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Assessing the COVID-19 Lockdown Impact on Global Air Quality: A Transportation Perspective

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Abstract: To address the COVID-19 pandemic, governments worldwide implemented mandatory restrictions. As an unintended consequence of these responses, significant air pollution reductions have been recorded across the world. We provide cross-national evidence on the causal impact of pandemic-induced lockdowns on air quality. Using daily air pollution data between 1 January and 31 December 2020, covering 596 major cities in 77 countries, we analyzed the data with a generalized difference-in-differences approach. The results show that lockdown restrictions reduced global concentrations of NO_2 by 21~35%, PM_{10} by 14~26%, $PM_{2.5}$ by 9~18%, CO by 6~16%, and SO_2 by 5~16%, while the O_3 concentrations increased by 15~29% under eight specific lockdown measures. Furthermore, a simultaneous equations model suggests that reductions in public and private mobility, measured by changes in public transportation and car ridership, partly explain the observed decreases in air pollution. These findings have significant implications for ongoing global efforts to mitigate air pollution and underscore the pivotal role of public transit in achieving this goal.

Keywords: air quality; COVID-19; lockdowns; transportation; simultaneous equations model

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1. Introduction

By early 2021, the cumulative number of confirmed cases of the coronavirus surpassed 100 million, with the death toll exceeding two million across more than 200 countries, territories, or regions around the world from the beginning of the pandemic [1]. Since only confirmed COVID-19 deaths are counted, the actual death toll is likely much higher due to unreported cases or the lack of diagnostic confirmation. Owing to the virus's high transmissibility and infectivity, governments have implemented various behavioral restrictions, including school closures, travel bans, social distancing measures, and nationwide lockdowns, to curb its spread in the absence of effective medical treatment or vaccines.

Among these non-pharmaceutical interventions (NPIs), lockdowns, characterized by restrictions on leaving homes and halting economic activities, have been widely regarded as the most effective means of reducing COVID-19 transmission. Data from the Oxford Coronavirus Government Response Tracker (OxCGRT) indicate that over 180 countries have enacted partial or full lockdowns since the onset of the pandemic. These unprecedented measures represent the largest quarantine effort in public health history and have precipitated a significant global economic downturn. Economic studies have confirmed the

negative effects of COVID-19 pandemic on a range of consequences: for instance, unemployment [2–4], households' spending [5,6], small business owners' losses [7], and income inequality [8].

After approximately three months of lockdowns, many countries began easing social restrictions, but the virus resurged in the fall of 2020, prompting renewed lockdowns and continued economic disruptions. Despite these challenges, lockdown measures inadvertently led to significant reductions in air pollution worldwide [9–11], primarily due to decreased social interactions and reduced economic activity. Major sources of ambient air pollution—industry, transportation, residential energy use, and power generation—experienced substantial declines during lockdowns, particularly in traffic and industry activity, contributing to improved air quality [12–15]. A growing body of literature examines the relationship between COVID-19 lockdowns and air pollution. Much of the current literature is limited to case studies focused on individual cities or countries, often analyzing air quality improvements in a single region during a narrow time window (e.g., during the first wave of lockdowns) [16,17]. Such localized studies fail to capture the global heterogeneity of air quality changes, which are influenced by diverse policy measures, urban infrastructure, and levels of industrialization. This fragmented approach makes it difficult to draw generalized conclusions about the broader environmental impacts of COVID-19-induced lockdowns. In addition, although many studies document reductions in specific pollutants, few investigate the underlying mechanisms that explain these changes. For example, there is limited analysis of how reductions in public and private transportation, industrial activity, and other human behaviors contribute to observed improvements in air quality. The absence of such mechanistic insights hampers the ability to design targeted policies that could replicate these benefits without imposing stringent lockdowns. With regards to the methodology and data, many existing studies rely on before-and-after comparisons or interrupted time-series analyses [17,18], which may not adequately address the non-random nature of lockdown implementation. Moreover, the lack of high-resolution data on human mobility and government policy responsiveness further constrains the ability to explore localized effects and policy variations. This paper aims to bridge this gap using daily COVID-19 policy data from OxCGRT, as well as COVID-19 Community Mobility Reports presented by Google maps, Apple mobility data, and various controls. Our study contributes to a growing and important body of work on the environmental impact of COVID-19 by providing richer analysis from a global perspective during the pandemic.

Firstly, we estimate the effect of COVID-19 lockdown measures on local air pollution levels across 596 major cities in 77 countries using a generalized difference-in-differences (DID) strategy within a narrow time window around each country's lockdown dates. Given concerns about the non-random implementation of lockdowns and the influence of unobserved factors, standard empirical approaches such as before-and-after comparisons and interrupted time-series designs may fail to address these issues. The DID approach provides a rigorous evaluation framework to tackle these identification challenges by introducing control groups [19].

