



How is COVID-19 affecting environmental pollution in US cities? Evidence from asymmetric Fourier causality test

Ugur Korkut Pata¹

Received: 1 June 2020 / Accepted: 8 July 2020 / Published online: 15 July 2020
© Springer Nature B.V. 2020

Abstract

This paper aims to examine the effects of the COVID-19 pandemic on PM_{2.5} emissions in eight selected US cities with populations of more than 1 million. To this end, the study employs an asymmetric Fourier causality test for the period of January 15, 2020 to May 4, 2020. The outcomes indicate that positive shocks in COVID-19 deaths cause negative shocks in PM_{2.5} emissions for New York, San Diego, and San Jose. Moreover, in terms of cases, positive shocks in COVID-19 cause negative shocks in PM_{2.5} emissions for Los Angeles, Chicago, Phoenix, Philadelphia, San Antonio, and San Jose. Overall, the findings of the study highlight that the pandemic reduces environmental pressure in the largest cities of the USA. This implies that one of the rare positive effects of the virus is to reduce air pollution. Therefore, for a better environment, US citizens should review the impact of current production and consumption activities on anthropogenic environmental problems.

Keywords PM_{2.5} emissions · COVID-19 · Asymmetric Fourier causality · Economic activities · The USA

Introduction

Many health, social, and economic problems have emerged with the outbreak of coronavirus disease 2019 (COVID-19) in Wuhan, China. In addition to causing pneumonia, the virus damages the heart, liver, and kidneys, as well as the immune system as a whole, as a result of which COVID-19 patients die due to multiple organ disorders (Huang et al. 2020). To date, no proven and effective treatment method has been identified against the virus (Cortegiani et al. 2020). The pandemic has spread rapidly from a single city to an entire country in as little as 30 days (Wu and McGoogan 2020). Since the virus is transmitted rapidly from person to person (Chan et al. 2020), numerous countries have called on their citizens to stay at home and apply social distancing rules to prevent the pandemic from spreading. Various lockdown measures have been implemented to flatten the pandemic curve, such as shutting down industries, halting vehicular traffic, increasing social distance, and stopping non-essential business activities (Bherwani et al. 2020). These measures, in turn, affect

economic production and consumption activities. In the COVID-19 era, industrial activities have slowed down, vehicle use has decreased, the demand for imported goods has decreased, and many countries have suspended air travel—both international and domestic. Economic activities and environmental pollution, especially air pollution, are closely related. Particle matter 2.5 (PM_{2.5}), one of the air pollution indicators, causes cardiovascular disease and lung cancer (Khan et al. 2017) and increases psychological distress, and for these reasons, the air pollution problem needs to be solved urgently (Xu and Liu 2020). In this respect, COVID-19 can be a solution for reducing PM_{2.5} emissions. Transport activities are significantly affected by COVID-19 lockdowns, resulting in less energy consumption and oil demand. As a result of lockdowns, it can be easily said that air quality has improved (Gautam 2020). However, COVID-19 also has some negative effects on the environment.

Zambrano-Monserrate et al. (2020) noted that despite the negative effects of COVID-19 on the environment due to increased waste and reduced recycling activities, the pandemic has also had a number of positive effects—for example, clean beaches, reduced environmental noise, and a reduction in nitrogen dioxide and particulate matter. The Copernicus Atmosphere Monitoring Service (CAMS) examines PM_{2.5} emissions in the atmosphere using satellite images from various countries. According to CAMS (2020), China's average PM_{2.5} emissions in February

✉ Ugur Korkut Pata
korkutpata@ktu.edu.tr; korkutpata@osmaniye.edu.tr

¹ Faculty of Economics and Administrative Sciences, Department of Economics, Osmaniye Korkut Ata University, 80000 Merkez/Osmaniye, Turkey

