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Original Research

Vicious Cycle of Economic Growth, PM2.5 and COVID-19: Evidence from G7 Countries

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Abstract

Developed countries with high use of fossil fuels in production can harm the environment by contributing more to the formation of greenhouse gases on a global scale. Air pollution is expected to increase the number of COVID-19 cases in G7 countries with significant industrial output. The aim of the study is to reveal the awareness of the role of air pollution due to traditional industrial production which caused the spread of the epidemic, both on economic growth and its role in the spread of the epidemic. Research is based on monthly data covering the period 2019:12-2021:7. The empirical analysis has been utilized for the panel cointegration test and the dynamic causality analysis. Particles classified as PM2.5 have been utilized as air pollution indicators. Health expenses, in order to control general trends on economic growth and pollution, were also included in the study. The findings of this study indicate that PM2.5 particle ratios and COVID-19 cases are increasing while economic growth is taking place in the G7 countries. If these data are associated with the use of fossil fuels in industries, they will contribute to the creation of public policies that encourage a new generation of energy sources in production.

Keywords: PM2.5, COVID-19, economic growth, G7 countries

Introduction

The impact of air pollution on the ecological environment, human health and safety is being discussed around the world [1]. It is a well-known fact that economic expansion contributes to air pollution since fossil fuels are utilized in production. When fossil fuels, principally petroleum, coal, and natural gas, are burned, significant quantities of carbon are released into the atmosphere, creating air pollution. Thus, economic progress is attained on the one hand, while environmental damage happens on the other. As a result, rising expenses decrease the net contribution of growth. This scenario creates a virulent loop of economic expansion and air pollution. In this context, Simon Kuznets' work on economic growth and environmental variables is crucial from a theoretical standpoint. According to him, as the economy expands, the environmental quality increases and ultimately spirals downwards [2]. Porter's Hypothesis (PH) is another theory that seeks to explain the link between economic growth and pollution. Porter argued that improved conditions for the environment would improve manufacturing output [3]. Fine particulate matter PM2.5 ratios are thought to be an indicator of environmental air pollution [4]. A study conducted for Kazakhstan for

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the period between 1992-2013 found a positive relationship between air pollution and economic growth [5]. From 1997 to 2010, economic efficiency was increasing due to a decrease in primary PM2.5 emissions in China. In similar studies conducted in China, it has been found that labour productivity [6] and economic efficiency [7] decrease as PM2.5 concentration increases. [8, 9]. Two different studies have been conducted for the economy of Azerbaijan between tourism-based economic growth and the ecological environment. Accordingly, a long-term positive relationship has been found between the two variables [10, 11]. It has been found that PM2.5 and PM10 particulate matter increased the economic health cost in China between 1975-2005 and between 2014-2015 [12]. The study using the EKC model for African countries has found a long-term relationship between emissions such as PM and per capita income from 1995 to 2010 [13]. It has been found that motor vehicle exhaust, coal decarbonization, and industrial emissions are among the most important sources of air pollution in Shandong. In Beijing [14], in Shanghai [15] PM2.5 pollution causes premature deaths [16]. For the period between 1996-2018, it has been concluded that FDI inflows to Azerbaijan were not completely environmentally friendly [17]. In the study conducted using simulation techniques of GEOS-global Chem for the 16 of the world regions, it has been estimated that the health expenditure of ozone pollution would be $580 billion by 2050 and deaths from acute exposure would exceed 2 million. Similarly, other studies have shown that PM2.5 exposure can harm people's health, reduce their working capacity, shorten their life expectancy, increase their spending on healthcare, and impose large economic burdens on the entire society [18-20].

The chemical, physical, and biological quality of the air we breathe is altered by PM2.5. Individuals breathe 13,000-16,000 litres of air each day on average. As a result, air with degraded chemical, physical, and biological properties is extremely hazardous to human health. Every year, 7 million people in the globe die prematurely as a result of air pollution [21]. Furthermore, because PM2.5 particles have a high surface area and volume, some bacteria, viruses, fungus, and other pathogenic microorganisms, as well as some heavy metals, acid oxides, and organic pollution toxins, can be absorbed by them, resulting in higher toxicity [22, 23]. Airborne and fomite transmission of SARS-CoV-2 is possible since the virus may remain alive and infectious in aerosol for hours [24].

