Epidemics and electricity CO₂ emissions: a feedback investigation

Ya-Hui Huang¹ · Ke Wang² · Yiwei Wang² · Chun-ping Chang³

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Abstract

We examine the short-term and long-term causal effects between epidemics and electricity CO₂ emissions by using panel data from 30 countries over the period of 1990 to 2017. The results show that there is bidirectional relationship between epidemics and electricity CO₂ emissions, especially in OECD and Asian countries.

Keywords Epidemics · Air quality · Panel data

JEL codes Q53 · I18

Introduction

The emergence and spread of coronavirus disease (COVID-19) in 2019 make an epidemic once again become the focus of global attention (Anderson et al. 2020; Velavan and Meyer 2020). There are various causes for the outbreak of epidemics. Despite the pathological explanation, some scholars have paid attention to the relationship between environmental quality and epidemic diseases 30 years ago. Leggett (1990) thinks that the change in air quality is bringing about a secondary effect that cannot be ignored—that is, it provides more favorable living conditions for epidemics. Since then, the discussion on the relationship between epidemics and environment has continued to expand. Saadi (2010) believes that long-term exposure to air pollution will significantly increase the risk of respiratory epidemics, while Thiering and Heinrich (2015) indicate a link between air pollution and type 2 diabetes (T2D). At the same time, epidemics also bring about environmental changes. After the COVID-19 outbreak, the topic of epidemics and environment has seen a trend of further expansion. Craven et al. (2020) find that NO_x pollution in Beijing decreased by 59% during the period of COVID-19's impact. Chen et al. (2020) also believe that COVID-19 actually

improved air quality due to the reduction of travel traffic. Therefore, it seems to us that it is necessary to pay attention to the relationship between epidemics and environmental quality. On the one hand, it can deepen our understanding of epidemics and bring inspiration to prevent and control their spread. On the other hand, environmental governance is an eternal topic. It is necessary to remind people to treat environmental problems more carefully after COVID-19.

We argue in this paper that air pollution accelerates the expansion of the epidemic by creating an appropriate environment for transmission, and the spread of the epidemic also has an impact on the environment by changing people's way of life and production (Kumar et al. 2020). Most of the recent literature has focused only on cross-sectional analysis and data from a few countries, such as China and the USA, to investigate the impact of air quality on specific epidemics or the short-term impact of COVID-19 on air quality (Hoang and Jones 2020; Chen et al. 2020).

Our research contributes to the literature in two important ways. We believe that the causal analysis of epidemics and environment should be long-term and extensive, which is more conducive to finding their internal relationship, and it is necessary to consider the role of dynamic factors, because if air pollution can lead to epidemics, the history of air pollution is also crucial to explain the formation and spread of current epidemics. Therefore, we have adopted panel data based on 30 countries for 29 years, using panel VECM estimation to confirm the bidirectional equilibrium between epidemics and air quality in the long run, Banerjee and Carrion-i-Silvestre (2015) cointegration test and PANICCA results also offer strong evidence that they have a cointegration relationship when endogeneity is considered. Furthermore, three subsamples and

✉ Chun-ping Chang
cpchang@g2.usc.edu.tw

¹ Graduate Institute of Adult Education, National Kaohsiung Normal University, Kaohsiung, Taiwan

² School of Economics and Finance, Xi'an Jiao Tong University, Xi'an, Shaanxi, China

³ Shih Chien University, Kaohsiung, Taiwan

CO₂ emissions from different sectors provide deeper evidence that the long-term relationship between epidemics and air quality varies for different regions and economic environments.

In OECD and Asian countries, this bidirectional relationship is stronger, while in Africa, due to the imperfect development of its own electricity and industrial sectors, epidemics do not seem to have a long-term bidirectional relationship with their CO₂ emissions, but the transport sector, as the main source of emissions in Africa, is still affected by epidemics.

Data and methodology

Data description

Using panel data from 30 countries from 1990 to 2018, this paper examines the relationship between epidemics and air quality. In terms of epidemics, we collect three variables, number, death, and effect of epidemics in the 30 sample countries over the years to describe the impact of epidemics. According to the interpretation of EM-DAT, number refers to the number of occurrences of new epidemic cases or abnormal increases in original epidemic cases. Death refers to the number of new deaths when number appears. Effect refers to the estimated loss, expressed in US dollars ('000), and the figures are shown true to the year of the event. In terms of air quality, we use CO₂ (metric tons per capita emissions). In order to distinguish the sources of CO₂ emissions (Bereitschaft and Debbage 2012; Rahman et al. 2017), we also collect data from the electricity, industry, and transportation sectors. Table 1 shows the definitions of variables and data sources.