2020 were between 20 and 30% lower than the averages for the same month in 2017, 2018, and 2019. Similarly, some researchers have noted that the pandemic has reduced air pollution in various countries. For instance, Tobías et al. (2020) observed that the pandemic resulted in a reduction in emissions of nitrogen dioxide (NO₂), black carbon, and particulate matter with a diameter of less than 10 (PM₁₀) during the 2-week lockdown in Barcelona, Spain. Kerimray et al. (2020) concluded that the COVID-19 pandemic reduced PM_{2.5}, CO (carbon monoxide) and NO₂ emissions during the 27-day lockdown in Almaty, Kazakhstan. Moreover, Dantas et al. (2020) reported that the pandemic reduced CO and NO₂ emissions in Rio de Janeiro, Brazil, from March 12, 2020 to April 16, 2020. Sharma et al. (2020) found that the pandemic decreased PM₁₀, PM_{2.5}, CO, and NO₂ emissions in 22 Indian cities during the lockdown period. However, understanding the effect of the COVID-19 quarantine processes on environmental pollution requires more than the use of satellite data (Bao and Zhang 2020). Therefore, Asna-ashary et al. (2020) empirically investigated the pollution–COVID-19 nexus and reported a negative relationship between PM_{2.5} emissions and positive shocks in COVID-19 cases in 31 Iranian provinces.

The pandemic has also reduced air pollution in the USA, the world's largest economy, whose production and consumption activities cause a high rate of air pollution. The first patient identified with COVID-19 in the USA was seen in Washington State on January 20, 2020, and as the pandemic spread rapidly, the USA became the country with the highest number of both cases and deaths. As of April 13, 2020, at least one COVID-19-related death had occurred in each of the 50 states of the USA. As of May 4, 2020, 1,212,000 cases and 69,921 deaths had been reported in the USA. On the same date, the global number of cases was 3,639,000 and the global number of deaths 252,240 (European Center for Disease Prevention and Control 2020). The USA thus accounted for 33% and 27% of worldwide COVID-19 cases and deaths, respectively. The number of cases and deaths continues to increase in the USA and the rest of the world, and the spread of the COVID-19 virus in one country can adversely affect other countries. However, the virus may have more of a positive effect on the environment during lockdown in places with a high population. For both reasons, we empirically analyzed the impact of worldwide COVID-19 cases and deaths on PM_{2.5} emissions in eight US cities with populations over 1 million.

The rest of the paper is organized in the following manner: “Data and methodology” provides the data and methodology, while “Methodology” presents and discusses the empirical results obtained in the study. Finally, “Results and discussion” gives a summary of the findings and concludes the study.

Data and methodology

Data

In this study, we examined the effect of COVID-19 on environmental pollution in eight US cities (New York, Los Angeles, Chicago, Phoenix, Philadelphia, San Antonio, San Diego, and San Jose) for the period of January 15, 2020 to May 4, 2020. Since environmental pollution data for Houston and Dallas were not available, these cities were excluded from the analysis. Data relating to worldwide COVID-19 cases and deaths were obtained from the European Center for Disease Prevention and Control (2020), while the PM_{2.5} data (daily per cubic meter air, µg/m³) for the eight US cities were collected from the United States Environmental Protection Agency (2020). The data utilized in the study are converted into natural logarithm to obtain a more stable data variance. The descriptive statistics of the data are illustrated in Table 1.

In terms of PM_{2.5} emissions, information from Table 1 illustrates that Los Angeles has the highest mean and median values followed by Chicago and San Diego. On the contrary, Phoenix and San Jose have the lowest PM_{2.5} emissions. Moreover, Skewness statistics demonstrate that 7 out of 10 variables are skewed (except PM_{2.5} emissions in Los Angeles, Phoenix, and Philadelphia), and Kurtosis statistics illustrate that all variables are leptokurtic. The Jarque-Bera test statistics indicate that PM_{2.5} emissions in six US cities are normally distributed based on a 5% significance level (except Chicago and San Diego). Regarding the COVID-19 variables, both the number of the cases and deaths do not follow the normal distribution.

