The Nexus Between COVID-19 Factors and Air Pollution

Rehana Parvin

Department of Statistics, International University of Business Agriculture and Technology, Dhaka, Bangladesh.

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ABSTRACT

BACKGROUND AND OBJECTIVE: There have been significant effects of the current coronavirus-19 (COVID-19) infection outbreak on many facets of everyday life, particularly the environment. Despite the fact that a number of studies have already been published on the topic, an analysis of those studies' findings on COVID-19's effects on environmental pollution is still lacking. The goal of the research is to look into greenhouse gas emissions and air pollution in Bangladesh when COVID-19 is under rigorous lockdown. The specific drivers of the asymmetric relationship between air pollution and COVID-19 are being investigated.

METHODS: The nonlinear relationship between carbon dioxide (CO_2) emissions, fine particulate matter ($PM_{2.5}$), and COVID-19, as well as its precise components, are also being investigated. To examine the asymmetric link between COVID-19 factors on CO_2 emissions and $PM_{2.5}$, we employed the nonlinear autoregressive distributed lag (NARDL) model. Daily positive cases and daily confirmed death by COVID-19 are considered the factors of COVID-19, with lockdown as a dummy variable.

RESULTS: The bound test confirmed the existence of long-run and short-run relationships between variables. Bangladesh's strict lockdown, enforced in reaction to a surge of COVID-19 cases, reduced air pollution and dangerous gas emissions, mainly CO_2, according to the dynamic multipliers graph.

KEYWORDS: Bound test, greenhouse gas emissions, nonlinear autoregressive distributed lag, Coronavirus-19, Bangladesh, fine particulate matter

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CORRESPONDING AUTHOR: Rehana Parvin, Department of Quantitative Sciences, International University of Business Agriculture and Technology (IUBAT), 4 Embankment Drive Road, Sector 10, Uttara, Dhaka, 1230, Bangladesh. Email: rehana.parvin@iubat.edu

Introduction

The Coronavirus-19 (COVID-19) has spread throughout the world. As of February 6, 2022, there have been over 435 million overall cases and 5.95 million deaths globally since the virus was first discovered in Wuhan, China. The World Health Organization (WHO) proclaimed such infections to be a pandemic on January 30. In horizontal transmission, the virus spreads indirectly through contaminated surfaces like plastic and stainless steel and directly across intimate interactions via respiratory secretions produced by sneezes and coughs.[1] Severe acute respiratory syndrome Coronavirus 2 (SARS-CoV-2) is a corona virus that causes severe acute respiratory syndrome.[2-4] Although the virus's intermediate point of origin and mode of transmission to humans are unknown, the virus's ability to spread quickly from human to human has been established.[5] Direct contact or droplets formed by coughing, sneezing, or talking were the most common ways for the virus to spread from person to person.[2,6,7] In the worst-case scenario, COVID-19 can result in kidney failure, pneumonia, and even death.[2,8]

The world has seen a massive growth in environmental contamination during the last few decades. Pollution of the environment is a serious problem that continues to endanger people's lives. As pollution concentrations grow, so do the number of respiratory infections.[9] In the contemporary global environment, where economic operations are rising, pollutants are increasing at a quicker rate. Pollution from the environment causes a wide variety of illnesses. It has a detrimental influence on human health through increased infection susceptibility.[10] Without a doubt, developing countries are the most affected. Traditional pollution sources, such as drinking water contaminated by waste, poor hygiene, and poor indoor air quality emissions, are still being addressed.[11] Pollution in the environment has reached alarming levels all across the world. Greenhouse gas emissions have increased because of economic development, industrialization, and urbanization.[2,11,12] As a result, harmful chemicals such as atmospheric carbon dioxide (CO_2) are emitted into the environment, contaminating the atmosphere, and increasing its warmth. This is what has contributed to the depletion of the stratospheric gradient, which has had a significant impact on modern society.

COVID-19 will have a significant economic impact, but there is a bright side that might mitigate some of its unfortunate facts. Reduced human interference in the environment has given nature a "healing time" as states have practiced social isolation and quarantine for more than a month. One notable effect that is being noticed is on the air quality, which is being felt by everyone and documented in numerous official reports.[13] Marine life is more active, smog has made way for clear skies, and major cities' pollution levels have significantly dropped. The situation today is a "reset" for nature and humans, giving us the opportunity to observe and assess how humans are affecting the environment. These positive impacts have allowed us to reevaluate our impact on our surroundings.[14] As a result, we deduce that quarantine measures have improved the air quality in Bangladesh, inspiring us to investigate the quality of the air and the impact of environmental pollutants' associations with COVID-19 in Bangladesh as well as around the world.

Without a doubt, the new corona virus has wreaked havoc on the ecology and climate around the planet. Because of the lockdowns, there has been a considerable reduction in transport activity, which has resulted in a huge reduction in air pollution. Since the epidemic, China's CO_2 emissions and nitrogen oxide (NO_2) emissions have decreased by 25% and 50%, respectively, according to Zhang et al.[15] Lockdowns have been established in almost every country to prevent the spread of the corona virus, which has resulted in a reduction in industrial activities as well as transportation services. As a result, global pollution levels have decreased considerably.

Bangladesh is a densely populated, tiny country that is well-balanced. The weather in Bangladesh can be changeable.[16] Bangladesh seems to be the third country in South Asia to be affected, after Pakistan and India.[17] On March 8, 2020, Bangladesh announced the first COVID-19 outbreaks at the Institute of Epidemiology, Disease Control, and Research (IEDCR). The city of Dhaka, Bangladesh's capital, has been the hardest hit. Bangladesh's government issued a 10-day curfew as a first step to combat the epidemic from March 26, 2020, to May 30, 2021. The Bangladesh government then enforced a 21-day lockdown from April 5, April 26, 2021, as the second stage. Finally, from July 1 to August 31, 2021, Bangladesh's government implemented a partial lockdown. To try to stop the spread of COVID-19, Bangladesh's authorities implemented quarantines and lockdowns. All other organizations, including educational institutions, are closed save for emergency services (eg, medical, fire, police, food supply, and so on) to urge people to stay at home. Except for the conveyance of vital commodities and emergency services, all public transportation services (eg, buses, trucks, trains, planes, etc.) were suspended. Following the announcement of the lockdown, the government and administration made the difficult decision to implement it, which included no social gatherings, a significant reduction in vehicles and public transportation, and the complete closure of industries, shopping malls, and non-emergency administrative buildings, among other things. Figure 1 depicts the overall scenario in Bangladesh during and after the lockdown.

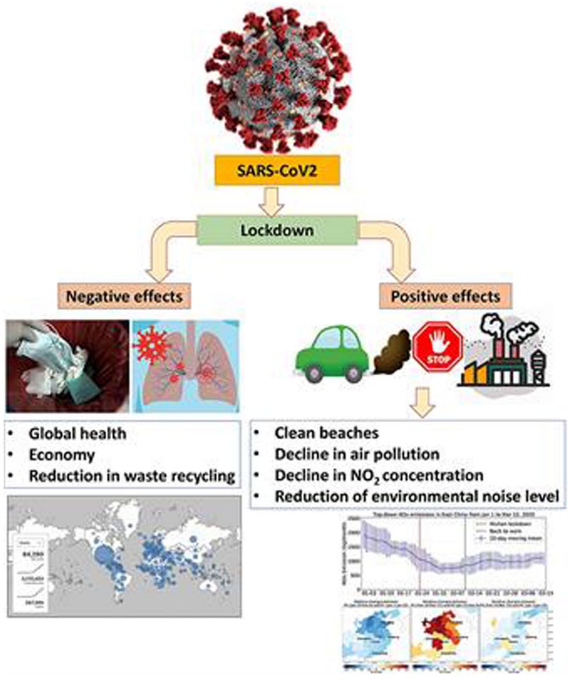

Figure 1. COVID-19, lockdown and the effects on the world. Adapted from "Kumar et al."[18]

Industrial output, educational establishments, building activities, and small and large-scale businesses were all affected by the long-term shutdown. It has had a significant negative impact on the economy, and a great number of individuals are experiencing difficulties in their daily lives as a result. Because of the uncontrollable COVID-19 scenario, Bangladesh's government declared a red, yellow, and green zone on June 16, 2020, based on the number of people infected. During the lockdown, nature has a chance to recover while residents maintain social distance, quarantine at home, and engage in as few outside activities as possible. As a result, during the lockdown, Bangladesh observed a blue sky in the Dhaka metropolis for more than 100 days.