Epidemiological studies have found substantial links between long-term exposure to PM2.5 and chronic illnesses such as heart disease, stroke, and lung cancer, as well as mortality from these diseases [25-28]. Several studies have found a link between air pollution exposure and respiratory system illness [29-32]. Air pollution is also known to impair the immune system, limiting people's capacity to fight infection, according to the European Public Health Alliance [33]. Furthermore, pollution harms children's lung development and increases the prevalence of chronic respiratory disorders (CRDs) such as asthma and chronic obstructive pulmonary disease (COPD) in polluted areas [34, 35]. Discovered a positive connection between measles incidence and PM10 particulate matter in western China between 1986 and 2005. According to [36], the majority of positive cases of highly pathogenic avian influenza (HPAI) H5N2 in Iowa (USA) in 2015 may have been caused by an airborne virus spread by fine particulate from infected farms in the same or neighboring states. Similarly, the relationship between particulate matter exposure and COVID-19 incidence was investigated in 355 Dutch towns; Italy [37-39] and the United States [40, 41]. According to these studies, a small increase in long-term exposure to PM2.5 leads to a significant increase in the number of COVID-19 cases and the death rate [42]. Concluded that COVID-19 cases and morbidity were associated with the levels of certain air pollutants in the UK.

Due to the virus's rapid spread, the war against it raised health-care costs while also having a detrimental impact on the industry [43]. IT has been confirmed that, in more than 130 countries, covid-19 cases have negatively affected economic growth. Because intimate contact between numerous people increases the danger of transmission, many big and small businesses in the economic sector were forced to curtail or totally cease operations. The extension of the pandemic era has resulted in staff layoffs in various industries. Because of all these negatives, optimistic projections for global economic growth have transformed into gloomy forecasts. As a result, economists have begun to speculate on how much the global economy will contract rather than increase.

As all countries across the world globalize economically, they become interdependent [44, 45]. Thus, a crisis in any country will affect all the other countries, particularly the ones having a trade relationship with that country [46, 47]. The effects of these crises will be harsher; when they occur especially in the countries which have an important role in the world's economy [48]. Since the 2008 global crisis occurred in the USA, it has spread all around the world rapidly and the effects have been extremely severe regardless of the size of the countries [49], similarly, the pandemic has also impacted all countries across the globe. During this process, G7 countries, especially the USA, have been adversely affected.

Although the G7 countries make up only 11% of the world's population, their share in the world's economic production is %33 [50]. These countries are the most developed industrial countries in the world and their production mainly depends on fossil fuels. Therefore, negative situations which may take place in the G7 countries will devastate small and medium developing economies even more with the multiplier effect. Compared to ordinary countries, the G7 countries are always in the limelight. In that case, any measures

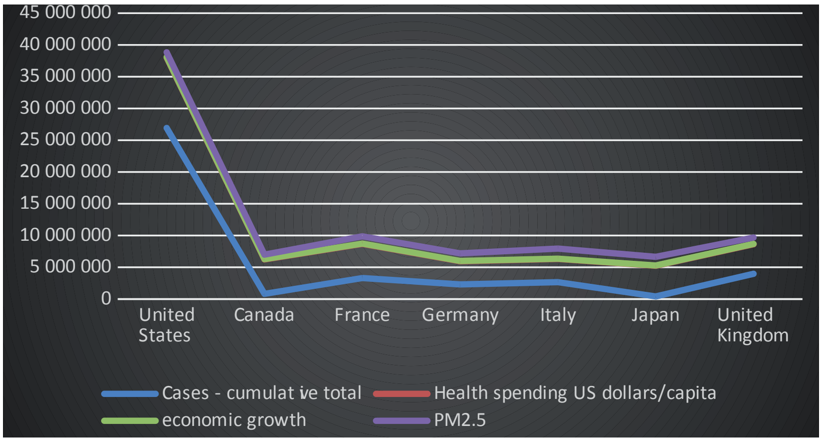

Fig. 1. G7 Countries, COVID-19 Cases, GDP, PM2.5 and Health Spending, (2019-2021).

taken by the G7 countries to fight the coronavirus will be a role model for other countries.