After investigating the characteristics of the variables, we applied Fourier Lagrange multiplier (LM) unit root and asymmetric Fourier causality tests.

Methodology

Fourier Lagrange multiplier unit root test

Enders and Lee (2012) developed the LM-based Fourier unit root test on the basis of Gallant's (1981) Fourier approximation. This approximation captures smooth structural shift using a small amount of low frequency information. The first step to implement the Fourier LM unit root test is shown in Eq. (1):

$$\Delta x_t = \beta_0 + \beta_1 \Delta \sin\left(\frac{2\pi kt}{T}\right) + \beta_2 \Delta \cos\left(\frac{2\pi kt}{T}\right) + z_t \quad (1)$$

In the first-differenced regression, Δ represents the difference operator, β_0 indicates the constant term, k denotes a particular frequency, and β_1 and β_2 illustrate the amplitude and

Table 1 Descriptive statistics of the variables

Variables	Mean	Median	Maximum	Minimum	Skewness	Kurtosis	JB
lnNew York PM _{2.5}	1.791	1.824	2.821	0.262	− 0.429	3.419	4.228 (0.120)
lnLos Angeles PM _{2.5}	2.238	2.174	3.608	1.360	0.463	2.493	5.151 (0.076)
lnChicago PM _{2.5}	2.177	2.186	2.960	0.741	− 0.609	2.991	6.868 (0.032)
lnPhoenix PM _{2.5}	1.786	1.757	2.867	0.693	0.205	3.010	0.781 (0.676)
lnPhiladelphia PM _{2.5}	1.882	1.902	2.980	0.875	0.052	3.439	0.781 (0.676)
lnSan Antonio PM _{2.5}	2.019	2.041	3.077	0.587	− 0.204	2.716	1.146 (0.563)
lnSan Diego PM _{2.5}	2.062	2.157	3.072	0.788	− 0.538	2.419	6.917 (0.031)
lnSan Jose PM _{2.5}	1.798	1.808	2.674	0.741	− 0.131	2.530	1.339 (0.511)
lnCases	11.679	11.646	15.058	4.110	− 0.994	3.608	20.027 (0.001)
lnDeaths	8.408	8.299	12.417	0.693	− 0.747	3.042	10.348 (0.005)

JB Jarque-Bera, () probability values

displacement of the frequency approximation. With the estimated coefficients β_0 , β_1 , and β_2 , the detrended series is formed as in Eq. (2):

$$\begin{aligned} \tilde{S}_t &= x_t - \tilde{\psi} - \tilde{\beta}_0 t - \tilde{\beta}_1 \sin\left(\frac{2\pi kt}{T}\right) - \tilde{\beta}_2 \cos\left(\frac{2\pi kt}{T}\right), \quad t \\ &= 2, \dots, T \end{aligned} \tag{2}$$

where $\tilde{\psi} = x_1 - \tilde{\beta}_0 - \tilde{\beta}_1 \sin\left(\frac{2\pi kt}{T}\right) - \tilde{\beta}_2 \cos\left(\frac{2\pi kt}{T}\right)$, and x_1 is the first observation of x_t . At the last stage, the Fourier LM unit root test was performed using the detrended series:

$$\begin{aligned} \Delta x_t &= \varphi \tilde{S}_{t-1} + \alpha_0 + \alpha_1 \Delta \sin\left(\frac{2\pi kt}{T}\right) \\ &+ \alpha_2 \Delta \cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^k \vartheta_i \Delta \tilde{S}_{t-i} + v_t \end{aligned} \tag{3}$$

In Eq. (3), the null hypothesis of unit root ($H_0: \varphi = 0$) is tested using the t -statistic. The test statistic (τ_{LM}) depends only on the frequency k . Therefore, the critical values tabulated by Enders and Lee (2012) are a function of k . In addition, the authors used F-statistics to test the significance of the Fourier component as follows:

$$F_\mu(k) = \frac{(SSR_0 - SSR_1)/q}{SSR_1(k)/(T-k)} \tag{4}$$

where q indicates the number of regressors, SSR_0 denotes the sum of squared residuals from the regression without Fourier approximation, while SSR_1 represents SSR from the regression containing the trigonometric terms. When the F-statistic is greater than the critical value, it is convenient to use the Fourier LM unit root test; otherwise, more reliable and powerful results can be obtained using conventional unit root tests without a Fourier term.