Table 2 shows the descriptive statistics of all variables. We use the logarithmic form for both death and effect. The average value of CO₂ in 1995 was 4.56 increasing to 4.89 in 2005 and 5.34 in 2015. In addition, the CO₂ emissions of all sectors also showed an upward trend, indicating that the air quality is deteriorating. The average number of epidemics also increased

from 0.45 in 1995 to 1.41 in 2005, and only declined in 2015. From the standard deviation point of view, CO₂ in 1995 was 5.13 keeping 5.19 in 2005 and 5.29 in 2015, showing a relatively stable performance, and the results of CO₂ emissions in all sectors were also consistent. However, the standard deviation of the number fluctuates greatly, indicating that the outbreak of epidemics may be concentrated in some years.

PANICCA panel unit root test

Whether a series is in a stationary or nonstationary state, the PANICCA test (Reese and Westerlund, 2016) can find whether the state is driven by common factors or idiosyncratic components. Such discrimination is of practical significance. For example, when the nonstationarity of the series comes from common factors, each factor will have a stronger contagion effect in all samples, which will make the effect of relevant policy opinions more significant. If the situation is the opposite, then when the nonstationarity of the series comes from an idiosyncratic component, we do not recommend adopting the same strategy for all samples.

Supposing the variable we are going to observe is Y , the data generation process (DGP) is represented by the following common factor model:

$$Y_{i,t} = \beta'_i D_{t,p} + \xi'_i G_t + \sigma_{i,t}, \quad (1)$$

where $D_{t,p}$ presents a vector polynomial trend defined by $D_t = (1, \dots, t^p)'$ and $(p+1) \times 1$; ξ_i represents the corresponding vector of factor loadings; G_t is a $r \times 1$ vector that stands for the common factors; and $\sigma_{i,t}$ represents a unit-specific error.

Banerjee and Carrion-i-Silvestre cointegration test (BC)

Compared with the Westerlund and Edgerton (2008) test, the BC cointegration test (2015) puts forward more strict conditions for the model, which only allows a horizontal

Table 1 Variable definitions and data sources

Variable	Definition	Source
CO ₂	CO ₂ emissions (metric tons per capita)	OECD
CO ₂ electricity	CO ₂ emissions from electricity and heat producers per capita/year	OECD and IEA
CO ₂ industry	CO ₂ emissions from manufacturing industries and construction per capita/year	OECD and IEA
CO ₂ transport	CO ₂ emissions from transport per capita/year	OECD and IEA
Number	Epidemic number per year	EM-DAT
Death	Epidemic total death per year	EM-DAT
Effect	Epidemic total effect per year constant at US dollars	EM-DAT

OECD data sources: <https://databank.worldbank.org/>; IEA data sources: <https://www.iea.org/data-and-statistics/>; EM-DAT data sources: <https://www.emdat.be/>

Table 2 Descriptive statistics

Variable	Obs	Mean				Std Dev				Min				Max			
		1995	2005	2015	Total	1995	2005	2015	Total	1995	2005	2015	Total	1995	2005	2015	Total
CO ₂	870	4.56	4.89	5.34	4.91	5.13	5.19	5.29	5.16	0.16	0.23	0.48	0.10	19.27	19.59	18.76	20.18
CO ₂ electricity	840	1.49	1.74	1.72	1.67	1.99	2.01	1.76	1.95	0.04	0.04	0.07	0.02	8.13	8.54	6.19	9.19
CO ₂ industry	840	0.68	0.71	0.77	0.73	0.73	0.67	0.81	0.77	0.02	0.04	0.04	0.01	2.66	2.14	3.28	4.52
CO ₂ transport	840	1.01	1.16	1.26	1.20	1.32	1.43	1.29	1.92	0.03	0.04	0.05	0.02	5.77	6.12	5.30	28.87
Number	870	0.30	0.56	0.2	0.48	0.53	1.00	0.48	0.95	0				2	5	2	8
Death	870	0.45	1.41	0.55	1.16	1.25	1.95	1.77	2.05	0				5.99	5.92	7.84	8.95
Effect	870	2.41	2.34	1.18	2.23	4.12	3.24	2.85	3.70	0				11.63	10.76	8.54	14.29