The current study will look at the impact of carbon emissions and $PM_{2.5}$ on sustainable development during COVID-19. All human activity was prohibited under the lockdown laws and regulations, and Bangladeshi citizens were prohibited from returning to their homes. During the lockdown, people stopped activities every day and cut traffic emissions, and companies did not contribute to pollution or harmful gas emissions. The main objective of this study is to look into the relationship between lockdown and the carbon dioxide emissions, as well as the type and direction of that relationship in the long and short runs.

COVID-19 has also taught us some important things. All of these are tied to human survival, readiness, and environmental responsibility, all of which will contribute to future pandemic control. Lockdowns of many varieties are proving useful not only in breaking the chain of illnesses, but also in repairing the environment. In various parts of the world, pollution levels have decreased, and nature has begun to reclaim its territory. What matters is what we learn as a species because of this. Will we be able to dramatically cut our carbon footprint? Will there be any limits on traveling that aren't necessary? Will we cut back on the quantity of contaminants we throw into ecosystems so that nature can breathe? Will all stakeholders, including governments, organizations, and individuals, band together to combat the environmental plague that has been ravaging the world for decades, claiming lives and destroying biodiversity? Vaccines or other measures, as well as coordinated efforts across national and continental borders, will be used to combat the deadly COVID-19, the most explosive pandemic in a century, sooner or later. A fresh viewpoint is required to address some of the fundamental concerns raised by the epidemic. To stop these pandemics in their tracks, humanity must work together. The best method to prevent pandemics is to focus all your efforts on achieving environmental sustainability goals.

The effect of temperature on the distribution of COVID-19 in diverse situations has been studied in several recent articles. Most investigations failed to discover a direct association between the COVID-19 pandemic and the temperature, according to Bilal et al.[19] The air has reached its purity and has become healthy throughout this critical period. According to Muhammad et al,[20] during the COVID-19 lockdown period, the world's most polluting cities, including China, Spain, France, Italy, and the United States, cut nitrogen dioxide (NO_2) emissions by up to 30%. Because of COVID-19's role as a catalyst for lower air pollution emissions in industrial economies and the consequent decline in carbon monoxide, nitrous oxide, and carbon dioxide airborne transmissions, the quality of the air has significantly improved.[21] Transportation, businesses, and industrial closures have consequently contributed to a significant drop in greenhouse gas emissions (GHG) emissions, resulting in a 50% reduction in air pollution in New York compared to 2019 and a 40% reduction in coal use in China, as well as a 25% drop in GHG emissions overall.[22]

Fayaz[21] has investigated the lock-down COVID-19 effects on the air pollution indices in Iran and its neighbors. In India's megacity Delhi, Mahato and Pal,[23] revisiting air quality during lockdown and influenced by the second surge of COVID-19, discover that both the nationwide lockdown and the city-scale restriction are responsible for improving the city's air quality, though the rate of improvement was higher (39%) during the first cycle of lockdown (nationwide) than during the second cycle of lockdown (city-scale). A case study from Indian cities demonstrates negligible effects on the persistent property of urban air quality, which Chelani and Gautam[24] studied during the COVID-19 pandemic. According to Dang and Trinh,[25] "The Beneficial Impacts of COVID-19 Lockdowns on Air Pollution: Evidence from Vietnam," NO_2 concentrations drop by 24% to 32% 2 weeks after the COVID-19 lockdown.

Lockdown has also had an effect on the air pollution indices in the highest producer of greenhouse gas regions, such as China in $PM_{2.5}$ and NO_2,[26] the United States in $PM_{2.5}$ and NO_2,[27] the UK in nitric oxide (NOx), with about 50% reductions and increases in Ozone gas ($O_{3)}$ and Sulfur di oxide ($SO_{2)}$),[28] and South Korea in $PM_{2.5}$, PM_{10}, NO_2, and Carbon monoxide (CO).[29] The decline and changes of NO_2, $PM_{2.5}$, and PM_{10} have been observed in Asia[30] and Iran.[31]

During the lockdown, Delhi, India's capital, saw considerable improvements in air quality and a reduction in the rate of specific air pollutants.[32] Air pollutants and aerosol concentrations have a positive association,[33] and aerosol concentrations have decreased because of the reduction in major air pollutants. Overall, the epidemic has wreaked havoc on the global economy, affecting the environment either directly or indirectly. The COVID-19 epidemic enhanced air and water quality, decreased noise, and helped to rehabilitate the environment.[34,35] The COVID-19 pandemic in the region is linked to the transportation sector's emissions of environmental pollutants like $PM_{2.5}$, PM_{10} , NO_2 , CO, O_3 , and SO_2 in South American economies, according to research by Bilal et al[36] and find that $PM_{2.5}$, PM_{10} , NO_2 , CO, O_3 , and SO_2 are significant factors in the fight against the COVID-19 pandemic in South America.

Because of its worldwide upheaval, COVID-19 has had a multitude of ecological and environmental impacts. Because of movement restrictions and a significant slowdown in socio-economic activities, environmental performance has improved in many places, and water contamination has been reduced in different parts of the world as well. The environmental effects of COVID-19 on the environment are shown in Figure 2. As factories, transportation, and businesses have closed, GHG emissions have plummeted. According to Henriques,[37] New York's air pollution levels will have dropped by nearly half because of virus-control measures. Heavy industry closures in China were expected to account for roughly half of the reduction in Nitrous oxide (N_2O) and CO emissions.[38] Additionally, nitrogen oxide (NO) pollutants are indeed a leading indicator of the world economy and so many countries, including Canada, the United States, India, and China. They observed a decrease in nitrogen oxide output because of the current closure, according to Biswal et al[39]; Saadat et al[35]; and Somani et al.[34] NO_2 and $PM_{2.5}$ levels in Delhi, India's capital was similarly lowered by over 70%.[40] During India's nationwide shutdown, $PM_{2.5}$ and PM_{10} levels were reduced by 46% and 50%, respectively. According to Henriques,[37] automobiles and aircraft are estimated to be big emitters, with 72% and 11% of greenhouse gases in the transportation sector, respectively. In China, for example, the epidemic caused a reduction of about 50% to 90% of outbound and 70% of domestic flights, resulting in a reduction of nearly 17% of national CO_2 emissions by January 20, 2020.[41] Furthermore, the COVID-19 pandemic is said to have cut global air travel by 96% compared to the same period last year,[42] with long-term environmental consequences.