Also, the accuracy of PM2.5 exposure estimates varies significantly by location. Accuracy is poorer in regions with few monitoring stations and in areas with very high concentrations such as Africa, the Middle-East and South Asia. Accuracy is generally good in regions with dense monitoring station networks (such as G7 countries) [51]. The G7 countries have around 38% of the global total cases [52].

For the Fig. 1 analysis, we analyzed the OECD database and the World Bank and World Health Organization (WHO) data. Accordingly, while economic growth is taking place in G7 economies, on the one hand, PM2.5 particle rates, COVID-19 cases and health expenditures are also increasing on the other hand.

"If there is a link between economic growth and air pollution, there could be a comparable association between COVID-19 and economic growth," our hypothesis said. The research aims to contribute to the literature by providing a different perspective to the industrial economies facing COVID-19 epidemic in combating the pandemic. The study differs from prior studies in that it attempts to demonstrate the relationship of economic growth with COVID-19 and PM2.5 particles (vicious cycle). It is the first study in this setting. A small number of studies using similar variables have been found. However, in these studies, it has been observed that the direction of the relationship between the variables and the way they were handled were different from our study. Other studies are separately subject to air pollution - economic growth, air pollution-health expenditures, and air pollution-COVID-19 relationship. The rest of this article has been edited as follows: Chapter 2 gives a review of the Theoretical Framework. Chapter 3 describes the data and methodology used. Chapter 4 presents the empirical results. Chapter 5 demonstrates the interpretation and discussion of the results.

Materials and Methods

Data Sources

To assess the relationship between air pollutant (PM2.5)[1] concentrations and COVID-19 virus (COV-19), economic growth (GDP) and health expenditures (HE) in G7 Countries, monthly country-level data has been used in the study. We constructed our panel using Organization for Economic Co-operation and Development (OECD), World Health Organization and The World Bank database and expressed in natural logarithms. Research is based on monthly data covering the period 2019:12-2021:7.

Methodology

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 [53]. Panel data models examine cross-sectional and time-series effects. Therefore, it provides multiple observations for each series [54]. The ability to detect impacts on the dependent variable that cannot be observed or measured is one of the most significant aspects of panel data analysis [55]. In panel data analysis, the balanced panel data model is used if the number of cross-sectional data and their time series are equal. The imbalanced panel data model is developed if there is an inequality between these data. Generally, the panel data regression equation is as follows [56]:

1 "Particulate matter contains microscopic solids or liquid droplets that are so small that they can be inhaled and cause serious health problems. Some particles less than 10 micrometers in diameter can get deep into your lungs and some may even get into your bloodstream. Of these, particles less than 2.5 micrometers in diameter, also known as fine particles or $PM_{2.5}$, pose the greatest risk to health." [58].

$$Y_{it} = \beta 1 + \beta_2 X_{2it} + \beta_3 X_{3it} + u_{it} \quad (1)$$

In the equation, 'i' stands for cross-sectional data, while 't' stands for time series data variables. Long-term connections in panel data series are investigated using cointegration methods. Therefore, in our study on "Vicious Cycle of Economic Growth, PM2.5 and COVID-19: Evidence from G7 Countries", the panel cointegration test approach was used. The entire panel was first evaluated for cross-section dependency, as proposed by [57]. Later, the logarithmic values of the economic growth variables COV19, GDP, PM2.5, and HE were calculated, and the unit root test and other tests were performed using the logarithmic values of the variables. After the stationarity test was performed, the cointegration test, which is the second stage, was started. For the long-range relationship between the series, the Pedroni cointegration test was performed. The result of cointegration is determined by a majority decision based on 11 parameters. In the Pedroni cointegration test, eight out of 11 statistics showed that there was cointegration. Fully Modified Ordinary Least Squares and Dynamic Ordinary Least Squares techniques were used to assess the consistency of this test after identifying the cointegration relationship. Finally, the panel causality test was used to investigate the causative connections between COV19, GDP, PM2.5, and HE in G7 Countries.

