Vicious Cycle of Economic Growth, Pm2.5 and COVID-19 Case of G7 Countries

Rıdvan KARACAN*

Abstract
Today, production is carried out depending on fossil fuels. Fossil fuels pollute the air as they contain high levels of carbon. Many studies have been carried out on the economic costs of air pollution. However, in the present study, unlike the former ones, economic growth's relationship with the COVID-19 virus in addition to air pollution was examined. The COVID-19 virus, which was initially reported in Wuhan, China in December 2019 and affected the whole world, has caused many cases and deaths. Researchers have been going on studying how the virus is transmitted. Some of these studies suggest that the number of virus-related cases increases in regions with a high level of air pollution. Based on this fact, it is thought that air pollution will increase the number of COVID-19 cases in G7 Countries where industrial production is widespread. Therefore, the negative aspects of economic growth, which currently depends on fossil fuels, is tried to be revealed. The research was carried out for the period between 2000-2019. Panel cointegration test and panel causality analysis were used for the empirical analysis. Particulate matter known as PM2.5† was used as an indicator of air pollution. Consequently, a positive long-term relationship has been identified between PM2.5 and economic growth. This relationship also affects the number of COVID-19 cases.

Keywords: Economic Growth, PM2.5, COVID-19, G7 Countries, Panel Cointegration Test and Panel Causality Analysis.

JEL Classification: H51, E01, O47, C23

Introduction
It is a known reality that economic growth causes air pollution as fossil fuels are used in production. With the emission of fossil fuels such as primarily petroleum, coal, and natural gas, high levels of carbon are mixed into the atmosphere, thus, causing air pollution. Thus, the economic growth is achieved on the one hand, while destruction due to air pollution occurs on the other. Therefore, increasing costs reduce the net contribution of growth. Consequently, air pollution negatively affects economic growth. This leads to a vicious cycle of economic growth and air pollution. Fine particulate matter PM2.5 ratios are considered as an indicator of air pollution in the environment. The negative impact of air pollution on economic growth comes into prominence by increasing health expenditures. Epidemiological studies have demonstrated strong causal relationships between prolonged exposure to PM2.5 and chronic diseases such as heart disease, stroke, and lung cancer and deaths due to these diseases (Davidson et al. 2007; Dockery et al., 1993; Krewski et al., 2009; Lepeule et al., 2012, Papa et al., 2009).

Therefore, the state makes health expenditures for the treatment of these diseases. The amount of the expenditures, in other words, the burden on the budget becomes great depending on the extent of the damage. Moreover, air pollution adversely affects the lung development of children and increases the prevalence of chronic respiratory diseases (CRDs) such as asthma and chronic obstructive pulmonary disease (COPD) in areas with high pollution (Republic of Turkey Ministry of Health, 2020). PM2.5 changes the chemical, physical, and biological quality of the air we breathe. The individuals breathe an average of 13,000-16,000 liters of air per day. Therefore, the air with deteriorated chemical, physical, and biological characteristics is very risky for human health. Every year, 7 million people die earlier due to air pollution in the world (Öztürk, 2017). Besides, the PM2.5 has a large proportion in terms of surface area and volume; therefore, some bacteria, viruses, fungi, and other pathogenic microorganisms and some heavy metals, acid oxides, organic pollution toxins can be absorbed by the PM2.5 particles, which leads to increased toxicity (Loomis et al., 2013; Hoek et al., 2013). Based on these facts, it was aimed to conduct a specific study on the COVID-19 virus, which was first reported in Wuhan, China in December 2019, and affected the whole world. The results of the conducted studies have suggested that