Methodology

Data description

The impacts of COVID-19's determinants on CO_2 emissions and $PM_{2.5}$ is studied using daily data on deaths, confirmed cases, and lockdowns. This study has utilized the time series data from March 18, 2020, until February 4, 2022. The data set is divided into 3 sections: before shutdown; throughout shutdown; and then after lockdown.[44,45] Next 10 days curfew has been declared by Bangladesh's government on March 26, 2020, to combat the epidemic, which was later extended until May 30, 2021. From April 5, 2021, to April 28, 2021, was the second full lockdown, and from July 1, 2021, to July 28, 2021, it was subjected to its third partial lockdown. The Directorate General

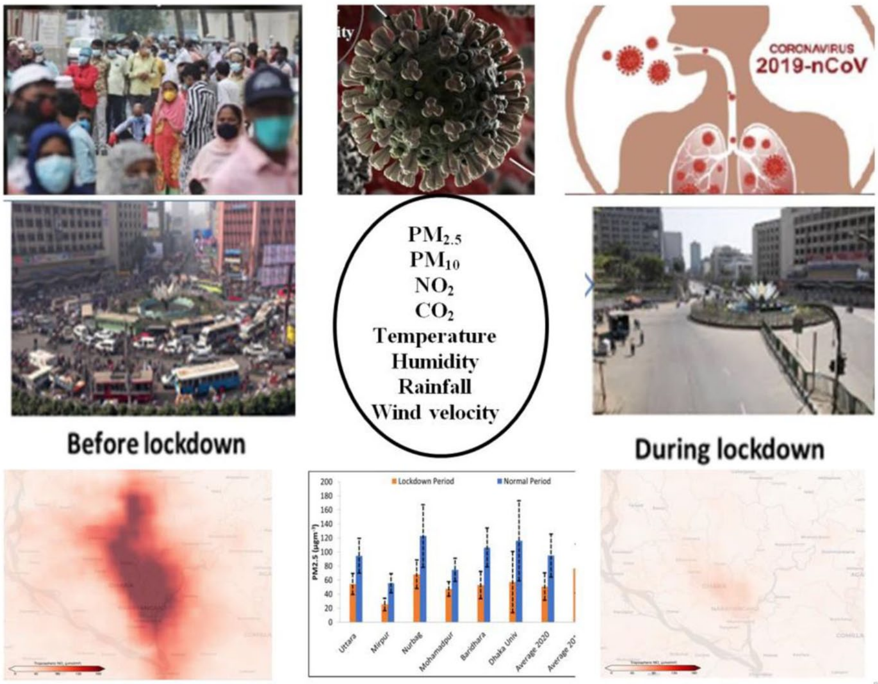

Figure 2. Total scenario during and before (after) lockdown in Bangladesh. Adapted from "Pavel et al."[43]

of Health Services (DGHS) collects COVID-19 confirmed cases and confirmed death data. The Bangladesh Meteorological Department (BMD) provided data on $PM_{2.5}$ and carbon emissions, respectively.

Methods

As reported by Shin et al[46] we utilized a NARDL model to investigate the long and short-run nonlinear interactions between the variables. Based on the previous work of Sarfraz et al,[44] our model will be as follows, taking into account the nonlinear link between daily-confirmed cases, daily confirmed fatalities, lockdown on carbon emission and $PM_{2.5}$:

$$CE = f(DC^{+}, DC^{-}, DD^{+}, DD^{-}, LD^{+}, LD^{-}) \tag{1}$$

$$LNPM = f(DC^{+}, DC^{-}, DD^{+}, DD^{-}, LD^{+}, LD^{-}) \tag{2}$$

The partial sum of positive and negative shocks in daily-confirmed cases (DC), daily confirmed deaths (DD), and lockdown (LD) has been estimated by the nonlinear autoregressive distributed lag (NARDL) approach. While some variables are nonlinearly related, the usual ARDL model can only look at the straight-line association across exogenous and endogenous variables.[47,48] The nonlinear ARDL model handles negative and positive changes in variables. The decomposition of the NARDL model into a partial sum of positive and negative changes is shown by the x_t in the following equation:

$$x_t = x_o + x_t^{+} + x_t^{-} \tag{3}$$

Where, $x_t^{+} = \sum_{i=1}^{t} \Delta x_t^{+} = \sum_{i=1}^{t} max\left(\Delta x_i, 0\right)$

And $x_t^{-} = \sum_{i=1}^{t} x_t^{-} = \sum_{i=1}^{t} minx\left(\Delta x_i, 0\right)$

Equation (2) can be included in the following NARDL equation with an unrestricted error correction representation:

$$\begin{aligned}\Delta CE_t = \beta &+ \sum_{i=1}^{q} \gamma_0 \Delta CE_{t-i} + \sum_{i=1}^{p} \gamma_1^{+} \Delta DC^{+}{}_{t-i} \\ &+ \sum_{i=1}^{p} \gamma_2^{-} \Delta DC^{-}{}_{t-i} + \sum_{i=1}^{p} \gamma_3^{+} \Delta DD^{+}{}_{t-i} \\ &+ \sum_{i=1}^{p} \gamma_4^{-} \Delta DD^{-}{}_{t-i} + \sum_{i=1}^{p} \gamma_5^{+} \Delta LNLD^{+}{}_{t-i} \\ &+ \sum_{i=1}^{p} \gamma_6^{-} \Delta LNLD^{-}{}_{t-i} + \theta_1 CE_{t-1} + \theta_2 DD_{t-1}^{+} \\ &+ \theta_3 DC_{t-1}^{-} + \theta_4 DC_{t-1}^{+} + \theta_5 DC_{t-1}^{-} + \theta_6 LD_{t-1}^{+} \\ &+ \theta_7 LD_{t-1}^{-} + \varepsilon_t\end{aligned} \tag{4}$$

$$\begin{aligned}\Delta LNPM_t = \beta &+ \sum_{i=1}^{q} \gamma_0 \Delta CE_{t-i} + \sum_{i=1}^{p} \gamma_1^{+} \Delta DC^{+}{}_{t-i} \\ &+ \sum_{i=1}^{p} \gamma_2^{-} \Delta DC^{-}{}_{t-i} + \sum_{i=1}^{p} \gamma_3^{+} \Delta DD^{+}{}_{t-i} \\ &+ \sum_{i=1}^{p} \gamma_4^{-} \Delta DD^{-}{}_{t-i} + \sum_{i=1}^{p} \gamma_5^{+} \Delta LNLD^{+}{}_{t-i} \\ &+ \sum_{i=1}^{p} \gamma_6^{-} \Delta LNLD^{-}{}_{t-i} + \theta_1 CE_{t-1} + \theta_2 DD_{t-1}^{+} \\ &+ \theta_3 DC_{t-1}^{-} + \theta_4 DC_{t-1}^{+} + \theta_5 DC_{t-1}^{-} + \theta_6 LD_{t-1}^{+} \\ &+ \theta_7 LD_{t-1}^{-} + \varepsilon_t\end{aligned} \tag{5}$$

The lag order of this model can refer to p and q. the long run nonlinear effects of DC, DD, and LD on CE are defined by $\beta_i = \theta_{i+1} / \theta_i$. Accordingly, $\sum_{i=1}^{8} \gamma_i{}'s$ are measure the short

Table 1. Descriptive statistics.

	CE	DC	DD	PM
Mean	0.508955	2677.530	41.39913	187.6909
Median	0.540000	1604.000	26.00000	193.0000
Maximum	0.680000	16 230.00	264.0000	365.0000
Minimum	0.180000	0.000000	0.000000	28.00000
Std. Dev.	0.169396	3278.136	53.15181	70.34621
Skewness	−0.829275	2.233254	2.488510	−0.028529
Kurtosis	2.274429	7.734113	8.886440	2.438407
Jarque-Bera	94.08414	1216.129	1705.875	9.147706
Probability	.000000	.000000	.000000	.010318

Here, Std. Dev. stands for standard deviation.

run nonlinear effects of DD, LD on CE. $\varepsilon_t{}'s$ is the error term for both models. According to Khan et al[49] and Sarfraz et al,[44] this article regarded lockdown as a dummy variable and 2 binary numbers like 0 are taken for unlocked period and 1 for shutdown period.