Equation to be Estimated

The impact of PM2.5, GDP and HE on COV19 can be modelled as follows:

$$COV19_{it} = \beta_1 + \beta_2 PM2.5_{it} + \beta_3 GDP_{it} + + \beta_4 HE_{it} + u_{it} \quad (2)$$

In order to reduce the difference between variables, log-linear form was used in panel data analysis and can be expressed decidedly:

$$\ln(COV19_{it}) = \beta_1 + \beta_2 \ln(PM2.5_{it}) + \beta_3 \ln(GDP_{it}) + \beta_4 \ln(HE_{it}) + u_{it} \quad (3)$$

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 [59]. The following equations were used in the tests:

$$CD_{LM} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{J=i+1}^{N} (T\hat{\rho}_{ij}^2 - 1) \quad (4)$$

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{J=i+1}^{N} \hat{\rho}\, ij \quad (5)$$

Panel Unit Root Analysis

Panel unit root tests were created to see if panel data remained stable over time. The following first-generation unit root tests are used in panel data analysis when there is no correlation between units [60, 61]: The Levin, Lin, Chu, Im Pesaran, and Fisher (ADF, PP) panel unit root tests include the following hypotheses:

H_0: There is a unit root in the series.

H_1: There is no unit root in the series.

The equation employed in the unit root test of Levin, Lin and Chu [62] is as follows:

$$\Delta Y_{it} = py_{i,t-1} + \sum_{L-1}^{pi} \theta_{iL} \Delta y_{it-L} + \alpha_{mi} d_{mt} + \varepsilon_{it} \quad (6)$$

In the Formula, "d_{mt}" deterministic variables vector, "α_{mi}" 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 [63]:

$$\Delta Y_{it} = (\rho_i - 1) Y_{i,t-1} + \mu_{it} \quad (7)$$

Pesaran Shin panel unit root tests include the following hypotheses:

H_0: There is a unit root in the series.

H_1: There is no unit root in the series.

The Fisher (ADF, PP) panel unit root tests utilize the following equation [64]:

$$\Delta y_{it} = \alpha y_{it-1} + \sum_{j-1}^{p_i} \beta_{ij} \Delta y_{it-j} + x_{it}' \delta + \varepsilon_{it} \quad (8)$$

If H_0: $\alpha = 0$ There is a unit root.

If H_1: $\alpha < 0$ There is no unit root.

Panel Cointegration Analysis

The cointegration technique is a well-known way to determine the link between the series of numerous cointegrations [65]. This allows for the testing of long- and short-term characteristics. From this point of view, the cointegration test is preferable to other analyses [66]. Pedroni Panel Cointegration Test Technology is another way for determining the presence of a panel data cointegration connection. In his prior works [67, 68], found that in heterogeneous panels, the cointegration connection was confined to models with two variables at most [69]. Filled this need by developing a technique for assessing the cointegration relationship in multivariable models. Pedroni tests provide several advantages, including the ability to use numerous explanatory factors, the ability to differentiate the cointegration vector in various segments of the panel, and the ability to allow for error heterogeneity [70]. The co-integration test of Engle-Granger (1987) is based on the residuals of a fake regression conducted using variables I (1). The residuals should be I (0) if the variable is integrated. On the other hand, if the variables are not combined, then I (1) will be the residue. The Engle-Granger paradigm was expanded by [71] utilizing the panel data equation as follows:

$$Y_{it} = \alpha + \delta_i t + \beta_{1i} x_{1i,t} + \beta_{2i} x_{2i,t} + \ldots + \beta_{Mi} x_{Mi,t} + ci, t \tag{9}$$

For t = 1,..., T; I = 1,..., N; m = 1,..., M, where y and x are assumed to be integrated with order one. The residuals will be *ci*, *t* I under the null hypothesis of no cointegration (1). The typical technique is to extract residuals from Equation (1) and then run the auxiliary regression to see if the residuals are I (1).

$$c_{it} = p_i c_{it-1} + u_{it} \tag{10}$$

The hypotheses of the Pedroni (1995 and 1999) panel cointegration test are as follows [72, 73]:

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

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

[74] suggested 7 panel cointegration test statistics.