* Associate Professor, Department of Economics, Kocaeli University, karacanr@gmail.com
† "Fine particulate matter (PM2.5) is an air pollutant that poses the greatest risk to health globally, affecting more people than any other pollutant (WHO, 2018). Chronic exposure to PM2.5 considerably increases the risk of respiratory and cardiovascular diseases in particular (WHO, 2018). For these reasons, population exposure to (outdoor or ambient) PM2.5 has been identified as an OECD Green Growth headline indicator” (OECD.Stat).
the virus is more effective in regions with a high level of air pollution. The fight against the virus both increased the health expenditures and affected the business life negatively due to its quick transmission. Since close contact of multiple persons increases the risk of transmission, many large and small enterprises in the economic field had to suspend or completely stop their activities. The prolongation of the period of the pandemic has turned into employee discharge in some industries. The optimistic forecasts about the economic growth in the world turned into pessimistic forecasts due to all these negativities. Therefore, economists have begun to consider how much the world economy would shrink rather than grow. The difference of the study from the previous studies is that it aims to reveal economic growth's interaction with COVID-19, and PM2.5 particles (vicious cycle). In this context, it is the first research. Our hypothesis was designed based on "If there is a relationship between economic growth and air pollution, there might be a similar relationship between COVID-19 and economic growth." The research was carried out for the period between 2000-2019. Panel Cointegration Test and Panel Causality Analysis were used for the empirical analysis. Particulate matter known as PM2.5 was used to identify air pollution. Therefore, scientific studies on the relationships between air pollution (PM2.5), COVID-19, and economic growth (GDP) were discussed firstly. Then, an empirical analysis was carried out. Evaluations were made in line with the findings obtained, and suggestions were presented in the conclusion part.

Theoretical Framework of the Relationship between Virus Infection Risk and Air Pollution

Several studies have revealed the association between exposure to air pollution and respiratory system disease (Brunekreef and Holgate, 2002; Xing et al., 2016; Liu et al., 2017; Zanobetti et al., 2003; Kelly and Fussel 2011; Polezer et al., 2018; Weber et al., 2016; Badyda et al., 2017). Epidemiological and toxicological studies also support the association between urban air pollution and an increase in the incidence and/or severity of airway diseases. Detrimental effects of ozone (O3), nitrogen dioxide (NO2), and particulate matter (PM), as well as traffic-related pollution as a whole, on respiratory symptoms and functions, are well documented. According to the European Public Health Alliance, air pollution is also known to weaken the immune system, thus compromising people’s ability to fight off infection (BBC, 2020). Ma et al. (2017) observed a positive correlation between the measles incidence and the particulate matter of PM10 in western China during the period between 1986-2005. Zhao et al. (2018) reported that the majority of the positive cases of highly pathogenic avian influenza (HPAI) H5N2 in Iowa (USA) in 2015 might have got an airborne virus that was carried by fine particulate from infected farms within the same state or neighboring states. The study carried out on the UK by Travaglio et al. (2020) concluded that COVID-19 cases and morbidity were associated with the levels of some air pollutants.

Theoretical Framework of the Relationship between COVID-19 and Air Pollution

Since the first cases of COVID-19, which has been named as novel coronavirus, were reported in December 2019, there are a few studies on the infection risk of the virus of the COVID-19 disease due to air pollution; however, they are proven studies. It is aimed to include the studies carried out on this subject under this heading.

Andree (2020) examined the correlation between exposure to particulate matter and COVID-19 incidence in 355 municipalities in the Netherlands. The results show that atmospheric particulate matter with a diameter of smaller than 2.5 micrometers is a highly significant predictor of the number of confirmed COVID-19 cases and related hospital admissions. The estimates suggest that the number of expected COVID-19 cases increase by almost 100% when the pollution concentration increases by 20%. Fattorini and Regoli (2020) provide additional evidence on the possible effect of air quality, particularly in terms of chronicity of exposure, on the spread of viral infection in various regions in Italy. Actual data on the COVID-19 outbreak in Italian provinces and corresponding long-term air quality evaluations were obtained from Italian and European agencies, and they were elaborated and tested for possible interactions. Their research reveals that; besides concentrations, the chronicity of exposure may have an effect on the anomalous variability of SARS-CoV-2, the virus of COVID-19 disease, in Italy. Data on the distribution of atmospheric pollutants (NO2, O3, PM2.5, and PM10) in Italian regions for the last 4 years, days exceeding regulatory limits, and years of the last decade (2010-2019) in which the limits have been exceeded for at least 35 days revealed that Northern Italy has been constantly exposed to
chronic air pollution. Van Doremalen et al. (2020) has indicated that the airborne and fomite transmission of SARS-CoV-2 is plausible since the virus can remain viable and infectious in aerosol for hours. Xiao et al. (2020) investigated whether long-term average exposure to fine particulate matter (PM2.5) was associated with an increase in the risk of COVID-19 deaths in the United States. According to this study, a small increase in long-term exposure to PM2.5 leads to a large increase in the COVID-19 death rate. Conticini et al. (2020) researched the correlation between the high level of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) mortality and the atmospheric pollution in Northern Italy. Indeed, Lombardy and Emilia Romagna are Italian regions with the highest level of virus mortality in the world; also, these regions are among the most polluted areas in Europe. Based on this correlation, this paper analyzes the possible relationship between pollution and the development of acute respiratory distress syndrome and eventually death. They provide evidence that people living in an area with high levels of pollutants are more prone to develop chronic respiratory conditions and more susceptible to any infective agent.