Asymmetric Fourier causality test

Researchers began to investigate causal relations between macroeconomic variables by using the Granger (1969) causality test. However, the Granger and many other causality tests in the literature, such as that by Toda and Yamamoto (TY; Toda and Yamamoto 1995), neglect structural breaks that may occur in the series. To compensate for this negligence, Enders and Jones (2016) and Nazlioglu et al. (2016) proposed the Fourier Granger and Fourier TY causality tests, respectively. These tests are performed by adding Fourier functions to the equation, just like the Fourier LM unit root test. The authors referred to above stated that the null hypothesis could be rejected more accurately using this approach. Nazlioglu et al. (2016) relaxed the assumption that the constant term does not change over time. The model used for the Fourier TY causality test is shown in Eq. (5):

$$\begin{aligned} y_t &= \alpha_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) \\ &+ \beta_1 y_{t-1} + \dots + \beta_{p+d_{\max}} y_{t-(p+d_{\max})} \\ &+ u_t \end{aligned} \tag{5}$$

In the equation, y_t represents the vector containing the variables of COVID-19 cases and deaths, and PM_{2.5} emissions, β is the coefficients matrix, t is the trend, T denotes the number of observations, γ_1 and γ_2 are the coefficients of the Fourier approximation that smooth structural shifts are captured, and d_{\max} is the maximum integration degree of the series that can be determined by a unit root test. In our study, the optimal lag length p and the Fourier frequency k are determined by the Akaike information criterion (AIC). In the single-frequency Fourier TY causality test, the null hypothesis of no causality is tested as $H_0: \beta_1 = \dots = \beta_p = 0$.

The reactions of people, firms, and decision units to positive and negative shocks are different. Analyzing the effects of both shocks as a whole leads to the hidden causal relationships being ignored. In order to reveal hidden causal relationships, Hatemi-J (2012) suggested separating variables into positive and negative shocks and applying the causality test to these shocks. Therefore, following Yilanci et al. (2019), we performed the asymmetric Fourier causality test by considering the cumulative positive and negative shocks of the variables. This test is applied by adding the shocks to the y_t in Eq. (5). All other procedures are the same as those of a single-frequency Fourier TY causality test. This test offers two main advantages. First, it allows the causal relationships between the positive and negative shocks of the variables to be examined separately. Second, in the asymmetric Fourier TY causality test, structural breaks with an unknown number, form, and date are taken into account in the analysis. Due to the advantages, the asymmetric Fourier TY causality test provides a more accurate rejection of the null hypothesis of no causality. While applying this approach, a variable can be transformed into positive and negative components, as in Eq. (6):

$$PM_{2.5,t} = PM_{2.5,t-1} + \varepsilon_{1t} = PM_{2.5,1,0} + \sum_{i=1}^t \varepsilon_{1i}^+ + \sum_{i=1}^t \varepsilon_{1i}^- \quad (6)$$

where $PM_{2.5,1,0}$ indicates the initial value of the relevant variable and ε_{1i}^+ and ε_{1i}^- represent positive and negative shocks, respectively. This process is carried out in the same way for each variable analyzed. The shocks are then included in the Fourier causality equation. In this study, we investigated whether there is a causal relation from positive shocks of COVID-19 to positive and negative shocks of $PM_{2.5}$ emissions. Because there is no cure for COVID-19, and therefore no negative shock for deaths and cases, we can only examine the positive shocks of COVID-19.