Secondly, we integrate various high-resolution datasets to achieve a more comprehensive and accurate quantification. City-level daily air pollution data were sourced from a station-based database, covering key measures of air quality, including $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2, and O_3, in 596 cities worldwide. These data are combined with government response information from the OxCGRT, which records eight policy indicators relevant to lockdown measures. This integration enables comparisons of lockdown effectiveness in reducing air pollution. Additionally, we incorporate mobility data, with public transit

usage derived from Google Community Mobility Reports (GCMR) and private vehicle usage from Apple Mobility Trends Reports (AMTRs), to capture changes in human mobility.

Finally, we explore the underlying mechanism linking lockdowns, air pollution, and human mobility, specifically: (a) lockdowns directly affecting human mobility; (b) extensive restrictions on mobility that influence social connections, economic activity, and their associated consequences; and (c) widespread reductions in work-related activities that likely resulted in a significant decrease in air pollution globally. Our study also introduces the transportation perspective by examining the roles of public transit and private vehicle usage in explaining global improvements in air quality.

By addressing these critical gaps, our study provides a more nuanced and globally relevant understanding of the environmental consequences of the COVID-19 pandemic. The findings hold significant implications for policymakers seeking to balance economic recovery with sustainable environmental goals. The remainder of this study is structed as follows. Section 2 details the data sources used in the analysis. Section 3 outlines empirical strategies and Section 4 presents the key results. In Section 5, we investigate the role of human mobility in global air quality improvements, while Section 6 provides further discussion of empirical results and mechanism analysis. Section 7 concludes the study.

2. Data

2.1. Lockdowns and Mobility Data

Accurate information on the timing of lockdown policies is a crucial identification strategy. To achieve this, we utilized data for the lockdown dates of all cities included in this study from the OxCGRT database. Since the COVID-19 outbreak, various government policy responses have been implemented with widely varying impacts across countries. A reliable dataset that records both the timing and stringency of these restrictions globally is indispensable for constructing comparable lockdown dates across countries. The OxCGRT, developed by a research team at the Blavatnik School of Government at the University of Oxford, serves this purpose effectively. The OxCGRT systematically collects information on NPIs implemented in response to COVID-19, including when these measures were enacted. This dataset encompasses eight containment and closure policies, seven health system policies, and four economic policies [20]. Our primary focus was on the containment and closure policies, as these include various lockdown measures, such as school and workplace closures and restrictions on residential and social gatherings. The reports included a Government Stringency Index, which quantifies the strictness of lockdown measures on a scale of $0-100$ based on eight policy metrics. Higher scores indicate stricter government response. This index enabled us to compare the stringency of lockdown measures across countries over the sample period under study. A detailed description of different indexes related to lockdown measures is presented in Table 1.

Figure 1 illustrates the geographic distribution of the stringency index over time, created using the mapping tool in ArcGIS 10.5. Before March 2020, when sweeping lockdowns had not been implemented, most countries exhibited a relatively low stringency index, with the exception of China, Korea, and Italy. However, this situation shifted by June 2020 as strict lockdown measures were widely adopted. During the second half of 2020, the trajectory of the stringency index in most countries remained similar to that observed earlier in the year. Many governments eased restrictions after June to stimulate economic recovery as the global pandemic situation appeared to stabilize. Nonetheless, with the onset of winter, most countries experienced a second wave of the virus, resulting in a marked increase in the global stringency index. These stringent measures significantly influenced how people lived, worked, learned, and interacted. This study suggests that fluctuations in the stringency index are likely associated with changes in air pollution levels.

Table 1. A summary of stringency index components.

Number	Name	Description
C1	School closings	0—no measures; 1—recommend closing; 2—require closing; 3—require closing all levels.
C2	Workplace closings	0—no measures; 1—recommend closing; 2—require closing for some sectors or categories of workers; 3—require closing for all-but-essential workplaces.
C3	Cancel public events	0—no measures; 1—recommend cancelling; 2—require cancelling.
C4	Restrictions on gatherings	0—no restrictions; 1—restrictions on very large gatherings (the limit is above 1000 people); 2—restrictions on gatherings between 101 and 1000 people; 3—restrictions on gatherings between 11 and 100 people; 4—restrictions on gatherings of 10 people or less.
C5	Close public transport	0—no measures; 1—recommend closing (or significantly reduce; volume/route/means of transport available); 2—require closing (or prohibit most citizens from using it).
C6	Stay at home requirements	0—no measures; 1—recommend not leaving house; 2—require not leaving house with exceptions for daily exercise, grocery shopping, and "essential" trips; 3—require not leaving house with minimal exceptions.
C7	Restrictions on internal movement	0—no measures; 1—recommend not to travel between regions/cities; 2—internal movement restrictions in place.
C8	International travel controls	0—no restrictions; 1—screening arrivals; 2—quarantine arrivals from some or all regions; 3—ban arrivals from some regions; 4—ban on all regions or total border closure.

All data are derived from the OxCGRT database, which spans 1 January 2020 to 31 December 2020. Each component indicator is measured on an ordinal scale and normalized by its maximum value to generate a sub-index score range from 0 to 100. The stringency index is calculated as the averages of these sub-index scores across the sample.