Theoretical Framework of the Relationship Between PM2.5 and Economic Growth

From the theoretical point of view, Simon Kuznets' study on economic growth and environmental factors has great importance. Kuznets (1955) suggested the Environmental Kuznets Curve (EKC) Theory for the studies on the empirical relationship between income inequality and per capita income. He stated that the relationship between economic growth and air pollution may be similar to an inverted U-shaped function which is known as EKC. The hypothesis suggests that environmental quality tends to improve as the economy grows, then environmental quality reaches the peak and makes a downward spiral. Porter's (1991) hypothesis (PH) is another theory that aims to explain the relationship between economic growth and pollution. Porter suggested that improving environmental conditions would increase productivity in production.

Dabo et al. (2014) presented an interdisciplinary study to measure the magnitudes of socioeconomic factors in driving primary PM2.5 emission changes in China for the period between 1997–2010. In their study, they used a regional emission inventory as input for an environmentally extended input-output framework and conducted a structural decomposition analysis. The results of their study revealed that the significant efficiency gained in China fully offset emissions growth triggered by economic growth and other drivers. Maji et al. (2017) applied an epidemiology-based exposure-response function to obtain the quantitative estimate of the health impact of particulate matter PM2.5 and PM10 across 190 cities in China for the period between 2014–2015. According to the results, the economic cost of the health impact due to PM10 was approximately US$ 304,122 million, which accounted for about 2.94% of China’s gross domestic product (GDP). Osabuohien, Efobi, and Gitau (2014) applied the EKC model to 50 African countries. The study, which analyzed data for the period between 1995 and 2010, found a long-term relationship between CO2 and particulate matter (PM) emissions and per capita income. Yin et al. (2017) assessed health impacts and external costs related to PM2.5 pollution in Beijing, China using different baseline concentrations and valuation methods. The results, including all the health impacts, revealed that the economic loss due to premature deaths accounted for more than 80% of the overall external costs. Matus et al. (2012) evaluated air pollution-related health impacts on the Chinese economy by using an expanded version of the Emissions Prediction and Policy Analysis model. Thus, they estimated that the marginal impact of welfare on the Chinese economy of ozone and particulate-matter concentrations above background levels increased from US$ 22 billion in 1975 to US$ 112 billion in 2005, despite improvements in overall air quality. Selin et al. (2009) assessed the human health and economic impacts of projected changes for the period between 2000–2050 in ozone pollution by using the MIT Emissions Prediction and Policy Analysis - Health Effects model in combination with the results of the global simulation of tropospheric chemistry by GEOS-Chem model. In 2000, they estimated that the health costs due to global ozone pollution above pre-industrial levels would be $580 billion by 2050 and that mortalities from acute exposure would exceed 2 million. According to these figures, the economic effects of emission changes far exceeded the effect of climate alone. He et al. (2018) examined day-to-day fluctuations in worker-level output at two manufacturing sites in China. According to their study, more prolonged exposure was found to have statistically significant adverse output effects, however, these effects are not large. According to this study, a substantial +10 µg/m3 PM2.5 variation sustained over 25 days reduced daily output by 1%. Wu et al. (2017) examined the
health and economic impacts of PM2.5 pollution under various air pollution control strategies and climate policy scenarios in the megacity of Shanghai. The results revealed that, without control measures, Shanghai’s mortality caused by PM2.5 pollution was estimated to be 192,400 cases in 2030, and the work time loss would be 72.1 h/cap annually. The corresponding GDP values and welfare losses would be approximately 2.26% and 3.14%, respectively. Similarly, other studies have found that exposure to PM2.5 could damage residents’ health, reduce their workforce capacities, and shorten their life expectancy, thereby further increasing their healthcare costs and imposing huge economic burdens on the whole community (Yang et al., 2018; Liu et al., 2017; Miao et al., 2017). Moreover, Zeng et al. (2019) used the spatial interpolation method to examine PM2.5 exposure in China in 2007 and found that economic loss was RMB 1,262.5 billion.