Results and discussion

In the first phase of the analysis, we investigated the stochastic properties of the variables to determine the maximum order of integration (d_{max}). Column 4 of Table 2 demonstrates that F-statistics are significant for all variables. Therefore, we decided to use trigonometric terms in unit root analysis and applied the Fourier LM unit root test to obtain more robust findings. According to the τ_{LM} statistics presented in Table 2, the raw data on COVID-19 cases and deaths contain a unit root. These variables are stationary in their first difference. At the same time, the $PM_{2.5}$ emissions of eight cities are stationary at level $I(0)$. To save space, the results of negative and positive components are not presented in the table. Positive and negative shocks of COVID-19 cases and deaths are also non-stationary at level.

After determining the order of integration of the variables as 1, we analyzed the effects of the worldwide COVID-19 cases on the $PM_{2.5}$ emissions of eight cities. According to the results presented in Table 3, we determined that the number of COVID-19 cases cause $PM_{2.5}$ emissions only in Chicago. However, when we used the asymmetric causality test, the findings changed significantly. The findings of the asymmetric Fourier causality test illustrate that an increase in the number of cases reduces $PM_{2.5}$ emissions in Los Angeles, Chicago, Phoenix, Philadelphia, San Antonio, and San Jose. Since there is no decrease in the number of cases and deaths, these variables do not have negative components. In addition, there is no relationship between the positive components of COVID-19 cases and $PM_{2.5}$ emissions. This is not surprising, since COVID-19 reduces use of fossil fuels such as oil and coal, which are primary air pollutants.

The causal relationships between worldwide COVID-19 deaths and $PM_{2.5}$ in US cities are displayed in Table 4. According to symmetric causality test results, COVID-19 deaths are the cause of $PM_{2.5}$ emissions in New York and Los Angeles. The results of the asymmetric Fourier causality test demonstrate that an increase in the number of deaths reduces the release of $PM_{2.5}$ emissions in New York, San Diego, and San Jose. Overall, an increase in the number of cases affects air pollution more than an increase in the number of deaths. Therefore, it can be said that an increase in COVID-19 cases caused people to take more precautions and thus slow down economic activities.

To sum up, COVID-19 deaths and cases positively affect environmental quality by reducing economic and social

Table 2 Fourier LM unit root test results

Variables	Level			First difference			
	τ_{LM}	p	k	F-statistics	τ_{LM}	p	k
lnNew York- $PM_{2.5}$	-4.312*	10	2	19.254*	-	-	-
lnLos Angeles- $PM_{2.5}$	-4.306*	12	3	25.268*	-	-	-
lnChicago- $PM_{2.5}$	-4.677**	10	1	20.375*	-	-	-
lnPhoenix- $PM_{2.5}$	-4.530**	11	1	25.372*	-	-	-
lnPhiladelphia- $PM_{2.5}$	-4.193**	12	1	28.731*	-	-	-
lnSan Antonio- $PM_{2.5}$	-4.435**	12	1	15.622*	-	-	-
lnSan Diego- $PM_{2.5}$	-4.113*	11	3	23.975*	-	-	-
lnSan Jose- $PM_{2.5}$	-4.902*	11	2	24.317*	-	-	-
lnCases	-0.104	12	2	12.324*	-6.313*	12	2
lnDeaths	1.240	11	2	13.996*	-5.416*	12	2

The critical values are obtained from Enders and Lee (2012). The unit root test results for negative and positive components are available upon request from the author

*, **, and ***statistical significance at 1%, 5%, and 10% levels, respectively

Table 3 The results of asymmetric Fourier causality test for COVID-19 cases

Null hypothesis	lnCases → lnPM _{2.5}			lnCases ⁺ → lnPM _{2.5}			lnCases ⁺ → lnPM _{2.5} ⁺		
	Test statistics	<i>p</i>	<i>k</i>	Test statistics	<i>p</i>	<i>k</i>	Test statistics	<i>p</i>	<i>k</i>
Cities									
New York	7.837	9	1	7.676	12	3	4.971	7	3
Los Angeles	18.720	12	1	28.949*	12	3	17.133	10	1
Chicago	21.032***	12	3	22.533**	12	1	17.436	12	1
Phoenix	18.074	12	1	24.059**	10	1	6.712	8	1
Philadelphia	13.337	8	1	19.378**	10	2	8.805	10	2
San Antonio	11.571	11	1	25.552**	11	2	9.318	12	2
San Diego	4.057	9	1	5.206	10	2	4.650	10	1
San Jose	8.677	12	1	23.261**	12	2	6.760	10	1