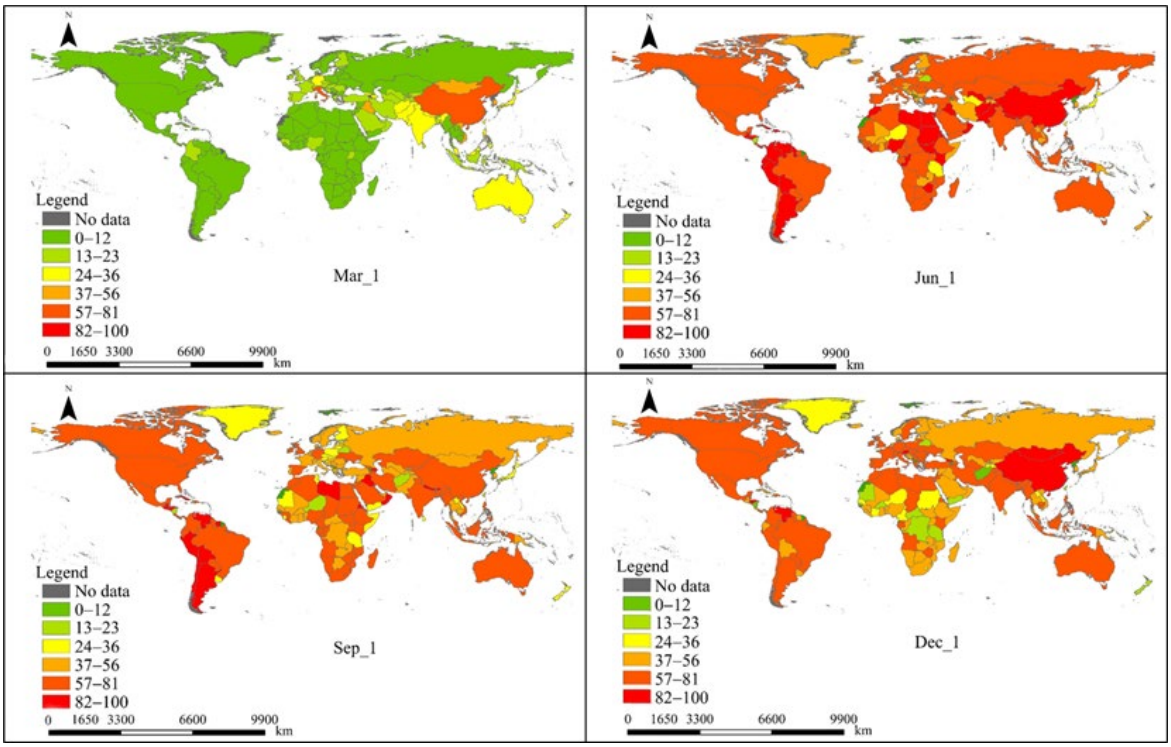

Figure 1. Spatial and temporal distribution of the stringency index around the world.

To examine a potential mechanism through which lockdowns influence air pollution, we incorporated a transportation perspective by collecting relevant data. The first dataset

utilized was the GCMR (more details about this dataset can be found at https://www.google.com/covid19/mobility/ (accessed on 1 March 2021)), which captures the relative change in people's mobility (percentage) compared to a baseline—the median value for the corresponding day of the week from 3 January to 6 February 2020 across 135 countries. The dataset categorizes travel into six types of locations: retail and recreation, transit stations, parks, pharmacies and groceries, residential areas, and workplaces. Since this study focused on transportation, we used the transit stations category to measure changes in public transport usage. Additionally, we gathered data on private vehicle usage from the AMTR (more information about AMTR can be found at https://covid19.apple.com/mobility (accessed on 1 March 2021)), which indicated the relative volume of directions requests on Apple Maps at the country, regional, or city level, compared to a baseline on 13 January 2020. Figure 2 illustrates the daily changes in both mobility indicators throughout the study period.