Panel v-Statistic:

$$T^2 N^{3/2} Z_{\vartheta N,T} \equiv T^2 N^{3/2} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{2} \right)^{-1} \tag{11}$$

Panel p-Statistic:

$$T\sqrt{N Z_{\hat{p},N,T-1}} \equiv T\sqrt{N} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{2} \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{12}$$

Panel t-Statistic: (non-parametric)

$$Z_{t,N,T} \equiv T\sqrt{N} \left(\hat{\sigma}_{N,T}^{2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{13}$$

Panel t-Statistic: (parametric)

$$Z_{t,N,T}^{*} \equiv T\sqrt{N} \left(\tilde{S}_{N,,T}^{*2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*2} \right)^{-1/2} \sum_{i=1}^{N} \sum_{t=1}^{T} \hat{L}_{11i}^{-2} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*} \tag{14}$$

Group p-Statistic:

$$TN^{-1/2} Z_{\hat{p},N,T-1} \equiv TN^{-\frac{1}{2}} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \hat{e}_{i,t-1}^{2} \right)^{-1} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{15}$$

roup t-Statistic: (non-parametric)

$$N^{-\mathbf{1/2}} Z_{t,\boldsymbol{N},\boldsymbol{T}} \equiv N^{-\frac{1}{2}} \sum_{i=1}^{N} \left(\hat{\sigma}_{N,T}^{2} \sum_{t=1}^{T} \hat{e}_{i,t-1}^{2} \right)^{-1} \sum_{t=1}^{T} \left(\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i \right) \tag{16}$$

Group t-Statistic: (parametric)

$$N^{-\mathbf{1/2}} Z_{t,N,T}^{*} \equiv N^{-\frac{1}{2}} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} s_i^{*2} \hat{e}_{i,t-1}^{*2} \right)^{-1/2} \sum_{t=1}^{T} \hat{e}_{i,t-1}^{*} \Delta \hat{e}_{i,t}^{*} \tag{17}$$

Results and Discussion

Empirical Results

Main text paragraph. The findings of the analysis are provided in this section. To begin, the descriptive statistics for the variables used in the model for the period 2019-21 are provided (Table 1).

Descriptive Statistics

According to Table 1, maximum GDP (89.72305), COV19 (80.52074) are found for the United States of America (USA), while minimum GDP (19.01282) and COV19 (32.49526) is for Canada. It is seen that the difference between the maximum and minimum values of the GDP is considerably greater than the dependent variable. The reason why the difference between the maximum and minimum values of

Table 1. Descriptive Statistics.

	COV19	GDP	PM2.5	HE
Average	57.38598	58.22558	38.64252	48.36503
Median	58.52843	63.10963	48.90312	51.38626
Maximum	80.52074	89.72305	52.76309	69.03738
Minimum	32.49526	19.01282	27.02345	37.84093
Standard deviation	8.102673	18.11213	7.12012	7.86084
Observation	147	147	147	147

Table 2. Horizontal Dependency Test Results.

Variable	CDLM		CD	
	Test Statistics	Probability	Test Statistics	Probability
COV19	-0.845	0.353	1.478	0.301
GDP	-0.298	0.071	1.304	0.091
PM2.5	-0.658	0.094	1.793	0.073
HE	-0.583	0.106	2.072	0.097

the independent variable GDP is higher than the dependent variable COV19 may be due to the volatility of the GDP variable. The same patterns are found (PM2.5) maximum (52.76309) and minimum (27.02345) for the US and Canada, respectively. Finally, found the highest level of Health Expenditure (HE) (69.03738) is for the US, while the lowest is for Japan (37.84093). 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

The tests, called first generation unit root tests are predictors Levin, Lin & Chu, Im Pesaran and Shin, ADF-Fisher, PP- Fisher tests. If the probability value of these tests is close to 0, it indicates that the series is stationary. If it is close to 1, it means there is a volume root problem. The logarithmic values of the economic growth variables COV19, GDP, PM2.5, and HE were computed, and the unit root test and other tests were done using the logarithmic values of the variables. The Schwarz information criteria were used to determine the ideal lag duration that removes the autocorrelation problem. The series was found to be non-stationary based on their level values. By taking the first differences, the series was made stationary. The findings are shown in Table 3.