term in the deterministic part of the stochastic process. At the same time, the BC cointegration test also considers possible breaks in the trends of data generation process, which gives it advantages in dealing with structural fracture and cross-section correlation problems. The data generation process is:

$$y_{it} = D_{it} + x'_{it}\delta_{it} + u_{it} \quad (2)$$

$$u_{it} = F'_i\pi_i + e_{it} \quad (3)$$

$$(I-L)F_t = C(L)w_t \quad (4)$$

$$(1-\rho_iL)e_{it} = H_i(L)\varepsilon_{it} \quad (5)$$

$$x_{it} = \kappa_i + x_{it-1} + G'_i\varsigma_i + \Xi(L)v_{it} \quad (6)$$

$$G_t = \Gamma(L)\varpi_i, \quad (7)$$

where $t = 1, \dots, T$ stands for the time term; $i = 1, \dots, N$ represents an individual; and y_{it} and x_{it} are the scalar and vector of a stochastics process, respectively.

Panel VECM

According to the BC cointegration test (2015), we realize that there is a co-integration relationship between epidemics and CO₂ emissions. In order to further determine the interaction between them, we use panel-VECM to conduct the Granger causality test. VECM first obtains the estimated residuals ε_{it} and v_{it} through (8) and (9):

$$CO2_{it} = \alpha_i + \delta_i t + \beta_i \text{number}_{it} + \varepsilon_{it} \quad (8)$$

$$\text{Epidemics}_{it} = \varphi_i + \gamma_i t + \chi_i CO2_{it} + v_{it} \quad (9)$$

After the residuals ε_{it} and v_{it} are obtained, we estimate the Granger causality model by a dynamic error correction:

$$\begin{aligned} \Delta CO2_{it} = & \theta_{1i} + \lambda_1 \varepsilon_{it-1} + \sum_k \theta_{11k} \Delta CO2_{it-k} \\ & + \sum_k \theta_{12k} \Delta \text{epidemics}_{it-k} + u_{1it} \end{aligned} \quad (10)$$

$$\begin{aligned} \Delta \text{Epidemics}_{it} = & \theta_{2i} + \lambda_2 v_{it-1} + \sum_k \theta_{21k} \Delta CO2_{it-k} \\ & + \sum_k \theta_{22k} \Delta \text{epidemics}_{it-k} + u_{2it} \end{aligned} \quad (11)$$

In Eqs. (10) and (11), θ_{12k} and θ_{21k} for all possible k are respectively the standard for judging whether there is a short-term associational relationship between CO₂ emissions and epidemics, under which the null hypotheses are $H_0: \theta_{12k} = 0$ and $H_0: \theta_{21k} = 0$. Here, λ is the standard to judge whether there is a long-term relationship between them, under which the null hypotheses are $H_0: \lambda_1 = 0$ and $H_0: \lambda_2 = 0$.

Results

PANICCA (Reese and Westerlund 2016a, b) unit root test consists of two models. When only constant terms are allowed in the model, $P = 0$. When both constant terms and trend terms are included in the model, $P = 1$. Because epidemics and CO₂ emissions are less affected by trends, we use $p = 0$ model for analysis. We divide the samples into full samples, OECD countries subsamples, Asian countries subsamples and African countries subsamples.¹ Table 3 shows the results of common factors and idiosyncratic factors of all kinds of samples when $p = 0$. When we pay attention to common factors, the ADF statistics of all variables are significant at the level of 1% except for the CO₂ emissions of Asian subsample countries. This result rejects the null hypothesis of unit root, indicating that there is a common factor of all sample countries that leads to the stability of variables. When we pay attention to idiosyncratic factors, we can find that CO₂ emissions are not significant at the level of 10% in both full samples and the subsamples, indicating that there are idiosyncratic factors in individual countries leading to the nonstationary of CO₂

¹ OECD countries used in this study are Belgium, Canada, Germany, Ireland, Korea, Mexico, UK, and USA. Asian countries are Bangladesh, China, India, Indonesia, Korea, Malaysia, Myanmar, Oman, Philippines, Singapore, and Thailand. African countries are Angola, Nigeria and Zimbabwe.