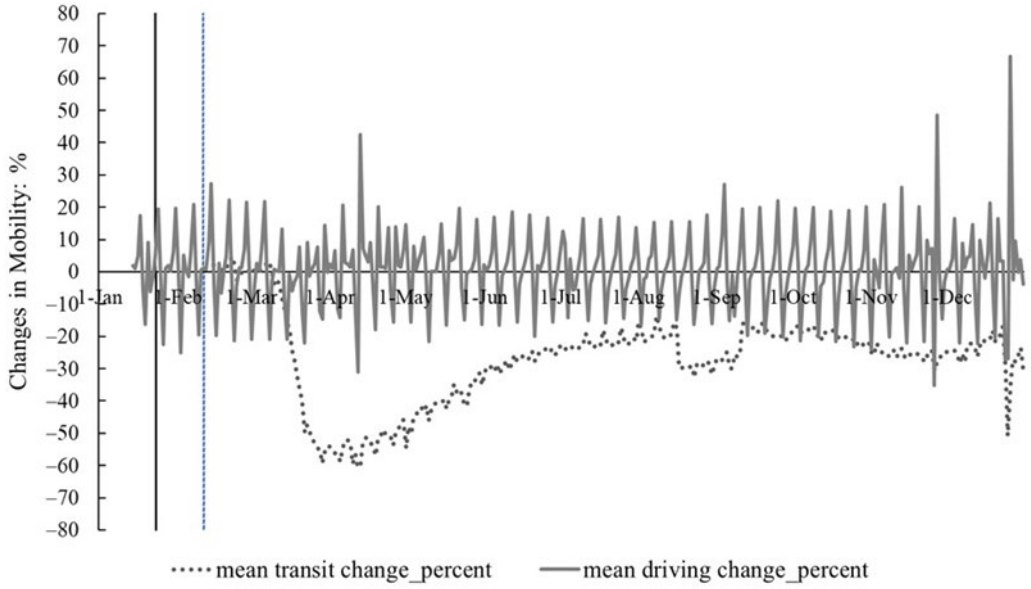

Figure 2. Changes in human mobility by public transit and private vehicles from 1 January 2020 to 31 December 2020. The solid black line marks the date of the Wuhan lockdown (23 January 2020), while the blue dashed line represents the date on which the novel coronavirus was officially named by WHO as COVID-19 (11 February 2020).

Public transit uses significantly declined in early March as the pandemic began to spread globally. While it gradually increased after late April, it never returned to baseline levels during the study period. A slight decrease was observed after October, as governments reintroduced stricter restrictions in response to the second wave, a development widely regarded as "inevitable". In contrast, private vehicle use exhibited frequent fluctuations, reflecting differing patterns between weekdays and weekends. The fluctuations were particularly pronounced in April and December, aligning with changes in government response stringency.

2.2. Air Quality Measures and Weather Data

The daily concentrations of six pollutants (SO_2, PM_{10}, $PM_{2.5}$, CO, NO_2, and O_3) for 596 major cities worldwide were sourced from the World Air Quality Index (WAQI) project for the period 1 January 2020 to 31 December 2020 (a detailed report regarding this data is available at the following website: https://waqi.info/ (accessed on 1 March 2021)). The WAQI database has compiled air quality data from over 12,000 in situ ground-based monitoring stations across approximately 1000 major cities since 2015. These data, derived

from both research-grade and government-grade sources, are detailed on the WAQI website. Given data availability and coverage, we used the median air quality value for each city as the dependent variable. In addition to air pollution data, the WAQI provides meteorological variables such as wind speed, temperature, and precipitation. Humidity, temperature, and wind speed are included as control variables in our empirical specification to mitigate meteorological effects on pollutant concentrations (precipitation was excluded due to its low observation frequency).

Figure 3 compares the 2020 monthly average ground-level $PM_{2.5}$ concentrations for all cities involved in the study with corresponding 2019 values as the baseline, revealing similar annual trends. However, $PM_{2.5}$ levels in 2020 are generally higher than those in 2019 on specific days after the Wuhan lockdown, coinciding with the global rise in stringency index. This divergence diminishes by the fourth quarter, corresponding to a relaxation of lockdown measures. The observed association between $PM_{2.5}$ concentrations and the stringency index underscore that declines in ambient air pollutant levels may follow COVID-19 lockdown measures.

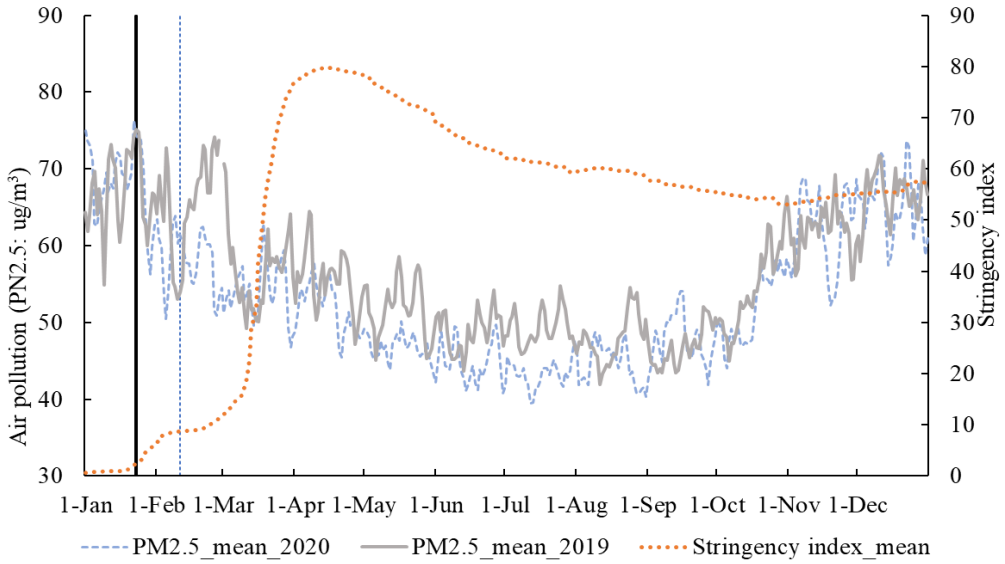

Figure 3. The global daily average concentrations of $PM_{2.5}$ and the average policy stringency index from 1 January 2020 to 31 December 2020. Air pollution is measured by $PM_{2.5}$ concentrations obtained from the WAQI. The solid black line marks the date of the Wuhan lockdown (23 January 2020), while the blue dashed line indicates the date the novel coronavirus was officially named by the WHO (11 February 2020). The stringency index is rescaled to a value from 0 to 100 (100 = strictest).