Optimal lag lengths and frequencies are selected by AIC. The maximum lag length set at 12 using the Schwert’s (1989) approach ($k_{max} = 12 \times (\frac{111}{100})^{1/4} = 12$)

*, **, and ***statistical significance at 1%, 5%, and 10% levels, respectively)

activities in eight cities with high populations in the USA. In line with the findings of Pata (2019), who stated that the 2001 economic crisis reduced carbon emissions in Turkey, our results indicate that the COVID-19 crisis reduced PM_{2.5} emissions in the selected US cities. Perhaps the only positive aspect of economic crises or pandemics is that they reduce human pressure on the environment. Humans destroy nature for the sake of their economic and social interests, and when human activities cease, nature can return to its balance. For this reason, humankind must review existing production and consumption activities with a view towards ensuring a cleaner environment and a more sustainable future.

Conclusions

This study investigates the effect of COVID-19 deaths and cases on environmental pollution in the USA. The results of

the asymmetric Fourier causality test demonstrate that COVID-19 reduces PM_{2.5} emissions in US cities. An increase in the number of cases of COVID-19 affects pressure on the environment more than an increase in the number of deaths. Another important finding of the study is that positive and negative shocks should be taken into consideration. When shocks are not studied separately, a unidirectional causality from COVID-19 to PM_{2.5} emissions is found for New York, Los Angeles, and Chicago. However, an increase in positive shocks of COVID-19 causes negative shocks of PM_{2.5} in the eight high-population cities studied. In other words, an increase in worldwide COVID-19 deaths and cases causes a reduction in PM_{2.5} emissions. The rapid spread of the virus in the USA, especially in New York, led the lockdown process to be introduced. This resulted in the industry and service sectors largely ceasing their production activities. The slow-down in economic activities led to a reduction in environmental pollution. This demonstrates that environmental pollution is a man-made phenomenon, and that people are harming the

Table 4 The results of asymmetric Fourier causality test for COVID-19 deaths

Null hypothesis	lnDeaths→lnPM _{2.5}			lnDeaths ⁺ → lnPM _{2.5} ⁻			lnDeaths ⁺ → lnPM _{2.5} ⁺		
	Test statistics	<i>p</i>	<i>k</i>	Test statistics	<i>p</i>	<i>k</i>	Test statistics	<i>p</i>	<i>k</i>
Cities									
New York	17.897***	10	3	15.446**	8	2	9.887	10	2
Los Angeles	24.804**	12	2	14.821	10	2	3.251	8	3
Chicago	4.557	9	2	6.731	9	2	3.446	9	2
Phoenix	16.117	9	2	13.216	9	2	8.978	11	2
Philadelphia	5.215	9	2	10.983	8	2	4.889	8	2
San Antonio	11.260	9	2	9.607	10	2	5.272	9	1
San Diego	12.923	10	1	18.260**	9	2	11.933	10	3
San Jose	7.948	10	1	51.190*	12	2	9.399	10	1

See notes for Table 2

natural environment in which they live. For this reason, perhaps, COVID-19 will assume its place as a pandemic that increased human awareness about environmental issues. Moreover, the effects of COVID-19 lockdown on air pollution will create an important opportunity to evaluate future air quality policies.