The NARDL model can be used in several ways. To see if the data was stationary, we performed the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. The study then used bound testing, as proposed by Shin et al[46] to check for the presence of co integration. Using the F-test, we checked the null hypothesis of $\theta_1 = \theta_2 = \theta_3 = \theta_4 = \theta_5 = \theta_6 = \theta_7 = 0$ jointly. Third, we use the Wald test to show both long run and short-run asymmetrical correlations between the variables. Finally, we show how a 1% difference in the positive and negative lag values of independent variables can cause asymmetric cumulative dynamic multiplier (CDM) effects. Obtaining the CDM of a unit change allows us to assess the asymmetric effect as well in x^+_{t-1} and x^-_{t-1} on y.

$$m_h^+ = \sum\nolimits_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x^+_{t-1}} \text{ and } m_h^- = \sum\nolimits_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x^-_{t-1}},\ \text{h} = 1,\ 2,\ 3\ldots \quad (6)$$

Results and Discussion

Table 1 summarizes CO_2 emissions, $PM_{2.5}$, newly confirmed illnesses, and newly confirmed deaths. CO_2 emissions (0.508955) and $PM_{2.5}$ (187.6909) are lower than in DC (2677.530) and DD (41.39913). The maximum and minimum values of variables clearly demonstrate the relationship between CO_2 emissions and COVID-19. CO_2 emissions range from 0.680000 to 0.180000, with a maximum of 0.680000 and a minimum of 0.180000. Bangladesh observed a decrease in CO_2 emissions and $PM_{2.5}$ levels during COVID-19, while the number of new confirmed cases and deaths increased. DC (3278.1136) and DD (53.15181) have drastically elevated standard deviations. CO_2 emissions and $PM_{2.5}$ have standard deviations of 0.169396 and 70.34621, respectively. Positive skewness is seen in the most recent confirmed cases and deaths, while negative skewness is seen in CO_2 emissions and $PM_{2.5}$. The data for CO_2 emissions and $PM_{2.5}$ variables have a kurtosis value of less than 3 at a 1% level of significance, indicating that they are normally distributed, but newly confirmed cases and deaths reveal that they are not.[50,51] Figure 3 shows a graphic representation of CO_2 emissions and $PM_{2.5}$ data from January 1, 2020, to February 4, 2022. From Figure 3, it is observed that, during the lockdown period in Bangladesh, the CO_2 emissions and $PM_{2.5}$ have decreased dramatically. This finding is consistent with previous findings by Bilal et al[19]; Fayaz[21]; Mahato and Pal[23]; Chelani and Gautam[24]; and Dang and Trinh.[25] The contributions of each of our study variables are shown in Figure 4.

The study used unit root test to check the order of integration in time series data using the ADF and PP tests and the results are presented in Table 2. For the optimal lag structure, the Akaike information criterion (AIC) was employed. Daily positive cases, daily deaths, CO_2 emissions, and $PM_{2.5}$ levels are all stationary at level according to both tests. All factors of this study have shown I (0) according to the ADF and PP tests. Because the study variables are stationary at first difference, the results of both tests reveal that the variables are I (1). On the second difference, our data revealed that no variable was stationary. As a result, we may approximate equations (4) and (5) using the bound testing method. The optimal lag was determined using the conventional VAR model. Akaike information criterion (AIC) has been used to select the optimal lag for the NARDL model, which is "2."[45,52]

The bound test results of NARDL model for co integration have been shown in Table 3. The bound test shows that there is an inconclusive relationship in a linear ARDL way for model 1, because at 5%, the calculated value (F-statistic) of 3.04 is halfway between the required lower threshold of 2.86 and the

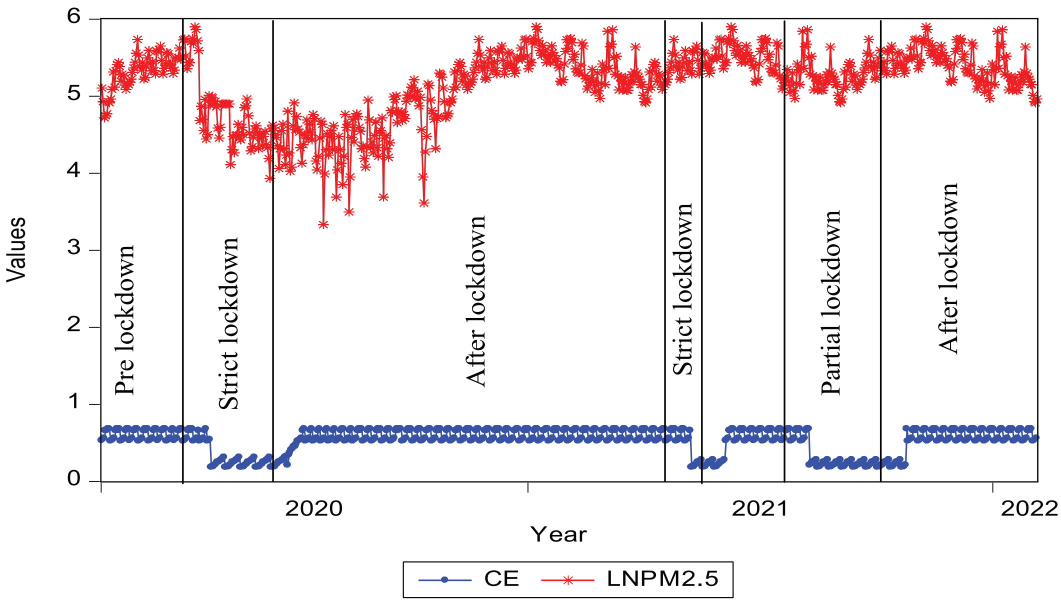

Figure 3. Carbon emission and $PM_{2.5}$ in Bangladesh during the pandemic.

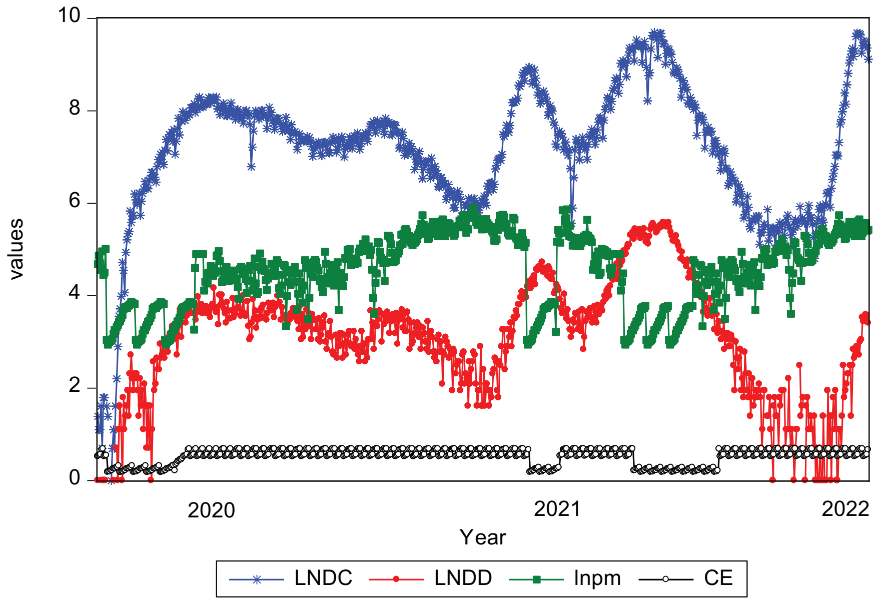

Figure 4. Contributions of all the study variables.