2.3. Summary Statistics

We subsequently matched both datasets into a single panel at the city-by-day level for the empirical analysis. Since the OxCGRT provides information on lockdown measures primarily at the national level, subnational-level data are available for selected countries. For this study, we used observations at the national level to capture the timing of lockdown measures affecting the cities of interest. Most of these cities, being major urban centers, experienced pandemic measures in alignment with the lockdown schedules recorded by the OxCGRT at the country level. In total, 596 cities in 77 countries and regions, covering approximately 81% of the global population, were included in this study (a full list of cities involved in this study is available upon request). The geographic distribution of the cities is depicted in Figure 4). Thus, the estimated results represent the association between pandemic-induced lockdowns and global air pollution levels.

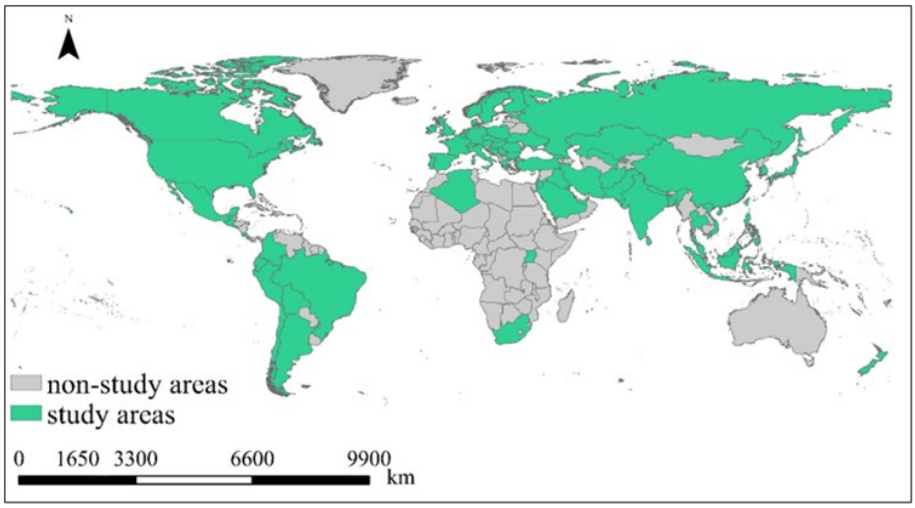

Figure 4. The geographic distributions of countries and regions involved in this study.

Figure 5 displays a scatterplot of $PM_{2.5}$ concentrations against the city-level stringency indices from March to November 2020. A notable downward trend in $PM_{2.5}$ concentrations emerged in April, becoming increasingly evident when compared with March. This trend continued until June as many countries eased restrictions to alleviate economic pressures. However, during the winter wave of coronavirus infections, governments reinstated national lockdown, which led to re-emergence of striking downward trends in November. This figure suggests a positive correlation between lockdown measures and improved air quality globally, warranting further empirical investigation.