The overall findings imply that PM_{2.5} emissions can decrease when people are prevented from harming the environment. PM_{2.5} emissions are generally due to transport activities and the use of fossil energy sources such as oil and coal. The US government can improve air quality by promoting substitution of fossil fuels with renewables, by enforcing strict execution of air quality control plans, and by implementing awareness-raising programs on environmental issues. In addition, the US government and the private sector can expand remote working opportunities brought by the COVID-19 in the coming period, thereby reducing air pollution. Following the COVID-19 pandemic, if the regulatory authorities in the US take the necessary measures, PM_{2.5} emissions in cities can be reduced, and thus, environmental quality can be improved.

References

- Asna-ashary M, Farzanegan MR, Feizi M, Sadati SM (2020) COVID-19 outbreak and air pollution in Iran: a panel VAR analysis (no. 16-2020). Joint Discussion Paper Series in Economics
- Bao R, Zhang A (2020) Does lockdown reduce air pollution? Evidence from 44 cities in northern China. *Sci Total Environ.* 139052. <https://doi.org/10.1016/j.scitotenv.2020.139052>
- Bherwani H, Nair M, Musugu K, Gautam S, Gupta A, Kapley A, Kumar R (2020) Valuation of air pollution externalities: comparative assessment of economic damage and emission reduction under COVID-19 lockdown. *Air Quality, Atmosphere & Health* 13:683–694. <https://doi.org/10.1007/s11869-020-00845-3>
- CAMS (2020) <https://atmosphere.copernicus.eu/amid-coronavirus-outbreak-copernicusmonitors-reduction-particulate-matter-pm25-over-china> (accessed 10 May 2020)
- Chan JFW, Yuan S, Kok KH, Toa KKW, Chu H, Yang J, Xing F, Liu J, Yip CCY, Poon RWS (2020) A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: a study of a family cluster. *Lancet* 395(10223):514–523. [https://doi.org/10.1016/S0140-6736\(20\)30154-9](https://doi.org/10.1016/S0140-6736(20)30154-9)
- Cortegiani A, Ingoglia G, Ippolito M, Giarratano A, Einav S (2020) A systematic review on the efficacy and safety of chloroquine for the treatment of COVID-19. *J Crit Care* 57:279–283. <https://doi.org/10.1016/j.jcrc.2020.03.005>
- Dantas G, Siciliano B, França BB, da Silva CM, Arbilla G (2020) The impact of COVID-19 partial lockdown on the air quality of the city of Rio de Janeiro, Brazil. *Sci Total Environ.* 729:139085. <https://doi.org/10.1016/j.scitotenv.2020.139085>
- Enders W, Jones P (2016) Grain prices, oil prices, and multiple smooth breaks in a VAR. *Studies in Nonlinear Dynamics & Econometrics* 20(4):399–419. <https://doi.org/10.1515/snde-2014-0101>
- Enders W, Lee J (2012) A unit root test using a Fourier series to approximate smooth breaks. *Oxf Bull Econ Stat* 74(4):574–599. <https://doi.org/10.1111/j.1468-0084.2011.00662.x>
- European Center for Disease Prevention and Control (2020) Download today's data on the geographic distribution of COVID-19 cases worldwide <https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide> (accessed 4 May 2020)
- Gallant AR (1981) On the bias in flexible functional forms and an essentially unbiased form: the Fourier flexible form. *J Econ* 15(2):211–245. [https://doi.org/10.1016/0304-4076\(81\)90115-9](https://doi.org/10.1016/0304-4076(81)90115-9)
- Gautam S (2020) COVID-19: air pollution remains low as people stay at home. *Air Quality, Atmosphere, & Health* 13:853–857. <https://doi.org/10.1007/s11869-020-00842-6>
- Granger CW (1969) Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society* 37(3):424–438. <https://doi.org/10.2307/1912791>