Unit root tests applied to the levels of the variables, t statistics, and probability findings are not stationary at the level of series, I (0), to be employed in econometric analysis, as shown in Table 3. To guarantee stability, the first differences in the series, I (1), are used. Table 4 displays the Pedroni Cointegration Test findings for four variables and 11 values of seven test statistics. As a result, these four factors, COV19 and GDP, PM2.5, and HE interact throughout time.

Findings of Cointegration Coefficients Using FMOLS and DOLS and Their Evaluation

Group-Mean FMOLS (Fully Modified Ordinary Least Squares) and DOLS (Dynamic Ordinary Least Squares) techniques will be used to assess the consistency of this test after identifying the cointegration relationship [75, 76]. The FMOLS approach eliminates the discrepancies caused by fluctuating variance, autocorrelation, and other issues in traditional fixed effect estimators. The DOLS technique is used to include dynamic components in the model. As a result, mistakes resulting from endogeneity issues in static regression are avoided [77]. Endogeneity and serial correlation adjustments are used to create the FMOLS estimator, which is defined as follows [78]:

$$\beta_{FM} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it}-\bar{x}_i)(x_{it}-\bar{x}_i)'\right]^{-1} \left[\sum_{i=1}^{N}\left(\sum_{t=1}^{T}(x_{it}-\bar{x}_i)\hat{y}_{it}^{*} + T\hat{\Delta}_{EM}^{*}\right)\right] \quad (18)$$

$\hat{y}_{it}^{*}$ = Endogeneity correction is provided by the transformed y variable; $\hat{\Delta}^{*}_{EM}$ = serial correlation correction term. The DOLS estimator may also be used to adjust for serial correlation and endogeneity. The DOLS estimator's equation is as follows:

$$y_{it} = \alpha_i + \beta x_{it} + \sum_{j=q_1}^{j=q_2} c_{ij}\,\Delta x_{i,t-j} + U_{it} \quad (19)$$

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

Variable	LLC (P-Value)		Pesaran, Shin (P-Value)		ADF-PP (P-Value)	
	Level	First dif.	Level	First dif.	Level	First dif.
COV19	0.7932	0.0000	0.0921	0.0001	0.1475	0.0000
GDP	0.0601	0.0002	0.9308	0.0000	0.0564	0.0000
PM2.5	0.5903	0.0000	0.0932	0.0001	0.1028	0.0000
HE	0.6435	0.0011	0.0212	0.0000	0.3774	0.0001

Table 4. Results of Pedroni (Engle-Granger based) Cointegration Test.

$PCOV19_{it} = \alpha_{it} + \beta_1 GDP_{it} + \beta_2 PM2.5_{it} + \beta_3 HE_{it} + u_{it}$				
Series: DCOV19, DGDP, DPM2.5, DHE				
	Statistics	Probability	Weighted Statistics	Probability
Panel v-Sta.	1.89804***	0.2109	-0.89073*	0.2073
Panelrho- Sta.	-7.04802***	0.0032	-3.03461***	0.0000
PanelPP- Sta.	-4.08045***	0.0041	-1.90630***	0.0020
PanelADF-Sta.	-5.00232***	0.0001	-2.05611***	0.0001
Alternative Hypothesis: Common AR Coefficients (in-between them)				
Group rho-Sta.	-3.06782***	0.0001		
Group pp-Sta.	-0.80012*	0.0028		
Group adf-Sta.	-6.17408***	0.0845		

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

c_{ij} = The first distinction is the explanatory variables' lead or lag coefficient.