Empirical Analysis

Data Set

Total "Economic Growth" and "Particulate Matter, PM2.5" were collected for the year of 2000 to 2019 from “OECD” and “The World Bank” respectively. For this purpose, we use Panel Cointegration Test and Panel Causality Analysis in this study. The equation for our model is as follows;

\[
PM2.5_{it} = \alpha_i + \beta_1 GDP_{it} + u_{it} \tag{1}
\]

Dependent Variable: PM2.5

Independent Variable: GDP

Method

Panel Data Analysis

Panel data has been used in most of the recent economic studies that contain econometric analysis. Because Panel data models provide a rich environment for improving the forecasting techniques and theoretical results (Greene, 2003: 284). Panel data models examine cross-sectional and time-series effects. Therefore, it provides multiple observations for each series (Hsiao, 2003:2). One of the most important characteristics of the panel data analysis is that it can determine the effects that cannot be observed or measured on the dependent variable (Baltagi, 2005:6). If the number of cross-sectional data and the time series of the cross-sectional data are equal, the balanced panel data model is applied in panel data analysis. If there is an inequality between these data, then the unbalanced panel data model is designed. In general, the panel data regression equation is as follows (Gujarati, 2004: 640):

\[
Y_{it} = \beta_1 + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \tag{2}
\]

In the equation, 'i' refers to cross-sectional data, and 't' refers to variables of the time series data. Cointegration approaches are used to examine long-term relationships in panel data series. Therefore, the panel cointegration test technique was used in the analyses. Primarily, the cross-section dependence, which was suggested by Pesaran (2006), was examined for the overall panel. Then, the panel unit root test was performed. Because the panel data models contain time series values, the stability of the series should be tested. Following the unit root analysis, a cointegration test, and finally a causality analysis was conducted to examine the long-run equilibrium relationship between the variables.

Testing Horizontal Section Dependency

Examination of cross-sectional dependence among the countries in the panel data is of great importance for obtaining healthy results. Therefore, the cross-sectional dependence test was performed before carrying out the analysis. In the study, CDlm and CD tests were performed to determine the cross-section dependence (Pesaran, 2004). The following equations were used in the tests:

\[
CD_{LM} = \frac{1}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} (T \hat{\rho}_{ij}^2 - 1) \tag{3}
\]

\[
CD = \frac{2T}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \tag{4}
\]

Panel Unit Root Analysis
Panel unit root tests have been developed to determine whether panel data are stationary over time. In cases where there is no correlation between units in panel data analysis, the following first-generation unit root tests are applied: Levin, Lin, Chu (2002), Im, Pesaran, Shin (2003) and Fisher (ADF, PP), Hadri (2000) and Breitung (2000) (Sarıkovanlık, 2017). In the present study, the following first-generation unit root tests were applied: Levin, Lin, Chu (2002); Fisher (ADF, PP), and Im, Pesaran, Shin (2003).

The hypotheses of the Levin, Lin, Chu, Im Pesaran and Fisher (ADF, PP) panel unit root tests are as follows:

- **H₀**: The series has a unit root.
- **H₁**: The series does not have a unit root.

The equation used in Levin, Lin and Chu panel unit root test is as follows (Baltagi, 2005):

\[
\Delta Y_{it} = p Y_{i,t-1} + \sum_{L=1}^{p} \theta_{L} \Delta Y_{i,t-L} + \alpha_{m} d_{mt} + \varepsilon_{it} \tag{5}
\]

In formula $d_{mt}$ deterministic variables vector, $\alpha_{m}$ is the coefficient vector of the model.