Table 2. Unit root test results.

VARIABLES	LEVEL		FIRST DIFFERENCE	
	ADF	PP	ADF	PP
DC	−2.9945**	−3.0339**	−3.3550**	−25.7885**
DD	−2.4170	−1.9465	−6.4312**	−38.7021**
LD	−2.9957**	−3.0842**	−26.1725**	−26.1723**
PM 2.5	−3.3488**	−4.8291**	−19.0774**	−33.6487**
CE	−3.2374**	−7.1342**	−6.9428**	−36.0105**

**refer significant at 5% levels of significance.

Table 3. Bounds test results for co-integration for model 1 and model 2.

MODEL 1 (LINEAR ARDL)					MODEL 2 (LINEAR ARDL)					
TEST	VALUE	SIGNIF.	LOWER BOUND, I(0)	UPPER BOUND, I (1)	TEST	VALUE	SIGNIF.	LOWER BOUND, I(0)	UPPER BOUND, I (1)	DECISION
F-statistic	3.04	10%	2.45	3.52	*F*-statistic	2.94	10%	2.62	3.42	Inconclusive
		5%	2.86	4.01			5%	2.74	3.61	
		2.5%	3.25	4.49			2.5%	2.75	3.99	
		1%	3.74	5.06			1%	3.15	4.43	
t-statistic	−3.09	10%	−2.57	−3.66	*t*-statistic	−3.12	10%	−2.32	−4.04	Inconclusive
		5%	−2.86	−3.99			5%	−2.86	−4.38	
		2.5%	−3.13	−4.26			2.5%	−3.32	−4.52	
		1%	−3.43	−4.6			1%	−3.43	−4.22	
MODEL 1 (NON- LINEAR ARDL)					MODEL 2(NON- LINEAR ARDL)					
TEST	VALUE	SIGNIF.	LOWER BOUND, I(0)	UPPER BOUND, I (1)	TEST	VALUE	SIGNIF.	LOWER BOUND, I(0)	UPPER BOUND, I (1)	DECISION
F-statistic	18.14	10%	2.12	3.23	*F*-statistic	14.14	10%	2.12	3.23	Co integration
		5%	2.45	3.61			5%	2.45	3.52	
		2.5%	2.75	3.99			2.5%	2.75	3.99	
		1%	3.15	4.43			1%	3.15	4.43	
t-statistic	−11.09	10%	−2.57	−4.04	*t*-statistic	−9.92	10%	−2.57	−4.04	Co integration
		5%	−2.86	−4.38			5%	−2.86	−4.38	
		2.5%	−3.13	−4.66			2.5%	−3.13	−4.66	
		1%	−3.43	−4.99			1%	−3.43	−4.99	

The critical values are from the Narayan[53].

higher limitation of 4.01. In a linear approach, the bound test demonstrates that there is an inconclusive decision. On the other hand, the results of the non-linear ARDL specification indicate the long-run cointegration existence as the value of the *F*-statistic is 14.14 is bigger than the value of 3.52 at 5%, showing that the non-linear ARDL specification is co-integrated. On the basis of the *t*-statistic, the same conclusion can be drawn.

Again, when the long-run co-integration connection between CO_2 emissions, $PM_{2.5}$, and COVID-19 drivers was proven, the next step was to find the key models (1) and (2) that have a discrepancy in the long run and in the short term. Table 4 summarizes the results of the long-run dynamic asymmetry estimation. At a 1% level of significance, the long-run CO2 emission coefficient (0.733299) is favorably significant. CO_2 emissions can be reduced by 0.733299% for every 1% increase in daily cases and daily deaths of COVID-19, according to the findings. At a 1% level of significance, the long-run value of $PM_{2.5}$ (0.753684), on the other hand, is positively significant. According to the findings, a 1% increase in daily cases and daily deaths of COVID-19 in a 0.753684% decrease in $PM_{2.5}$. Changes in DC, both positive and negative, have a favorable and large impact on carbon emissions, but DD has had inconsistent consequences. Positive or negative changes in LD, on the other hand, have a considerable negative impact on carbon emissions, according to our findings. Negative changes in DC, on the other hand, have a positive and substantial impact on $PM_{2.5}$, whereas DD has a negative impact on $PM_{2.5}$. According to our findings, changes in LD, whether positive or negative, have a significant mixed impact on $PM_{2.5}$.

Model 1 and Model 2's long and short run estimations are provided in Tables 5 and 6, respectively. Model 1 has demonstrated that DC+ has positive and significant effects on carbon emissions in the short run, while LD+, LD–, and LD (–1) have negative and significant effects. In model 2, only LD+ has a negative and substantial influence on $PM_{2.5}$ in the short run. COVID-19 determinants have considerable effects on

Table 4. NARDL estimate results.

MODEL 1					MODEL 2				
VARIABLE	COEFFICIENT	STD. ERROR	*t*-STATISTIC	*P*-VALUE*	VARIABLE	COEFFICIENT	STD. ERROR	*t*-STATISTIC	*P*- VALUE*
$CE(-1)$	0.733299**	0.047009	15.59895	.0000	$LNPM(-1)$	0.753684**	0.031691	23.78234	.0000
DC^{+}	2.15E−06**	7.52E−07	2.859127	.0044	DC^{+}	7.24E−06	4.41E−06	1.641014	.1013
DC^{-}	1.55E−05*	8.79E−06	1.759969	.0789	DC^{-}	1.16E−05**	5.40E−06	2.146818	.0322
$DC^{-}(-1)$	−1.26E−05	8.37E−06	−1.506634	.1324	$DC^{-}(-1)$	−0.000658**	0.000340	−1.933974	.0535
DD^{+}	−7.02E−05	5.38E−05	−1.304543	.1925	DD^{+}	−0.001127**	0.000410	−2.745668	.0062
DD^{-}	−0.000105**	5.87E−05	−1.790351	.0738	DD^{-}	−1.895206**	0.155456	−12.19126	.0000
LD^{+}	−0.008228	0.006445	−1.276536	.2022	LD^{+}	1.524997**	0.165946	9.189738	.0000
$LD^{+}(-1)$	−0.080988**	0.020139	−4.021342	.0001	$LD^{+}(-1)$	−0.185143**	0.040146	−4.611799	.0000
LD^{-}	−0.087631**	0.019296	−4.541310	.0000	LD^{-}	1.179796**	0.149135	7.910922	.0000
C	0.151467**	0.029103	5.204458	.0000	C	0.753684**	0.031691	23.78234	.0000

Here, Std. indicates standard.
**refer significant at 5% levels of significance and the significance value is 0.05. *refer significant at 10% levels of significance and the significance value is 0.1.

Table 5. NARDL short run and long run estimates for model 1.

