How is COVID-19 affecting environmental pollution in US cities? Evidence from Asymmetric Fourier Causality Test

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Abstract

This paper aims to examine the effects of the COVID-19 pandemic on PM$_{2.5}$ emissions in eight selected US cities with a population of more than 1 million. To this end, the study employs an asymmetric Fourier causality test for the period 15 January 2020 to 4 May 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 US. This implies that one of the rare positive effects of the virus is to reduce environmental pollution. Therefore, for a better environment, US citizens should review the impact of current production and consumption activities on anthropogenic environmental problems.

Keywords: PM$_{2.5}$; COVID-19; Asymmetric Fourier causality; Economic activities; the United States.

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1. 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. Thus, 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 spreads rapidly from a single city to the 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 the social distancing rules to prevent the pandemic from spreading. These measures, in turn, affect economic production and consumption. In the COVID-19 era, industrial activities have slowed down, vehicle use has decreased, demand for imported goods has gone down, and many countries have suspended air travel – both international and domestic. Economic activities and environmental pollution, especially air pollution, are closely related. For this reason, the pandemic can also affect environmental quality.

Zambrano-Monserrate et al. (2020) have noted that despite the negative effects of COVID-19 on the environment due to increased waste and reduced recycling activities, the pandemic also has 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 with the help of satellite images of various countries. According to CAMS (2020), China’s average PM$_{2.5}$ emissions in February 2020 were between 20% and 30% lower than the average for the same month in 2017, 2018, and 2019. Similarly, some researchers have noted that the pandemic reduces air pollution in various countries. For example, Tobias et al. (2020) observed that the pandemic resulted in a reduction in emissions of nitrogen dioxide (NO$_2$), black carbon and
particulate matter with a diameter of less than 10 (PM$_{10}$) during the two-week lockdown in Barcelona, Spain. Kerimray et al. (2020) concluded that the COVID-19 pandemic reduced PM$_{2.5}$, CO (carbon dioxide) and NO$_2$ emissions in the 27-day lockdown in Almaty, Kazakhstan. Moreover, Dantas et al. (2020) reported that the pandemic reduced CO and NO$_2$ emissions in Rio de Janeiro, Brazil from 12 March 2020 to 16 April 2020. Sharma et al. (2020) found that the pandemic mitigated PM$_{10}$, PM$_{2.5}$, CO, and NO$_2$ emissions in 22 Indian cities during the lockdown period. However, understanding the effect of 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 that PM$_{2.5}$ emissions had a negative relationship with positive shocks of COVID-19 cases in 31 Iranian provinces.

As in the studies mentioned above, the pandemic has also reduced air pollution in the US. The US is the world's largest economy and its production and consumption activities cause a high rate of air pollution. The first COVID-19 patient in the US was seen in Washington State on 20 January 2020, and as the pandemic went on to spread rapidly, the US became the country with the highest number of deaths and cases. As at 13 April 2020, at least one COVID-19-related death had occurred in each of the 50 states of the US (Bashir et al. 2020). As at 4 May 2020, 1,212,000 cases of the disease had been reported in the US, and 69,921 deaths. As at 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 US accounts for 33% and 27% of worldwide COVID-19 cases and deaths, respectively. While the number of cases and deaths continues to increase in the US and in the rest of the world, the spread of the COVID-19 virus in one country can adversely affect other countries. At the same time, 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 a population of over 1 million.

2. Data and methodology

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 15 January 2020 to 4 May 2020. Since environmental pollution data for Houston and Dallas were not available, these cities are excluded from the analysis. Data relating to worldwide COVID-19 cases and deaths were obtained from the European Centre for Disease Prevention and Control (2020), while the PM$_{2.5}$ data (daily per cubic meter air, µg/m$^3$) for the eight US cities were collected from the United States Environmental Protection Agency (2020). After performing logarithmic transformations to the data, we applied Fourier Lagrange multiplier (LM) unit root and asymmetric Fourier causality tests.

2.1. 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 indicated in Eq. 1.

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

(1)

In the first-differenced regression, $\Delta$ represents the difference operator, $\beta_0$ indicates the constant term, $k$ denotes a particular frequency, and $\beta_1$ and $\beta_2$ illustrate amplitude and displacement of the frequency approximation. With the estimated coefficients $\beta_0$, $\beta_1$ and $\beta_2$, the detrended series is formed as in Eq. 2.

$$\tilde{s}_t = x_t - \tilde{\beta}_0 - \tilde{\beta}_1 \sin \left( \frac{2\pi kt}{T} \right) - \tilde{\beta}_2 \cos \left( \frac{2\pi kt}{T} \right), \quad \text{t}=2,\ldots, T$$

(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 is performed using the detrended series.

\[
\Delta x_t = \phi \Delta S_{t-1} + \alpha_0 + \alpha_1 \Delta \sin \left( \frac{2\pi kt}{T} \right) + \alpha_2 \Delta \cos \left( \frac{2\pi kt}{T} \right) + \sum_{i=1}^{k} \theta_i \Delta S_{t-i} + v_t
\]

(3)

In Eq. 3, the null hypothesis of unit root (H\(_0\): \( \phi = 0 \)) is tested using the t-statistic. The test statistic (\( \tau_{LM} \)) 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:

\[
F_{\mu}(k) = \frac{(SSR_0 - SSR_1)}{q} \frac{SSR_1(k)/(T-k)}{SSR_1}
\]

(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 with conventional unit root tests without a Fourier term.