On the other hand, Im Pesaran Shin unit root test is formulated in its simplest form as follows (Sarıkovanlık, 2017):

\[
\Delta Y_{it} = (\rho_{i}-1) Y_{i,t-1} + \mu_{it} \tag{6}
\]

The hypotheses of Im Pesaran Shin panel unit root tests are as follows:

- **H₀**: The series has a unit root.
- **H₁**: The series does not have a unit root.

The equation used in the Fisher (ADF, PP) panel unit root tests is as follows (Giray, 2011):

\[
\Delta y_{it} = \alpha y_{i,t-1} + \sum_{j=1}^{P} \beta_{ij} \Delta y_{i,t-j} + x_{i,t}^{'} \delta + \varepsilon_{it} \tag{7}
\]

If **H₀**: $\alpha = 0$ There is a unit root.

If **H₁**: $\alpha < 0$ There is no unit root.

### Panel Cointegration Analysis

The cointegration method is a strongly accepted method in determining multiple cointegration relationship between the series (Doğan et al., 2016). Thus, short-term and long-term parameters can be tested together. From this perspective, it is an indicator that the cointegration test is superior to other analyses (Pesaran, 2001). Another method used to determine the presence of a cointegration relationship for panel data is the Pedroni Panel Cointegration Test technique. According to previous studies of Pedroni (1995, 1997), the cointegration relationship in heterogeneous panels was limited to models with two variables at maximum. However, Pedroni (1999) filled this gap by introducing a method for determining the cointegration relationship in models with multiple variables. Pedroni tests have advantageous characteristics such as allowing multiple explanatory variables, differentiating the cointegration vector in different sections of the panel, and allowing heterogeneity of errors (Yardımcıoğlu, 2012). Engle-Granger (1987) cointegration test is based on the residuals of a spurious regression performed using I (1) variables. If the variables are cointegrated, then the residuals should be I (0). On the other hand, if the variables are not cointegrated, then the residuals will be I (1). Pedroni (1999) extended the Engle-Granger framework using the following equation containing panel data.

\[
Y_{it} = \alpha + \delta_{it} + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \ldots + \beta_{Mi} x_{Mi,t} + c_{i,t} \tag{8}
\]

for $t = 1, \ldots, T; i = 1, \ldots, N; m = 1, \ldots, M$; where $y$ and $x$ are assumed to be integrated with order one. Under the null hypothesis of no cointegration, the residuals will be $c_{i,t}$ I (1). The general approach is to obtain residuals from Equation (1) and then to test whether residuals are I (1) by running the auxiliary regression.

\[
c_{it} = p_{i} c_{it-1} + u_{it} \tag{9}
\]
The hypotheses of the Pedroni (1995 and 1999) panel cointegration test are as follows (Sarkinovanlik et al., 2018):

H0: There is no cointegration between variables. (H0: \( \pi_i = 1 \))

H1: There is cointegration between variables. (H0: \( \pi_i < 1 \))

Pedroni (1999) suggested 7 panel cointegration test statistics:

Panel v-Statistic:

\[
T^2 N^{3/2} Z_{\theta,NT} \equiv T^2 N^{3/2} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t}^2 \right)^{-1}
\]

Panel p-Statistic:

\[
T \sqrt{N} Z_{p,NT-1} \equiv T \sqrt{N} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t}^2 \right)^{-1/2} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t} \Delta \hat{\epsilon}_{i,t} - \hat{\lambda}_i \right)
\]

Panel t-Statistic (non-parametric):

\[
Z_{t,NT} \equiv T \sqrt{N} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t}^2 \right)^{-1/2} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t} \Delta \hat{\epsilon}_{i,t} - \hat{\lambda}_i \right)
\]

Panel t-Statistic (parametric):

\[
Z'_{t,NT} \equiv T \sqrt{N} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t}^2 \right)^{-1/2} \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \tilde{\epsilon}_{i,t} \Delta \hat{\epsilon}_{i,t} \right)
\]