SHORT RUN ESTIMATES					LONG RUN ESTIMATES				
VARIABLE	COEFFICIENT	STD. ERROR	*t*-STATISTIC	*P*-VALUE	VARIABLE	COEFFICIENT	STD. ERROR	*t*-STATISTIC	*P*-VALUE
$\Delta CE(-1)$	0.095340**	0.036371	2.621301	.0090	DC^{+}	8.06E−06**	3.58E−06	2.250760	.0247
ΔDC^{-}	1.60E−05**	5.00E−06	3.196725	.0015	DC^{-}	1.07E−05**	4.55E−06	2.362454	.0184
ΔLD^{+}	−0.010055**	0.038246	−0.262897	.0027	DD^{+}	−0.000263	0.000220	−1.196982	.2317
ΔLD^{-}	−0.018636	0.038253	−0.487191	.2263	DD^{-}	−0.000394	0.000250	−1.576559	.1154
$\Delta LD^{-}(-1)$	0.087413**	0.039197	2.230099	.0261	LD^{+}	−0.334515**	0.036236	−9.231601	.0000
CointEq(−1)*	−0.306239**	0.025566	−11.97822	.0000	LD^{-}	−0.328573**	0.023009	−14.28050	.0000

**refer significant at 5% levels of significance and the significance value is 0.05.

Table 6. NARDL short run and long run estimates for model 2.

SHORT RUN ESTIMATES					LONG RUN ESTIMATES				
VARIABLE	COEFFICIENT	STD. ERROR	*t*-STATISTIC	*P*-VALUE	VARIABLE	COEFFICIENT	STD. ERROR	*t*-STATISTIC	*P*-VALUE
C	1.179796**	0.117371	10.05183	.0000	DC^{+}	2.94E−05**	1.67E−05	1.763449	.0383
ΔLD^{+}	−1.895206**	0.139660	−13.57017	.0000	DC^{-}	4.71E−05**	1.94E−05	2.430300	.0153
CointEq(−1)*	−0.246316**	0.024614	−10.00721	.0000	DD^{+}	−0.002672**	0.001272	−2.100337	.0361
					DD^{-}	−0.004575**	0.001422	−3.217170	.0014
					LD^{+}	−1.502987**	0.164851	−9.117251	.0000
					LD^{-}	−0.751648**	0.143270	−5.246386	.0000

**refer significant at 5% levels of significance and the significance value is 0.05.

Table 7. NARDL diagnostic test and Wald test results.

MODEL 1		MODEL 1	
J-B [*P*-value]	.2415	J-B [*P*-value]	.4125
R-R [*P*-value]	.3187	R-R [*P*-value]	.4187
LM(1) [*P*-value]	.5214	LM(1) [*P*-value]	.4541
LM(2) [*P*-value]	.6369	LM(2) [*P*-value]	.5632
ARCH(1) [*P*-value]	.6254	ARCH(1) [*P*-value]	.3214
ARCH(2) [*P*-value]	.7841	ARCH(2) [*P*-value]	.7841
$DC_W[X^2, \text{p} - \text{value}]$	[12.2311, .0000]	$DC_W[X^2, \text{p} - \text{value}]$	[11.2585, .0000]
$DD_W[X^2, \text{p} - \text{value}]$	[14.2351, .0001]	$DD_W[X^2, \text{p} - \text{value}]$	[10.1287, .0101]
$LD_W[X^2, \text{p} - \text{value}]$	[10.4521, .0000]	$LD_W[X^2, \text{p} - \text{value}]$	[10.5741, .0002]

DC_W, DD_W, & LD_W Indicates the Wald test result for each variable.
**refers significant at 5% levels of significance (Parvin, 2022)[54].

carbon emissions and $PM_{2.5}$ in the long run, according to both model 1 and model 2. Furthermore, our data shows that, when compared to other factors, lockdown (LD) has a significant impact on carbon emissions and $PM_{2.5}$ according to both models. Our results are in line with different researchers from different countries, like Azam et al[55] and Sarfraz et al.[44] In the long run, a 1% improvement in LD resulted in a 0.344515% reduction in carbon emissions and a 1.502987% reduction in $PM_{2.5}$ .In comparison to carbon emissions, our findings show that lockout has a significant influence on $PM_{2.5}$ reduction. According to the data, CO_2 emissions and $PM_{2.5}$ began to decline from the beginning of the COVID-19 outbreak because individuals stayed at home to reduce the risk of infections. After a period of severe lockdown, CO_2 emissions and $PM_{2.5}$ levels have dropped dramatically.

Various good and negative environmental repercussions have been reported in each of the Southeast Asian countries because of the COVID-19 lockdown and restrictions. According to Kanniah et al,[56] the region's pollution levels, and haze pollution have both improved dramatically. Other countries throughout the world have also seen an improvement in air quality. The results show that the lockout has resulted in a significant increase in air quality and may serve as a vital method of decreasing emissions, which has an impact on urban sustainability in the long run. As a result, in the coming years, a short-term shutdown to manage unhealthy air pollution may be enforced. The COVID-19 lockout provided us with a once-in-a-lifetime chance to gather, evaluate, and analyze a wide range of real-time data in terms of long-term environmental sustainability. This includes greenhouse gas emissions, short-term air quality fluctuations, and meteorological data.

According to Barbier and Burgess,[57] these actual statistics could be used for prognostication and reaction studies, allowing for improved preparation at both the local and national scales. This information will be critical in persuading policymakers and stakeholders to collaborate to enhance climate change policies at the national and regional levels. According to Manzanedo and Manning,[58] these policies may strengthen the capability to handle eco-efficiency concerns not only in Bangladesh, but also internationally. Furthermore, in Asian countries, the COVID-19 lockout reduced energy consumption in the manufacturing industries while increasing power usage at the household and community level. Because of the current economic downturn in Asia, the development of renewable power and public transit is almost impossible.[59] However, in the long run, a small amount of money might be allocated to the establishment of innovative green energy sources such as solar power and gas storage for renewable power.

With a significance of 1% and a negative sign assumption, the ECT term verifies the long-term link between CO_2 emissions, $PM_{2.5}$, and daily cases and daily deaths of COVID-19. Some troubleshooting tests were carried out to prove the NARDL model's trustworthiness. The Jarque-Bera (J-B) parametric test, the Ramsey RESET test for conceptual framework, the Autoregressive Conditional Heteroskedasticity (ARCH) up to order 2 for heteroscedasticity problems, and the serial correlation LM test up to level 2 for serial autocorrelation were all used by the analysts to explore how error data is normally distributed. Table 7 shows the results of all the tests. NARDL models pass all diagnostic testing, indicating their dependability. The resilience of any quantitative approach must be checked for homogeneity of variances. The cumulative sum (CUSUM) and cumulative sum square (CUSUMSQ) stability tests were advocated by Brown et al.[60] The CUSUM and CUSUM Square tests were used to ensure that the model was stable. The results of these tests are shown in Figures 5 and 6, which show that both models are quite stable. The dynamic

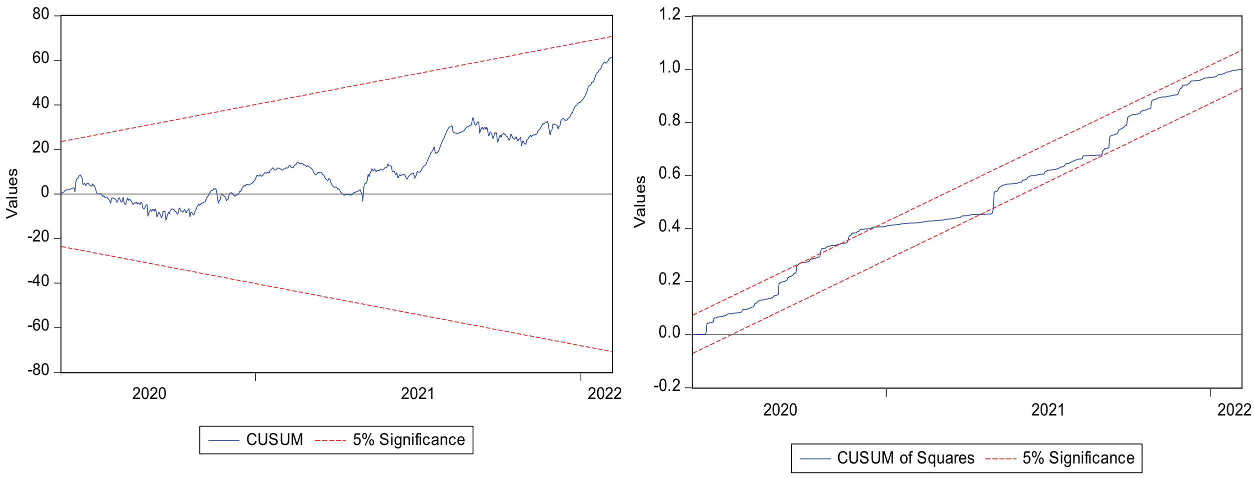

Figure 5. Stability check for model 1.