COV19 coincides with the findings by co- integration approach between GDP, PM2.5 and HE subsequent analysis of long-term effects of DOLS and FMOLS. It is an important consequence that economic growth is the cause of air pollution. The severity of this relationship was determined as DOLS (0.76) and FMOLS (0.72) (Table 5).

Panel Causality Analysis

Granger causality logic may be used to investigate causal relationships in panel data models as well as time series. The following is the equation for the panel causality model [79]:

$$y_{it} = \alpha_i + \sum_{k=1}^{k} y^{(k)} y_{it-k} + \sum_{k=1}^{k} \beta^{(k)} x_{it-k} + \varepsilon_{it} \quad (20)$$

Unit-specific effects are denoted α_1 by Also, for all units, $y^{(k)}$ and $\beta^{(k)}$ are the same. In contrast to Granger causality tests, causality tests in panel data analysis account for unit heterogeneity. As a result, the null hypothesis is written as H0: = 0, which says that X and Y have no causal link [80]. The following are the $\beta^{(k)}$ outcomes of causality in our model. Since this approach can be utilized in both cross-section dependency and heterogeneous panels, [81] the panel causality test was employed to investigate the causative connections between COV19, GDP, PM2.5, and HE in G7 countries.

GDP and COV19 were determined to have probability values of 0.0039 and 0.0020, respectively, as model variables. At a 5% significance level, these results show the existence of a two-way causal connection between COV19 and GDP. To put it another way, both factors cause each other. As a result, the entire study's link between PM2.5, GDP, and COVID-19 may be described as a vicious cycle. Finally, it is possible

Table 5. Results of Panel FMOLS and DOLS Methods (Panel Whole).

Dependent Variable COV19				
FMOLS				
Independent	Coefficient	t statistics	St. Error	Probability
lnGDP	0.720321	9.56302	0.518741	0.0001
lnPM2.5	0.358935	5.21742	0.092273	0.0000
lnHE	0.167931	9.76320	0.21083	0.0002
DOLS				
Independent	Coefficient	t statistics	St. Error	Probability
lnGDP	0.763309	9.458529	0.927431	0.0000
lnPM2.5	0.437409	5.168203	0.094572	0.0000
lnHE	0.201803	6.320282	0.210873	0.0001

Table 6. Results of Panel Causality.

Causality Aspect	W-Stat	Z-bar Stat	Probability
COV19 → GDP	0.8092	-0.4053	0.0039
COV19 ← GDP	2.9808	5.0002	0.0020
COV19 ← PM2	1.9684	3.4258	0.0045
COV19 → HE	1.8504	2.1093	0.0042

to conclude that there is a one-way causal connection between PM2.5 and HE.

Discussion

It has been stated by the World Health Organization that the Covid-19 virus can be transmitted more in closed and airless environments. Indoor environments are favourable environments for air-polluting particulate matter. Studies have shown that the risk of transmission of the Covid-19 virus is high in environments with a high concentration of particulate matter [82, 83]. Today, production is based on the use of fossil fuels. Hazardous gases produced by the combustion of fossil fuels enter the atmosphere and contaminate the air. As long as traditional methods of manufacturing rely on fossil fuels, health concerns will worsen due to air pollution. As a result, net contributions to economic growth will be reduced. The impacts of air pollution on human health are not confined to the harmful substances it contains. According to scientific research, incidences of contagious and lethal viruses are on the rise in areas with high levels of air pollution.