Table 3 PANICCA test

Sample	Variable	Common factors	Idiosyncratic component		
		$P = 0$	$P = 0$		
		ADF	P_a	P_b	PMSB
Full samples	CO2	−4.387***	0.643	0.762	0.989
	Number	−3.284***	−34.014***	−10.14***	−2.771***
	Death	−5.166***	−21.176***	−9.21***	−2.118**
	Effect	−5.385***	−34.430***	−8.652***	−1.428*
OECD	CO2	−1.033	2.043	3.654	5.051
	Number	−5.355***	−37.299***	−8.374***	−1.524*
	Death	−4.223***	−33.844***	−8.644***	−1.342*
	Effect	−5.384***	−23.712***	−6.313***	−1.230
Asia	CO2	−5.388***	0.968	1.564	2.473
	Number	−5.110***	−16.878***	−5.638***	−1.817**
	Death	−4.856***	−36.226***	−9.107***	−1.537*
	Effect	−4.517***	−33.721***	−8.663***	−1.501*
Africa	CO2	−4.481***	0.102	0.125	0.835
	Number	−3.878***	−18.595***	−5.248***	−1.251
	Death	−5.385***	−27.910***	−7.279***	−1.199
	Effect	−3.913***	−24.200***	−6.479***	−1.150

The ADF statistics represent the common factor. The test statistics of $P_{a,p}$, $P_{b,p}$, and $PMSB_p$ are valid for the idiosyncratic component. $P = 0$ shows only a constant in the model. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively

emissions. We assume that the nonstationary is due to the impact of epidemics.

Table 4 shows the results of model “two breaks” of BC cointegration test. According to the different CO₂ emission sectors, we divide them into four categories: per capita CO₂ emission, CO₂ emission of electricity sector, industrial sector, and transportation sector to observe whether CO₂ emission of different sectors will affect the relationship with epidemics.² It can be seen that when the dependent variable is CO₂ at the statistic of −12.08, the probability of rejecting the null hypothesis is 53.33% at the 5% significance level; while when the dependent variable is number at the statistic of −9.51, the probability of rejecting the null hypothesis is 56.67% at the 5% significance level, indicating that there is a cointegration relationship between CO₂ and number, which is also supported by the results of death and effect. Similarly, we can therefore conclude that all sectors of CO₂ emissions have a cointegration relationship with the number, death, and effect of epidemics.

According to the results of the two breaks model, we further describe the potential breakpoints of each sample country in the past 29 years. We can find that the first category of breakpoints

occurred in 1994–1998, and the second category of breakpoints occurred in 2008–2012. During the first turning point, the India plague broke out in 1994, and the first Norovirus patient appeared in 1995. In 1997, the highly lethal influenza A/H5N1 influenza virus was epidemic, while during the second turning point (Hall et al. 2013; Barberis et al. 2016), the H1N1 virus (2009) originated in Mexico broke out, causing up to 1.4 billion worldwide infections and 151,700–575,400 deaths (Girard et al. 2010). These two turning points are all in the period of global epidemic outbreak, which may be caused by the epidemic outbreak reducing people’s travel and production activities, thus changing CO₂ emissions.

After confirming the cointegration relationship between CO₂ emission and epidemics, Table 5 provides the results of panel VECM causality tests. We want to know not only whether there is short or long term relationship between CO₂ and number, but also be interest in whether this bi-directional relationship extends to all sectors of CO₂ emissions, and whether it is applicable to countries with different regions and economic levels. Therefore, panel A to panel L list all results of possible test in detail, so as to find a deeper relationship between CO₂ emissions and epidemics.

Panel A shows the test results of OECD countries, when the dependent variable is CO₂, the statistical value of number is 0.51, which is not significant at the level of 10%, indicating that there is no causal relationship between number and CO₂ in

² The data of per capita CO₂ emission we use ranges from 1990 to 2018, but due to limited data updating, when we discuss CO₂ emissions in the electricity, industrial and transport sectors, it is always between 1990 and 2017.