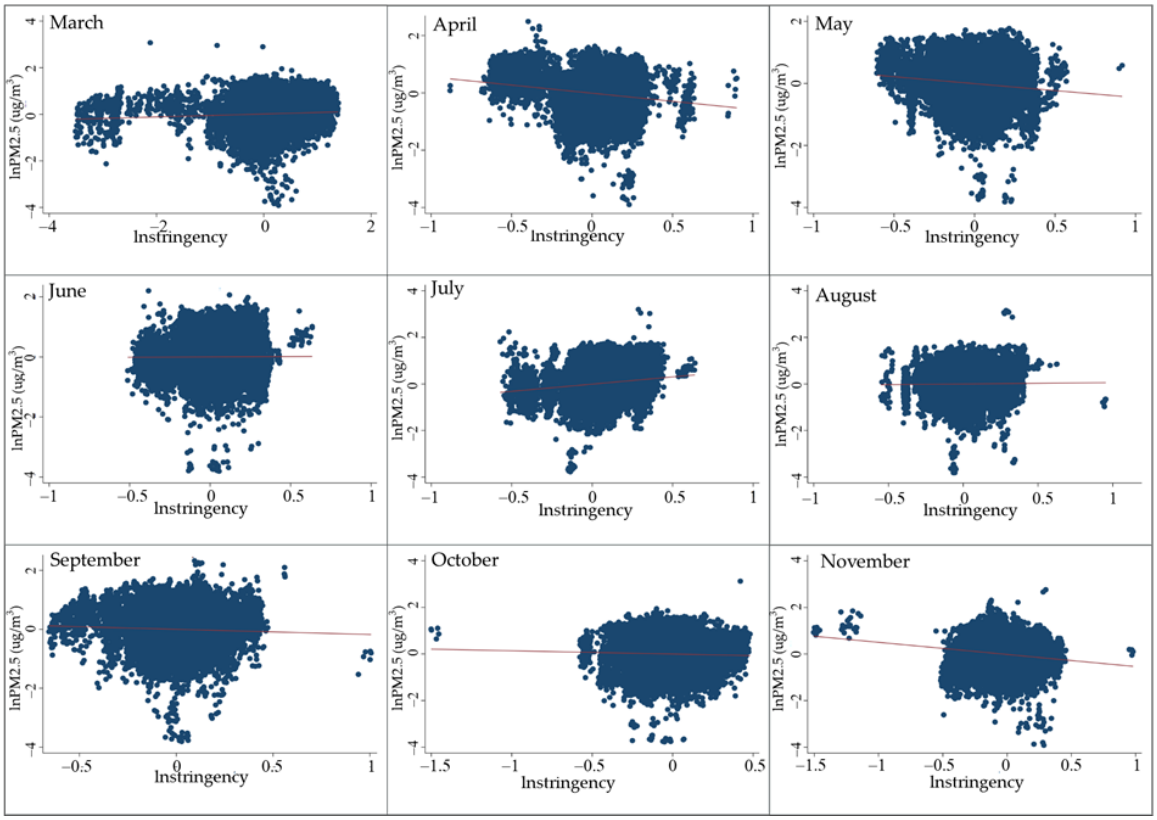

Figure 5. The daily stringency index and corresponding city-level $PM_{2.5}$ concentrations from March to November 2020. The solid red line represents the fit line between the stringency index and $PM_{2.5}$ concentrations.

Table 2 presents the summary statistics for the main variables. The mean stringency index during the sample period was 53.37, indicating globally stringent restrictions. The average change in public transit use was −31.38, while private vehicle use displayed a smaller average decline.

Table 2. Station-based air quality and weather variables (daily).

Variable	N	Mean	S. D.	Min	Max
$PM_{2.5}$	179,165	52.90	40.53	1	834
PM_{10}	176,040	26.17	24.58	1	884
SO_2	146,468	3.90	7.38	0	500
NO_2	175,522	9.18	7.18	0	183.8
O_3	163,557	19.76	10.87	0	274
CO	135,333	5.20	9.750	0.10	500
Humidity	202,790	69.06	22.40	0	122
Temperature	202,843	16.23	11.70	−50	247.6
Wind speed	200,335	3.100	13.71	0.10	289.8
Transit	163,563	−31.38	21.43	−95	48
Driving	169,571	100.71	40.35	8.74	670.5
Stringency index	213,232	53.37	26.29	0	100.00
Government response index	213,082	50.59	22.61	0	89.17
Containment and health index	213,220	50.84	22.78	0	91.35
Economic support index	212,178	49.22	33.43	0	100.00

Notes: The data range from 1 January 2020 to 31 December 2020. The mean $PM_{2.5}$ concentration exceeded the mean PM_{10} concentration, which diverges from common expectations. This discrepancy arises because all air pollutant data from aqicn.org (accessed on 1 March 2021) have been converted to the US EPA standard, where concentrations and AQI values may differ. For example, a $PM_{2.5}$ AQI of 50 for $PM_{2.5}$ corresponds to 15.5 μg/m^3, whereas a PM_{10} AQI of 50 corresponds to 55 μg/m^3. Further details can be found in the FAQ section of the aqicn.org (https://aqicn.org/faq/2013-02-02/why-is-pm25-often-higher-than-pm10/, accessed on 1 March 2021).

3. Empirical Model

3.1. Ordinary Least Squares Strategy

To estimate the relationship between COVID-related lockdowns and city-level air quality, we employed a fixed-effects panel data model:

$$\begin{aligned} Air\ quality^{p}_{mit} = \theta_1 City_i + \theta_2 Country_m + \theta_3 Date_t + \theta_4 Lockdown^{n}_{mit} + \\ \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \end{aligned} \quad (1)$$

where m, i, and t denote countries, cities, and days, respectively. $Air\ quality^{p}_{mit}$ represents the daily average concentration of pollutant p ($p \in \{ SO_2, NO_2, PM_{10}, PM_{2.5}, CO, O_3\}$). $Lockdown^{n}_{mit}$, n = C1, . . ., C8 represents eight distinct lockdown policy indicators defined in Table 1. We included controls to address potential confounders that may bias the ordinary least squares (OLS) estimates. These controls encompassed time fixed effects $Date_t$ (month-of-year and day-of-week fixed effects), city ($City_i$), and country fixed effects ($Country_m$) to mitigate the influence of unobservable, time-invariant characteristics. Weather variables ($Weather_{mit}$), such as daily temperature, wind speed, and humidity, account for meteorological factors, while a city-specific time trend ($Trend_{it}$) and a country-specific time trend ($Trend^{1}_{mt}$) address time-invariant confounders. The error term is denoted as δ_{mit}.