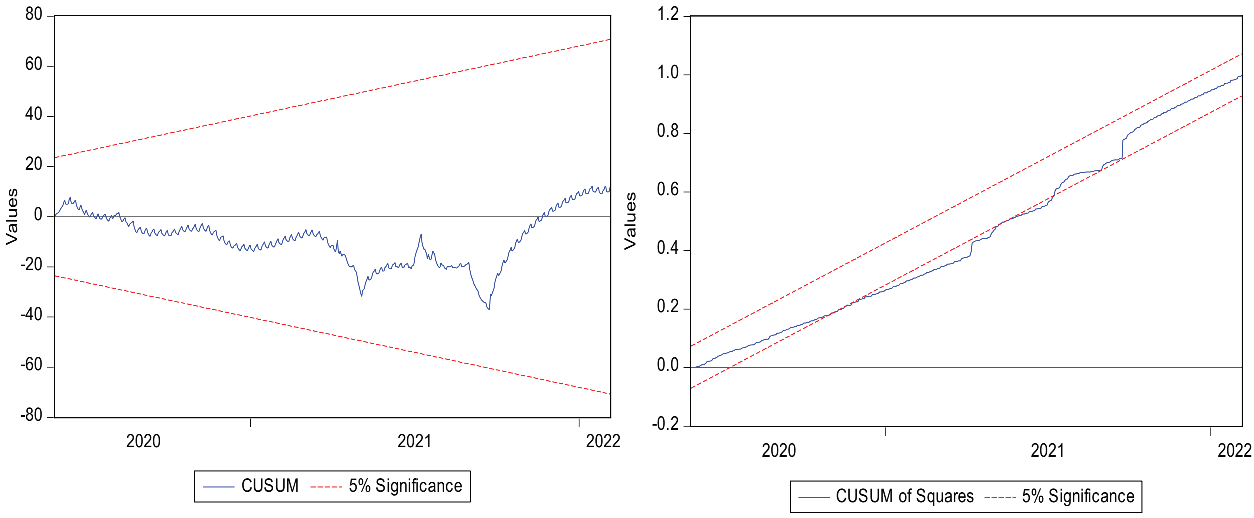

Figure 6. Stability check for model 2.

multiplier in Figures 7 and 8 show the inconsistency in the suggested long-run stability with return and volatility has been rectified. Each COVID-19 determinant's negative and positive shocks have been demonstrated to produce a regular combination of dynamic multiplier curves that are asymmetrical on CO_2 emissions and $PM_{2.5}$, respectively. To confirm the non-linearities between the variables under investigation, the Wald test was used. Table 7 demonstrates that at a 5% level of significance, there are asymmetries across variables.

The COVID-19 pandemic may be seen as a "blessing in disguise," where air quality is improving and the earth is reviving itself, according to the preliminary analysis of air quality data in the current study. By reducing air pollution through controlled emissions of major air pollutants, it is possible to significantly reduce a number of health problems like asthma, cardiovascular disease, respiratory conditions, and premature deaths. These favorable effects of an air pollution lockdown can reassure the government and authorities that strict air quality regulations and emission reduction plans can significantly enhance the environment and people's health. In addition, the Bangladeshi government may take the following actions to reduce financial risks associated with climate change, use cleaner or alternative fuels, like CNG or LPG, promote public transportation systems, such as the Metro, require engine-driven vehicles to be certified as PUC (Pollution Under Control) compliant by-passing tests for carbon monoxide and hydrocarbons, and implement adaptation policies.

Conclusion

The link between CO_2 emissions, $PM_{2.5}$, and COVID-19, as well as their drivers, was the subject of this study. Using daily data for Bangladesh from March 18, 2020, to February 4, 2022, the asymmetric relationship between CO_2 emissions, daily cases, daily deaths, and lockout in the COVID-19 timeframe is considered. To examine long-and short-run associations between variables, the NARDL model is utilized. The findings