Empirical Results

In this section, the results of the analyses are presented. Firstly, the descriptive statistics for the variables used in the model for the period between 2000-2019 are given. (Table 1)

**Descriptive Statistics**

| Variable | PM2.5 | GDP  |
|----------|-------|------|
| Average  | 56.45679 | 57.18351 |
| Median   | 58.43762 | 62.54985 |
| Maximum  | 79.67065 | 89.42572 |
| Minimum  | 32.19748 | 18.73490 |
| Standard deviation | 8.296351 | 20.03841 |
| Skewness | -0.51265 | -0.33753 |
| Jarque-Bera | 23.74268 | 47.54837 |
| Probability | 0.000000 | 0.000001 |
| Observation | 140 | 140 |

**Table 2. Horizontal Dependency Test Results**

| Variable | CDlm  | CD |
|----------|-------|----|
| Test Statistics | Probability | Test Statistics | Probability |
| PM2.5    | -0.853 | 0.273 | 1.549 | 0.208 |
| GDP      | -0.354 | 0.063 | 2.471 | 0.084 |
According to Table 2, the probability values of the variables are greater than 0.05. Accordingly, there is no cross-section dependence between the variables.

**Results of the Panel Unit Root Test and Their Evaluation**

Logarithmic values of the economic growth (GDP) and PM2.5 variables were calculated, and unit root test and other tests were performed using the logarithmic values of the variables. The optimal lag length that eliminates the autocorrelation problem was found using the Schwarz information criterion. It was observed that the series were not stationary according to their level values. The series was made stationary by taking the first differences. Tables 3 and Table 4 shows the results.

Table 3. “GDP” Panel Unit Root Test (First Difference of the Series is taken)

| Method                | t Statistics I (0) | Probability | t Statistics I (1) | Probability I (1) |
|-----------------------|-------------------|-------------|-------------------|------------------|
| Levin, Lin & Chu t    | -23.4431***       | 0.0000      | -6.38874***       | 0.0010           |
| Im Pesaran and Shin   | -9.01836          | 0.8480      | -13.7583***       | 0.0030           |
| ADF- Fisher Chi-      | 83.8941           | 0.2306      | 124.252***        | 0.0000           |
| PP- Fisher Chi-       | 133.608           | 0.0000      | -12.638***        | 0.0000           |

*** refers to a significance level of 1%.

Table 4. “PM2.5” Panel Unit Root Test (First Difference of the Series is taken)

| Method                | t Statistics I | Probability | t Statistics I (1) | Probability I |
|-----------------------|----------------|-------------|-------------------|--------------|
| Levin, Lin & Chu t    | -6.76263       | 0.6400      | -12.32241***      | 0.0001       |
| Im Pesaran and Shin W-| 5.42919        | 0.4510      | 9.23614***        | 0.0000       |
| ADF- Fisher Chi-Square| 0.0030         | 123.3562*** | 0.0000            |
| PP- Fisher Chi-Square | -48.1822       | 0.0790      | -170.2154***      | 0.0020       |

*** refers to a significance level of 1%.

As can be seen in Tables 3 and Table 4, according to the results of unit root tests applied to the levels of the variables, t statistics, and probability results are not stationary at the level of series, I (0), to be used in econometric analysis. Therefore, the first differences of the series, I (1), are taken to ensure stability.

Table 5. Results of Pedroni (Engle-Granger based) Cointegration Test

\[ PM2.5_{it} = \alpha_{it} + \beta_{1} GDP_{it} + u_{it} \]

| Seriler: DPM2.5 DGDP         | Statistics  | Probability | Weighted  | Probability |
|------------------------------|-------------|-------------|-----------|-------------|
| Panel v-STA.                 | 2.73603***  | 0.0164      | -1.43214* | 0.0657      |
| Panel rho-                   | -5.73521*** | 0.0346      | -2.49153***| 0.0401      |
| Panel PP- STA.              | -3.62433*** | 0.0001      | -1.76452***| 0.0031      |
| Panel ADF-                  | -4.67718*** | 0.0021      | -2.38516***| 0.0003      |