Table 4 Panel cointegration of BC (2015)

Model	Two breaks					
	CO ₂	Number	CO ₂	Death	CO ₂	Effect
Dependent variable	CO ₂	Number	CO ₂	Death	CO ₂	Effect
%	53.33	56.67	56.67	66.67	56.67	70.00
Statistic	– 12.08	– 9.51	– 6.774	– 23.93	– 18.46	– 158.18
	CO ₂ electricity	Number	CO ₂ electricity	Death	CO ₂ electricity	Effect
%	40.00	76.67	56.67	70.00	46.67	60.00
Statistic	10.11	– 209.56	– 37.08	– 73.19	– 90.04	– 88.98
	CO ₂ industry	Number	CO ₂ industry	Death	CO ₂ industry	Effect
%	76.67	73.33	36.67	66.67	63.33	70.00
Statistic	– 227.20	– 33.46	– 19.20	– 66.41	– 81.75	– 249.74
	CO ₂ transport	Number	CO ₂ transport	Death	CO ₂ transport	Effect
%	70.00	66.67	76.67	63.33	66.67	56.67
Statistic	– 73.92	– 102.51	– 27.38	– 55.67	– 35.48	271.01
Location of breakpoints (two breakpoints)						
Country	First one		Second one			
Angola	1995		2012			
Bangladesh	1998		2010			
Belgium	1994		2001			
Bolivia	2004		2008			
Bosnia and Herzegovina	1994		2005			
Brazil	1997		2004			
Canada	1996		2000			
China	1995		1999			
Colombia	1994		1999			
Ecuador	1998		2005			
El Salvador	2000		2012			
Germany	1997		2001			
Guatemala	2004		2009			
Honduras	1997		2013			
India	1994		2008			
Indonesia	1998		2011			
Ireland	2000		2008			
Korea	1996		2012			
Malaysia	2004		2008			
Mexico	2006		2010			
Moldova	2005		2012			
Myanmar	2004		2009			
Nigeria	2002		2012			
Oman	1995		2003			
Philippines	2003		2009			
Singapore	1995		2008			
Thailand	2004		2012			
UK	1994		2008			
USA	1998		2002			
Zimbabwe	1994		2013			

$\hat{N} = N = 12$. The Bai and Ng (2004) BIC is employed for estimating the optimum number of factors (). We use model 2 of the Banerjee and Carrion-i-Silvestre (2015) test, which allows for a stable trend and a cointegrating vector of the model

Table 5 Robustness estimation for panel causality

Dependent variable	Short run		Long run		
	Panel A: OECD_CO ₂				
ΔCO_2	ΔCO_2	ΔNumber	λ	$\lambda/\Delta\text{CO}_2$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.51	3.20***	—	3.78**
	9.90***	—	19.96***	134.67***	—
	Panel B: ASIA_CO ₂				
ΔCO_2	ΔCO_2	ΔNumber	λ	$\lambda/\Delta\text{CO}_2$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.37	3.67***	—	4.82***
	0.28	—	14.04***	66.04***	—
	Panel C: AFRICA_CO ₂				
ΔCO_2	ΔCO_2	ΔNumber	λ	$\lambda/\Delta\text{CO}_2$	$\lambda/\Delta\text{Number}$
ΔNumber	—	1.40	0.67	—	1.12
	1.31	—	7.64***	19.56***	—
	Panel D: OECD_CO ₂ electricity				
$\Delta\text{CO}_2\text{electricity}$	$\Delta\text{CO}_2\text{electricity}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{electricity}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.19	4.35***	—	6.45***
	4.26**	—	18.68***	116.84***	—
	Panel E: ASIA_CO ₂ electricity				
$\Delta\text{CO}_2\text{electricity}$	$\Delta\text{CO}_2\text{electricity}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{electricity}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	3.2**	0.76	—	2.4*
	0.34	—	13.86***	64.34***	—
	Panel F: AFRICA_CO ₂ electricity				
$\Delta\text{CO}_2\text{electricity}$	$\Delta\text{CO}_2\text{electricity}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{electricity}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.01	1.11	—	0.42
	0.14	—	7.38***	18.76***	—
	Panel G: OECD_CO ₂ industry				
$\Delta\text{CO}_2\text{industry}$	$\Delta\text{CO}_2\text{industry}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{industry}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.14	4.32***	—	6.40***
	1.69	—	18.91***	120.17***	—
	Panel H: Asia_CO ₂ industry				
$\Delta\text{CO}_2\text{industry}$	$\Delta\text{CO}_2\text{industry}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{industry}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.31	5.69***	—	11.01***
	0.82	—	14.00***	65.67***	—
	Panel I: Africa_CO ₂ industry				
$\Delta\text{CO}_2\text{industry}$	$\Delta\text{CO}_2\text{industry}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{industry}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	1.23	0.23	—	0.86
	1.08	—	6.92***	17.91***	—
	Panel J: OECD_CO ₂ transport				
$\Delta\text{CO}_2\text{transport}$	$\Delta\text{CO}_2\text{transport}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{transport}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.01	53.08***	—	939.97***
	0.43	—	18.15***	109.82***	—
	Panel K: Asia_CO ₂ transport				
$\Delta\text{CO}_2\text{transport}$	$\Delta\text{CO}_2\text{transport}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{transport}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.08	2.17**	—	1.65
	0.37	—	13.77***	63.43***	—
	Panel L: Africa_CO ₂ transport				
$\Delta\text{CO}_2\text{transport}$	$\Delta\text{CO}_2\text{transport}$	ΔNumber	λ	$\lambda/\Delta\text{CO}_2\text{transport}$	$\lambda/\Delta\text{Number}$
ΔNumber	—	0.81	2.99***	—	3.47**
	0.52	—	7.16***	18.25***	—