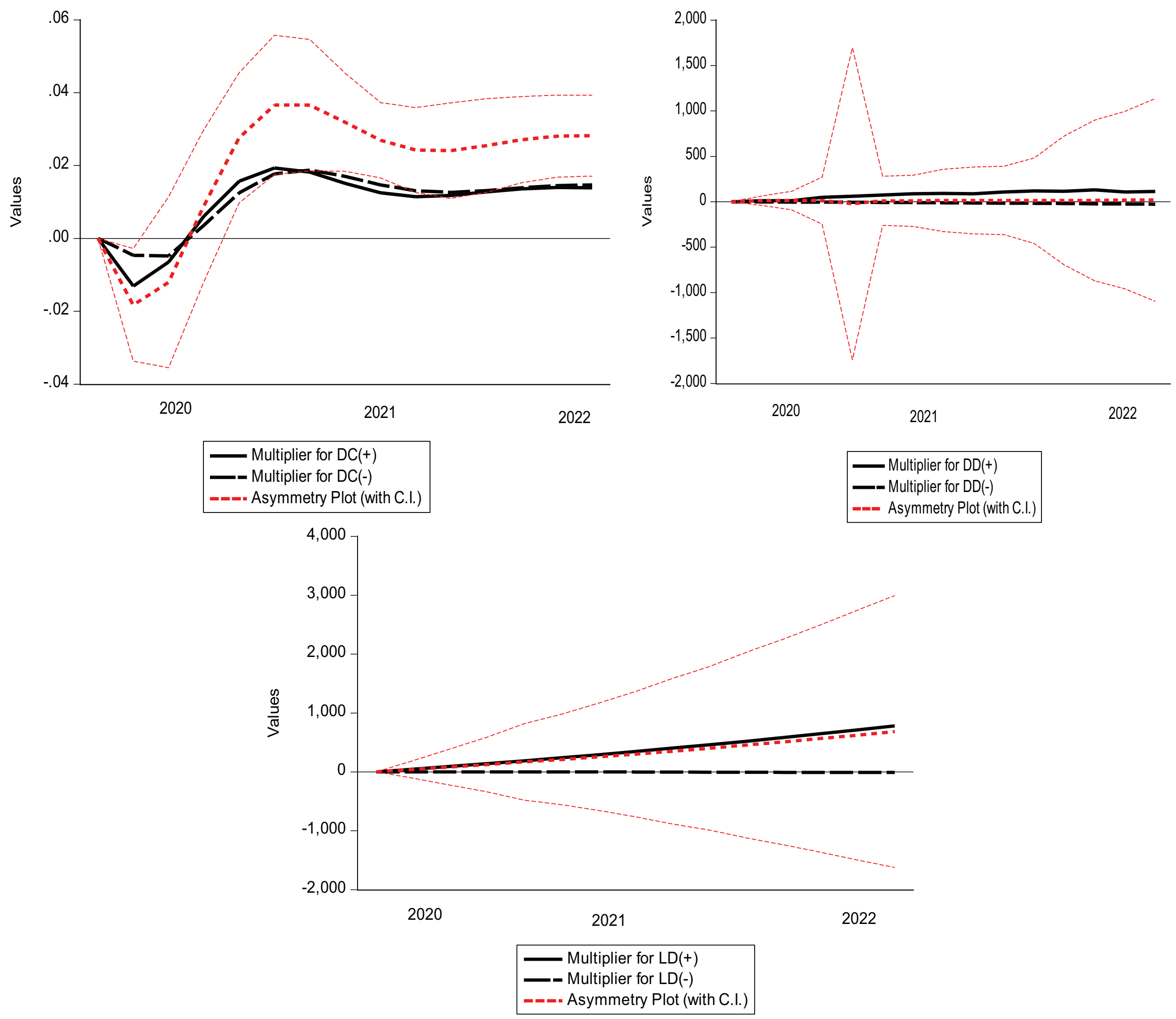

Figure 7. Dynamic multiplier graph COVID-19 determinants on carbon emissions.

of this study support the long-term link in Bangladesh between CO_2 emissions, $PM_{2.5}$, and COVID-19 determinants. Both long-run and short-run relationships between variables were verified by the bound test. According to the dynamic multipliers graph, Bangladesh's rigorous lockdown, which was implemented in response to a spike in COVID-19 cases, mainly reduced air pollution and hazardous gas emissions. The Wald test was performed to confirm the nonlinearities between the variables under study, and it revealed a nonlinear relationship between them. The dynamic multipliers graph shows the COVID-19 determinants' positive and negative effects on carbon emissions and $PM_{2.5}$. CO_2 emissions and $PM_{2.5}$ are negatively influenced by the strict lockdown in Bangladesh.

The lockdown undoubtedly helped to reduce CO_2 emissions and $PM_{2.5}$ levels in Bangladesh's environment, but it was simply a temporary solution done under extraordinary circumstances. Bangladesh's human and industrial activities are unhealthy and damaging to the environment, as evidenced by the shutdown. The Bangladesh government, policymakers, and environmentalists should promote environmentally friendly activities. To improve environmental purity and sustainability, impose restrictions on industries in terms of harmful gas emissions by the policymaker.

Even though we present some rather intriguing findings, we also want to draw attention to some shortcomings in the prior work. Firstly, the current study only focuses on Bangladesh, which is struggling with a lack of medical and financial resources to combat this pandemic. As a result, we encourage future research to examine the exposure of global pandemics like COVID-19 over a larger dataset in order to examine how environmental pollutants may have contributed to the spread of the current pandemic. The development of statistical tests that account for spatial information will be one of the future directions of this research.

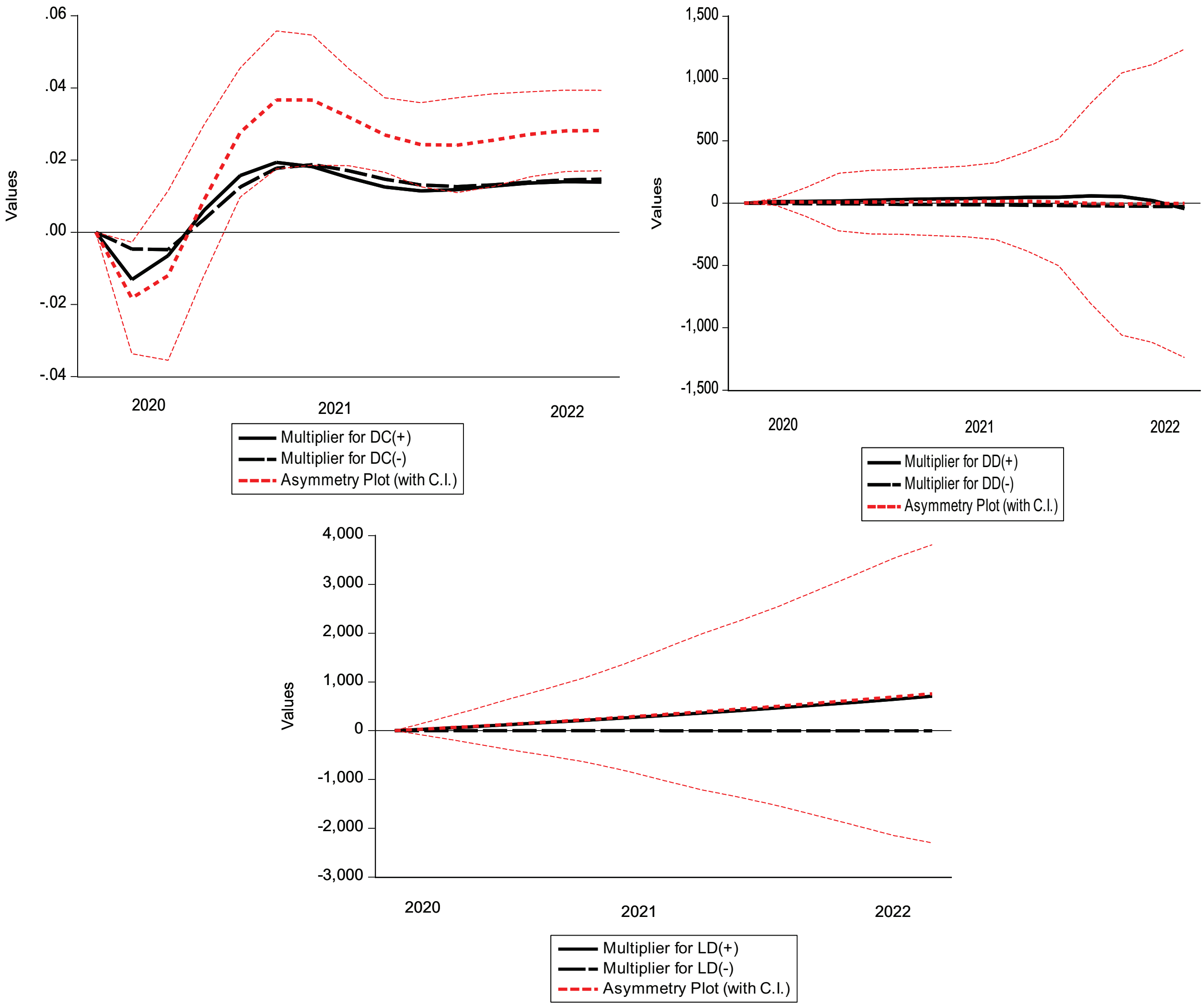

Figure 8. Dynamic multiplier graph COVID-19 determinants on PM 2.5.

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Author Contributions

Conceptualization and approval: Rehana Parvin; methodology: Rehana Parvin; software: Rehana Parvin; analysis: Rehana Parvin; data curation: Rehana Parvin; validation: Rehana Parvin; draft preparation: Rehana Parvin; visualization: Rehana Parvin; review and editing: Rehana Parvin; supervision: Rehana Parvin.

Code Availability

IBM SPSS and Eviews 10 were utilized for statistical analysis and code will provide to the corresponding author upon reasonable request.

Consent to Participants

Informed consent was obtained from all individual participants included in the study.

Consent to Publish

The participant has consented to the submission of the case report to the journal.

Data Accessibility

The data has been provided in the form of a zip file for online submission as a supplementary file.

Ethical Approval

Not applicable.

Supplemental Material

Supplemental material for this article is available online.

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