- Hatemi-J A (2012) Asymmetric causality tests with an application. *Empir Econ* 43(1):447–456. <https://doi.org/10.1007/s00181-011-0484-x>
- Huang C, Wang Y, Li X, Ren L, Zhao J, Hu Y, Zhang L, Fan G, Xu J, Gu X, Cheng Z, Yu T, Xia J, Wei Y, Wu W, Xie X, Yin W, Li H, Liu M, Xiao Y, Gao H, Gou L, Xie J, Wang G, Jiang R, Gao Z, Jin Q, Wang J, Cao B (2020) Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *Lancet* 395(10223):497–506. [https://doi.org/10.1016/S0140-6736\(20\)30183-5](https://doi.org/10.1016/S0140-6736(20)30183-5)
- Kerimray A, Baimatova N, Ibragimova OP, Bukenov B, Kenessov B, Plotitsyn P, Karaca F (2020) Assessing air quality changes in large cities during COVID-19 lockdowns: the impacts of traffic-free urban conditions in Almaty, Kazakhstan. *Sci Total Environ.* 139179. <https://doi.org/10.1016/j.scitotenv.2020.139179>
- Khan MF, Hwa SW, Hou LC, Mustaffa NIH, Amil N, Mohamad N, Sahani M, Jaafar SA, Nadzir MSM, Latif MT (2017) Influences of inorganic and polycyclic aromatic hydrocarbons on the sources of PM_{2.5} in the Southeast Asian urban sites. *Air Quality, Atmosphere & Health* 10(8):999–1013. <https://doi.org/10.1007/s11869-017-0489-5>
- Nazlioglu S, Gormus NA, Soytaş U (2016) Oil prices and real estate investment trusts (REITs): gradual-shift causality and volatility transmission analysis. *Energy Econ* 60:168–175. <https://doi.org/10.1016/j.eneco.2016.09.009>
- Pata UK (2019) Environmental Kuznets curve and trade openness in Turkey: bootstrap ARDL approach with a structural break. *Environ Sci Pollut Res* 26(20):20264–20276. <https://doi.org/10.1007/s11356-019-05266-z>
- Schwert G (1989) Tests for unit roots: a Monte Carlo investigation. *J Bus Econ Stat* 20:147–159. <https://doi.org/10.1198/073500102753410354>
- Sharma S, Zhang M, Gao J, Zhang H, Kota SH (2020) Effect of restricted emissions during COVID-19 on air quality in India. *Sci Total Environ* 728:138878. <https://doi.org/10.1016/j.scitotenv.2020.138878>
- Tobías A, Carnerero C, Reche C, Massagué J, Via M, Minguillón MC, Alastuey A, Querol X (2020) Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. *Sci Total Environ* 138540:138540. <https://doi.org/10.1016/j.scitotenv.2020.138540>
- Toda HY, Yamamoto T (1995) Statistical inference in vector autoregressions with possibly integrated processes. *J Econ* 66(1):225–250. [https://doi.org/10.1016/0304-4076\(94\)01616-8](https://doi.org/10.1016/0304-4076(94)01616-8)
- United States Environmental Protection Agency (2020) Outdoor air quality data <https://www.epa.gov/outdoor-air-quality-data/download-daily-data> (accessed 4 May 2020)
- Wu Z, McGoogan JM (2020) Characteristics of and important lessons from the coronavirus disease 2019 (COVID-19) outbreak in China: summary of a report of 72 314 cases from the Chinese Center for Disease Control and Prevention. *Jama* 323(13):1239–1242. <https://doi.org/10.1001/jama.2020.2648>

- Xu Y, Liu H (2020) Spatial ensemble prediction of hourly PM_{2.5} concentrations around Beijing railway station in China. *Air Quality, Atmosphere & Health* 13:563–573. <https://doi.org/10.1007/s11869-020-00817-7>
- Yilanci V, Ozgur O, Gorus MS (2019) The asymmetric effects of foreign direct investment on clean energy consumption in BRICS countries: a recently introduced hidden cointegration test. *J Clean Prod* 237: 117786. <https://doi.org/10.1016/j.jclepro.2019.117786>
- Zambrano-Monserrate MA, Ruano MA, Sanchez-Alcalde L (2020) Indirect effects of COVID-19 on the environment. *Sci Total Environ* 138813:138813. <https://doi.org/10.1016/j.scitotenv.2020.138813>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.