Thailand	283,763.5	30,832.95	106,499.2	177,937,521	18.6
Australia	375,907.8	54,247.48	125,588.2	177,820,594	10.6
Japan	1135,886	24,911.49	38,956.54	592,954,518	9.3
Macau (SAR, China)	2068.18	11.65	150.57	10,673,181	35.7
Hong Kong (SAR, China)	43,644.63	476.45	3147.40	21,658,654	41.2
Singapore	37,535.41	1908.56	2385.8	33,502,179	14.9
Korea rep	620,302.4	32,624.7	14,979.34	314,848,507	9.7
Malaysia	248,288.9	15,310.25	34,270.67	123,598,043	10.7
Indonesia	563,324.5	93,138.92	223,315.7	438,646,077	15.8
New Zealand	34,381.79	11,879.94	28,657.66	77,820,594	3.1
Philippines	122,287.1	12,762.02	57,169.78	140,245,710	1.5
Cambodia	9919.23	16,685.37	35,914.91	11,219,656.8	37.3
Fiji	2046.18	343.84	714.60	2,539,966	6.8
Myanmar	25,280.3	26,782.71	80,636.51	91,186,689	5.3
Lao PDR	17,762.95	8986.91	15,011.34	13,694,039	39
Vanuatu	146.68	108.66	254.15	109,552	8.7
Mongolia	25,368.31	3547.86	6257.10	24,747,313	11.1
Brunei	7664.03	342.37	4539.36	2,571,307	15.7
Vietnam	192,667.8	34,494.26	113,563.7	214,272,393	20.4
Solomon Islands	168.68	2656.01	1449.15	2,6784,049	5.7
Timor-Leste	495.04	225.54	732.07	550,508	7.9
French Polynesia	770.07	37.41	99.05	856,346.66	
Micronesia, Fed. Sts	142.01	11.07	31.37	—	—
Korea, Dem. People's Rep	28,283.57	3306.06	18,983.42	20,105.076	6.8
Papua New Guinea	7535.68	1234.08	2142.86	5356.65	0.9
Tonga	128.34	22.15	61.44	90.98	1.2
Samoa	245.68	40.28	132.87	174.76	1.3
Kiribati	80	20	10	56.81	1.0
Guam	75	17	9	50.76	0.9

Data represented for GHG emissions and ecological footprint is obtained from World Bank (2019) and Global Footprint Network (2019), respectively. The country-wise WPUI is representing the average values of the index for the period 1996 to 2018 and obtained from WPUI (2020).

Table 11 List of East-Asia and Pacific (EAP) countries in the sample

Lower-income EAP economies		Higher-income EAP economies	
Low-income economies (GDP per capita of $1045 or less)	Lower-middle-income economies (GDP per capita of $1046 to $4095)	Upper-middle-income economies (GDP per capita of $4096 to $12,695)	High-income economies (GDP per capita of $12,695 or more)
Guam	Myanmar	Fiji	Australia
Korea, Dem. People's Rep	Philippines	China	French Polynesia
Kiribati	Micronesia Fed. Sts	Indonesia	Korea, Rep
	Mongolia	Malaysia	Japan
	Vanuatu	Tonga	Brunei
	Vietnam	Thailand	Singapore
	Papua New Guinea		Hong Kong(SAR, China)
	Timor-Leste		Macau (SAR, China)
	Cambodia		New Zealand
	Lao PDR		
	Samoa		
	Solomon Islands		

The EAP countries are classified into various income groups based on the World Bank's (2021) classification.

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Ping Pang: writing – original draft.
Wei Fang: data analysis, writing – original draft.
Sajid Ali: writing-review, data analysis.
Muhammad Khalid Anser: proofreading, writing – review.

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Declarations

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