3.2. Difference-in-Differences Method

Despite the robustness of Equation (1), potential confounders such as omitted variable bias and simultaneity may compromise the OLS estimates. For example, high air pollution levels could exacerbate COVID-19 transmission [13,21,22], prompting governments to implement stricter mobility restrictions. The variation in enforcement across countries and

time points allowed us to apply a DID approach to isolate the causal effect of lockdown on air quality. Using the DID approach, we compared air quality outcomes in cities enforcing lockdown measures (treated cities) with those in cities without such measures (control cities) within a 100-day window before and after lockdown implementation. There are many types of air pollution sources, such as mobile sources and stationary sources; the stationary sources would change dramatically in the longer term. However, lockdown measures have little impact on overall stationary sources; a short time window around the lockdown dates contributes to capturing air quality change attributable to lockdown measures. Unbiased and transparent DID evidence can provide timely and accurate information on causal estimates [23] and has been widely used in the literature to estimate the causal effects of a specific event [24,25]. The model is specified as follows:

$$\begin{aligned} Air\ quality^{p}_{mit} = \theta_1 T_Lockdown^{n}_{mit} + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \\ \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \end{aligned} \quad (2)$$

where the variable $T_Lockdown^{n}_{mit}$ is a binary variable indicating whether a lockdown policy (i.e., C1, …, C8) is active in city i of country m on day t that equals one after the enforcement of lockdowns on date τ ($\tau - 100 \leq t \leq \tau + 100$) and zero otherwise. Following Dang and Trinh [26], we defined the lockdown date as the first day on which the specific lockdown policy became positive to make them comparable across different countries. The rest of control variables are the same as above.

In order to estimate Equation (2) unbiasedly, the parallel trends assumption must be satisfied; that is, no pollution gap would have been observed without the implementation of COVID-19 lockdowns. We conducted an event study analysis to show the parallel trends hold in the pretreatment period between the treatment and control groups to address this concern. We ran the following regression:

$$\begin{aligned} Air\ quality^{p}_{mit} = \textstyle\sum_{d \neq -1} \mathbf{1}_{d=t} * \beta_d + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \\ \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \end{aligned} \quad (3)$$

where $\mathbf{1}_{d=t}$ is a dummy variable indicating whether a city has been placed under lockdown at different periods. Further, $-100 \leq d \leq 100$ denotes leads and lags of the implementation of COVID-19 lockdowns. The 1-day interval prior to implementing lockdown measures (i.e., $d = -1$) is set as the base interval, which is omitted in our specification. The coefficient estimates of β_d measure the air pollution gap between cities in the pretreatment period and posttreatment period. We expected β_d to be negative with $d \geq 0$ and that lockdown measures would lead to a reduction in air pollution. Meanwhile, β_d would be close to zero with $d \leq -2$ if there were no discernible pre-trend differences between the treatment and control groups. Figure 6a–h visually present the estimated values of β_d within the event window along with their pointwise 95% confidence intervals.

The results demonstrate that pretreatment trends are flat, indicating no significant differential trends before the lockdown. In contrast, there is a gradual and significant reduction in average air pollution levels within the 100 days following the enforcement of lockdown policies. This finding mitigates the concerns about time-varying treatment effects in applying the DID strategy across multiple time periods. Furthermore, air pollution levels exhibit a progressively larger decline over time, consistent with the descriptive statistics in Figure 3. These results suggest that lockdown measures create a marked break in air pollution levels, occurring around the time of their implementation. This observation validates the control group cities as a suitable counterfactual for the treatment group. The analysis is repeated for five additional air pollutants, with similar patterns observed. Due to space constraints, detailed results are omitted but are available upon request.