The main purpose of this study is to reveal that the economic growth due to the use of fossil fuels causes air pollution and that Covid-19 cases are associated with it. To do so, the Pedroni cointegration test has been performed. There are 7 cointegration statistics in Pedroni cointegration analysis. By combining the weighted statistics for the first four tests to the seven test statistics, 11 values have been produced. The majority decision decides on cointegration according to these 11 parameters. The probability values show that the probability values of the 8 tests are less than 0.05. The H0 hypothesis, which was the null hypothesis, in this case, has been rejected. Accordingly, a long-term relationship between COVID-19, GDP, PM2.5 and HE has been found in the G7 countries. The most important feature that distinguishes this study from other studies is the direction of the relationship between the variables. According to the results of the causality analysis, a bidirectional causality relationship has been found between economic growth and Covid-19. This result is important for the originality of the study. In the literature, only two studies have been found that are similar to our study in terms of research results. One of these studies was conducted for the 25 largest cities in India for the years between 1980-2018 [84]. The other study was conducted for the state of New York from June 3 to June 26, 2020 [85]. However, these studies were carried out at the regional level, unlike our study. At the same time, the direction of the relationship between the variables was evaluated unilaterally in the form of economic growth air pollution- covid-19. In other studies, the causal relationship between the variables is as follows; Air Pollution (PM2.5) → COVID-19 → Economic Growth, respectively. Accordingly, Covid-19 restrictions have a negative impact on economic growth and a positive effect on the prevention of air pollution. Our other conclusions are that Covid-19 cases negatively affect economic growth. These findings imply that the influence of Covid-19 on economic growth is in agreement with the results of [5, 11, 12, 14]. A one-way causal link between PM2.5 and COVID-19 has been identified. These findings imply that the influence of PM2.5 on COVID-19 is in agreement with the results of [86-90]. Finally, a one-way causal relationship has been established between PM2.5 and health expenditures. Implying that the influence of PM2.5 on health expenditures is in agreement with the results of [91, 92].

In terms of the results of our article, other developed countries, especially the G7 countries, should abandon the fossil fuel-dependent growth model. In this context, the reduction of carbon emissions is of great importance in terms of fighting Covid-19 and similar outbreaks. If these data are associated with the use of fossil fuels in industries, they will contribute to the creation of public policies that encourage a new generation of energy sources in production.

Conclusions

Our results showed evidence of a direct relationship between economic growth, air pollution and COVID-19 pandemic in G7 countries. As economic expansion accelerates, so does the density of PM2.5 particulate matter in the atmosphere. Because of the linear link between COVID-19 and PM2.5, there is an upward trend from economic growth to PM2.5, and from PM2.5 to COVID-19 cases. In these circumstances, the negative impact on economic development will be exacerbated by COVID-19 cases and healthcare costs will rise as air pollution worsens. This will result in a vicious cycle of economic expansion, air pollution, and COVID-19 cases. Therefore, reducing exposure to high levels of PM2.5 concentration can prevent deaths due to the Covid-19 pandemic.

The COVID-19 virus's economic cost, or its negative influence on economic growth, happens both indirectly and directly. Health expenditures include indirect costs. Direct costs are more visible in manufacturing and employment. Because intimate contact between numerous people increases the danger of transmission, many big and small businesses in the economic sector were forced to curtail or totally cease operations. The extension of the pandemic era has resulted in staff layoffs in various industries. If an existing issue cannot be entirely removed, reducing its negative impacts will be extremely beneficial. In the current scenario, the COVID-19 virus is still present. There have been scientific studies that explain how people get infected by the virus and which environments are more dangerous in this context. It is true that measures like social isolation, mask use, travel restrictions, and curfews were effective in the fight against COVID-19 following the epidemic. Such efforts, however, are short-term, cyclical, and only apply during the epidemic. So, even if the pandemic is over, these are the measures to be taken again in the next pandemic. In addition, there are non-cyclical but permanent measures different from cyclical measures. You do not need these measures again when they are applied once. Prevention of air pollution due to fossil fuels can be given as an example.

To break the vicious loop between economic growth, PM2.5, and the COVID-19 virus, and to minimize the number of COVID-19 cases, the fossil-fuel-based production system should be abandoned. Instead, alternative manufacturing models should be preferred. In this perspective, it is critical to prioritize and increase production based on renewable energy sources such as wind, solar, and hydro. Mitigation can be achieved through activities in the Land Use, Land-Use Change and Forestry (LULUCF) sector that increase the removals of greenhouse gases from the atmosphere or decrease emissions by halting the loss of carbon stocks [93]. This will also boost economic growth's net contribution. Also, the effects of air pollution are mostly being observed in the major industrial countries. But air pollutants can be transported by wind, causing pollution to other countries. Therefore, international cooperation is crucial.

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Conflict of Interest

The authors declare no conflict of interest.

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