**Alternative Hypothesis: Common AR Coefficients (in-between them)**

| Group rho-                  | -3.41553*** | 0.0012 |
| Group pp-STA.              | -0.43158*   | 0.0578 |
| Group adf-                 | -4.51625*** | 0.0154 |

*** refers to a significance level of 1%.

Table 5 shows the results of the Pedroni Cointegration Test for 2 variables and 11 values of 7 test statistics. The results of weighted statistics for the first 4 tests were added to the 7 test statistics. According to these 11 values, the decision of the majority determines the result of cointegration. Considering the probability values, it is seen that the probability values of 9 tests are less than 0.05. In this case, the H0 hypothesis, which is the null hypothesis, is rejected. Accordingly, these two variables, GDP and PM2.5 act together in the long run.
Findings of Cointegration Coefficients using FMOLS and DOLS and Their Evaluation

After determining the cointegration relationship, the Group-Mean FMOLS (Fully Modified Ordinary Least Squares) and DOLS (Dynamic Ordinary Least Squares) methods developed by Pedroni (2000-2001) will be used to determine the consistency of this test. The deviations arising from changing variance, autocorrelation, and other problems in standard fixed effect estimators are eliminated by using the FMOLS method. Dynamic elements are included in the model with the DOLS method. Thus, errors arising from the problems of endogeneity in static regression are eliminated (Kök et al, 2010:8). The FMOLS estimator is constructed by making endogeneity and serial correlation corrections, and it is defined as follows (Dritsaki and Dritsaki, 2014):

$$ \beta_{FM} = \left[ \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{jt} - \bar{x}_j) \right]^{-1} \left[ \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i) \hat{y}_{it}^* + T \hat{\Delta}_{EM} \right] $$

(17)

$$ \hat{y}_{it}^* = \text{The converted y variable to provide endogeneity correction; } \hat{\Delta}_{EM} = \text{serial correlation correction term. Serial correlation and endogeneity can also be corrected using the DOLS estimator. The equation for the DOLS estimator is as follows:}$$

$$ y_{it} = \alpha_i + \beta_1 x_{it} + \sum_{j=1}^{q_2} c_{ij} \Delta x_{it-j} + U_{it} $$

(18)

c_{ij} = \text{The first difference as the lead or lag coefficient of the explanatory variables.}

**Table 6. Results of Panel FMOLS and DOLS Methods**

| Independent variable | PM2.5 Panel Whole | FMOLS | DMOLS |
|----------------------|-------------------|-------|-------|
|                      | Coefficient | t statistics | Coefficient | t statistics |
| PM2.5                | 0.687842** | 13.53841 | 0.445265** | 39.43234 |

*** refers to a significance level of 1%.

According to the results of the panel FMOLS and DOLS tests, economic growth (GDP) variable was found to be statistically significant and positive at the significance level of 1% as expected. Accordingly, for the overall panel, air pollution PM2.5 measure increases as the economic growth increases. These variables act together in the same direction in the long run.

**Panel Causality Analysis**

The logic of Granger causality is valid for examining the causality relationship in panel data models as in the time series. The equation of the model to be used for panel causality is as follows (Sarkovkanlik et al., 2018):

$$ y_{it} = \alpha_i + \sum_{k=1}^{K} (y_{it-k}) + \sum_{k=1}^{K} \beta(k) x_{it-k} + \varepsilon_{it} $$

(19)

Where "$$\alpha_i$$" denotes unit-specific effects. Also, "$$y^{(k)}$$" and "$$\beta^{(k)}$$" are the same for all units. Unlike Granger causality tests, causality tests in panel data analysis take into account the heterogeneity between units. Accordingly, the null hypothesis is designed as $$H_0: \beta^{(k)} = 0$$, and it states that there is no causal relationship between X and Y (Sarkovkanlik et al., 2018). The results of causality in our model are as follows.

Dumitrescu and Hurlin (2012) panel causality test was used to determine the causal relationships between PM2.5 and economic growth in G7 Countries. Because this method can be used in both cross-section dependence and heterogeneous panels.