### 2.2. 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 (1995) (TY), 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 rejection of the null hypothesis could be made more accurately with this approach. Nazlioglu et al. (2016) relaxed the assumption that
the constant term did not change over time. The model used for the Fourier TY causality test is indicated in Eq. 5.

\[ y_t = \alpha_0 + \gamma_1 \sin \left( \frac{2\pi kt}{T} \right) + \gamma_2 \cos \left( \frac{2\pi kt}{T} \right) + \beta_1 y_{t-1} + \ldots + \beta_{p+d_{\text{max}}} y_{t-(p+d_{\text{max}})} + u_t \]  

(5)

In the equation, \( y_t \) represents the vector containing the variables of COVID-19 cases and deaths and PM\(_{2.5}\) emissions, \( \beta \) is the coefficients matrix, \( t \) is the trend, \( T \) denotes the number of observations, \( \gamma_1 \) and \( \gamma_2 \) are the coefficients of the Fourier approximation that smooth structural shifts are captured, and \( d_{\text{max}} \) 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, which indicates that there is no causal relationship, is tested as \( H_0: \beta_1 = \ldots \beta_p = 0 \).

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 ignoring the hidden causal relationships. 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 single frequency Fourier TY causality test. A variable can be separated into positive and negative shocks, as in Eq. 6.

\[ \text{PM}_{2.5t} = \text{PM}_{2.5t-1} + \varepsilon_{1t} = \text{PM}_{2.5t-1,0} + \sum_{i=1}^{1} \varepsilon_{1i}^+ + \sum_{i=1}^{1} \varepsilon_{1i}^- \]  

(6)

where \( \text{PM}_{2.5t-1,0} \) indicates the initial value of the relevant variable, and \( \varepsilon_{1i}^+ \) and \( \varepsilon_{1i}^- \) represent positive and negative shocks, respectively. This process is carried out in the same way for each

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variable analyzed. The shocks are then included in the Fourier causality equation. In this study, we have investigated whether there is a causal relation from positive shocks of COVID-19 to positive and negative shocks of environmental pollution. Because there is no cure for COVID-19, and there is therefore no negative shock for deaths and cases, we can only examine the positive shocks of COVID-19.

3. 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 \( (d_{\text{max}}) \). Column 4 of Table 1 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 \( \tau_{LM} \) statistics presented in Table 1, 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.

| Table 1 Fourier LM unit root test results |
|------------------------------------------|
| Variables | \( \tau_{LM} \) | p | k | F-statistics | \( \tau_{LM} \) | 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 |

Notes: *, ** and *** indicate statistical significance at 1%, 5% and 10% levels, respectively. 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.
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 2, 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. There is no relationship between the positive components of number of 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 polluters.

### Table 2 The results of asymmetric Fourier causality test for COVID-19 cases

| Cities        | Test statistics | p  | k  | Test statistics | p  | k  | Test statistics | p  | k  |
|---------------|----------------|----|----|----------------|----|----|----------------|----|----|
| 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  |

Notes: *, ** and *** indicate statistical significance at 1%, 5% and 10% levels, respectively. Optimal lag lengths and frequencies are selected by AIC. The maximum lag length set at 12 using the Schwert’s (1989) approach ($k_{max}=12\times(\frac{111}{100})^{1/4} =12$).

The causal relationships between worldwide COVID-19 deaths and PM$_{2.5}$ in US cities are displayed in Table 3. 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$_{2.5}$ 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.

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

| Cities          | Null hypothesis | lnDeaths $\rightarrow$ lnPM$_{2.5}$ | Test statistics | lnDeaths $\rightarrow$ lnPM$_{2.5}$ | Test statistics | lnDeaths $\rightarrow$ lnPM$_{2.5}$ | Test statistics |
|-----------------|-----------------|-------------------------------------|-----------------|-------------------------------------|-----------------|-------------------------------------|-----------------|
| 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                                |

Notes: See notes for Table 2.

To sum up, COVID-19 deaths and cases positively affect environmental quality by reducing economic and social activities in eight cities with high populations in the US. In line with those 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. When human activities cease, nature can return to its balance. For this reason, humankind needs to review existing production and consumption activities with a view to ensuring a cleaner environment and a more sustainable future.

**4. Conclusions**

This study investigates the effect of COVID-19 deaths and cases on environmental pollution in the US. 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. With the rapid spread of the virus in the US, especially in New York, the lockdown process was introduced. This resulted in the industry and service sectors largely ceasing their production activities. The slowdown 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 natural environment in which they live. For this reason, perhaps, COVID-19 will take its place as a pandemic that increased human awareness about environmental issues.

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