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The parameters λ are the error-correction items to examine the long-run relationship between CO₂ and number

short term. But in the long run, the statistical value of number is 3.20, which is significant at the level of 1%. In addition, the statistical value of the joint test of CO₂ and number is 3.78, which is significant at the level of 5%, indicating that the outbreak of epidemics has a long-term impact on CO₂ emissions. The more the number of outbreaks of epidemic, the lower the air quality will be. This result is inconsistent with the views of Craven et al. (2020) and Chen et al. (2020), but we have reason to believe that the improvement of air quality is only the short-

term fluctuation brought by the epidemics, because many industries have been strongly affected under the epidemic, especially catering, tourism, transportation, and service industries, millions of people are suddenly out of work and wondering how to support their families (Kumar et al. 2020). In this case, government will continue to pay attention to the epidemic prevention and control and economic reconstruction work, and relax the supervision of environmental protection, so the future air quality decline is an inevitable trend.

Furthermore, when number is the dependent variable, the statistical value of CO₂ is 9.90, which is significant at the level of 1%, indicating that the change of CO₂ affects number in the short term. This result is consistent with Saadi (2010), indicating that changes in air quality may cause epidemics in the short term. From the results of panel D, panel G, and panel J, it seems that this short-term impact is caused by CO₂ emissions from the electricity sector, because the impact of the industrial and transport sectors on number is not significant. That is to say, in OECD countries, more attention should be paid to the control of CO₂ emissions from the electricity sector so as to prevent future epidemics. In the long run, the statistical value of CO₂ is 19.96, and the statistical value of the joint test of number and CO₂ is 134.67, both of them are significant at the level of 1%. It shows that the long-term pollution emission will also impact the epidemics.

The results of Asian countries are similar to those of OECD countries, except that there is no short-term bidirectional relationship between air quality and epidemics, which shows that in OECD countries with more developed economies, people's health is more dependent on the environment, and changes in short-term air quality may cause epidemics.

The results of African countries are shown in panel C, panel F, panel I, and panel L respectively. We can find that when the dependent variable is CO₂, except for the sector of transport, the impact of epidemics on other sectors is not significant. Part of the reason for this result may be that the sample size from African countries is too small, but due to the long-term impact of CO₂ on number, we can assume that it is the different levels of economic development that lead to the differences in results. Africa's transport sector has been significantly affected by epidemics, which means that epidemics have changed at least the way people travel, but because of the underdevelopment of the rest of sectors, the impact is insignificant.

Conclusion

We used panel data from 30 countries over the period of 1990 to 2018 to study the short-term and long-term causal effects between epidemics and air quality. In summary, although the results of OECD, Asian and African countries are slightly different, it can be concluded that there is a long-term bidirectional relationship between epidemics and air quality. No matter in any sector of any region, CO₂ has a long-term impact on number, indicating that continuous improvement of the environment is an important strategy to prevent and reduce the outbreak of epidemics, and the possible improvement of the environment caused by epidemics is not a long-term phenomenon. The more developed economies are more vulnerable in some ways. Although the electricity and industrial sectors in Africa seem to be unaffected, with the development of the economy, it is always difficult to avoid the environmental damage caused by epidemics.

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