**Table 7. Results of Panel Causality**

| Causality Aspect | W-Stat | Z-bar Stat | Probability |
|------------------|--------|------------|-------------|
| PM2.5 \(\rightarrow\) GDP | 0.7635 | -0.3647 | 0.0042 |
| GDP \(\leftarrow\) PM2.5 | 3.4576 | 4.6285 | 0.0021 |
The probability values of GDP and PM2.5 as the variables of the model were found to be 0.0042 and 0.0021, respectively. These values reveal the presence of a two-way causal relationship between PM2.5 and economic growth (GDP) at the significance level of 5%. In other words, both variables are the cause of each other. Therefore, it can be stated that the relationship between PM2.5, GDP, and COVID-19 is a vicious cycle for the overall study.

**Discussion and Conclusions**

It is a known fact that economic growth provides benefits in all respects. However, how the growth is achieved is of great importance as the growth itself. In fact, this is one of the main economic problems that need to be solved in every period. The brief answer to this question is to make maximum production with minimum cost. The production can be carried out efficiently only by this way. The costs incurred during the production stage are not only the costs that concern the manufacturer. The production also has social costs. Such costs are generally not accounted for and overlooked; however, their effects occur later, just like the wastes generated after production affect human health negatively.

Today, production is carried out depending on fossil fuels. Hazardous gases arising from the use of fossil fuel mix into the atmosphere and pollute the air. Therefore, as long as production is carried out by conventional methods depending on fossil fuels, health problems will increase in line with air pollution. This in return will lead to a decrease in net contributions in economic growth. The effects of air pollution on human health are not limited to the hazardous gases it contains. Scientific studies have revealed that cases of infectious and deadly viruses increase in regions with intense air pollution.

In this context, it was interpreted that the virus of COVID-19 disease (SARS-CoV-2), which was first reported in Wuhan, China in December 2019 and affected the whole world, would increase the number of air pollution-related cases in G7 Countries with widespread industrial production. The research was carried out for the period between 2000-2019. "Pedroni Panel Cointegration Test" and "Panel Causality Analysis" were used for the empirical analysis. Particulate matter known as PM2.5 was used as an indicator of air pollution.

7 test statistics were found using the Pedroni cointegration analysis. 11 values were obtained by adding the results of weighted statistics for the first 4 tests to the 7 test statistics. According to these 11 values, the decision of the majority determines the cointegration. According to the probability values, it is seen that the probability values of 9 tests are less than 0.05. In this case, the H0 hypothesis, which was the null hypothesis, was rejected. Accordingly, it has been concluded that these two variables, GDP (economic growth) and PM2.5, act together in the long term. According to the results of causality analysis, a two-way causality was found between PM2.5 and economic growth. In this context, the findings obtained can be briefly interpreted as follows: As economic growth increases, the air pollution PM2.5 particulate matter density also increases. Due to the linear relationship between COVID-19 and PM2.5, it can be said that there is an upward trend from economic growth to PM2.5, and from PM2.5 to COVID-19 cases. In this context, the negative impact on economic growth will be higher due to the fact that COVID-19 cases will increase as air pollution increases. This will lead to a vicious cycle between economic growth, air pollution, and COVID-19 cases.

The economic cost of the COVID-19 virus, in other words, its negative impact on economic growth occurs both indirectly and directly. Indirect costs are reflected in health expenditures. Direct costs rather emerge in production and employment. Since close contact of multiple persons increases the risk of transmission, many large and small enterprises in the economic field had to suspend or completely stop their activities. The prolongation of the period of the pandemic has turned into employee discharge in some industries.

If an existing factor cannot be eliminated completely, minimizing its negative effects will provide great benefit. The COVID-19 virus is still active in the current situation. This being the case, medicine, or vaccine against the virus has not been developed yet. However, there are scientific studies explaining how the virus is infected and in which environments it is more intense. In this context, measures to reduce air pollution due to production will be of great benefit. In order to eliminate the vicious cycle
between economic growth (GDP), PM2.5, and COVID-19 virus and to reduce the number of COVID-19 cases, it is of great importance to place emphasis on and expand production based on renewable energy sources such as wind, solar, and hydro. This will also increase the net contribution of economic growth.
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