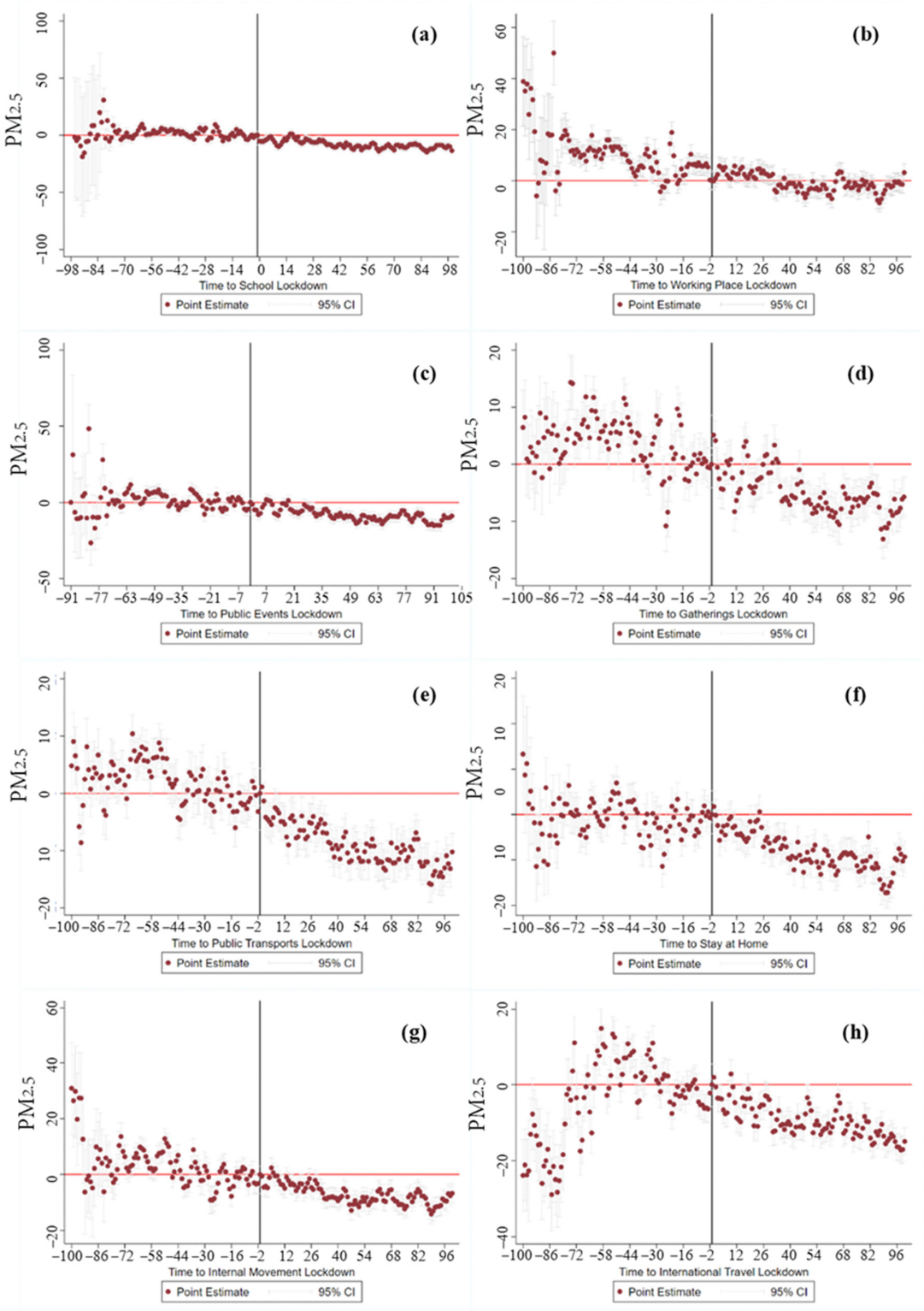

Figure 6. Event study-based tests for parallel trends: $PM_{2.5}$. These figures present the results of the parallel trend tests using an event study analysis. Each panel displays the daily coefficients and their 95% confidence intervals within the 100-day window surrounding the implementation of lockdown measures (subfigures (**a**–**h**) represents event study results for lockdowns of school, working place, public events, gatherings, public transports, stay at home, internal movement and international travel, respectively). The reference interval is set as the day prior to the enforcement of the lockdown measures (the solid black line). The unit for $PM_{2.5}$ is $\mu g/m^3$.

Following the establishment of causal impacts of COVID-19 lockdown measures on air pollution, the underlying mechanisms remain to be explored. One key mechanism is mobility restrictions. Intuitively, as governments impose restrictions to curb virus transmission, reduced mobility leads to a significant drop in traffic-related emissions, a primary source of air pollution. To investigate this hypothesis, we focused on transportation-related emissions, a primary source of air pollution. We focused on transportation-related impacts using data from GCMR and AMTR. Specifically, changes in public transit and private vehicle use were analyzed as the mediator through a simultaneous equation model to evaluate their effects on air pollution levels.

First, we estimated the correlation between lockdowns and the mediator (i.e., human mobility), as specified in Equation (4):

$$ln(Human_mobility^{j}_{mit}) = \alpha + \theta_1 T_Lockdown^{n}_{mit} + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \quad (4)$$

where $ln(Human_mobility^{j}_{mit})$ is the logarithm of human mobility measured by the change in travel by transport mode j. We also used the country-level mobility data to reflect the corresponding change at the city level in that country out of data availability. Additional controls had the same implications as Equation (2).

In the second specification, we correlated the mediator with air pollution; the equation with the same set of control variables as in Equation (4) was specified as follows:

$$Air\ quality^{p}_{mit} = \theta_1 ln(Human_mobility^{j}_{mit}) + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \quad (5)$$

Last, we needed to introduce the mediator into Equation (5), considering that it may be correlated with air pollution, as both of them would be affected by human mobility restrictions. Thus, the impacts of COVID-19 lockdowns on air pollution levels with the mediator being controlled should be examined; the corresponding framework is specified as:

$$Air\ quality^{p}_{mit} = \theta_0 T_Lockdown^{n}_{mit} + \theta_1 ln(Human_mobility^{j}_{mit}) + \theta_2 City_i + \theta_3 Country_m + \theta_4 Date_t + \boldsymbol{\theta_5} Weather_{mit} + \theta_6 Trend_{it} + \theta_7 Trend^{1}_{mt} + \delta_{mit} \quad (6)$$

where control variables are defined as in Equations (4) and (5).

4. Empirical Results

In this section, we first examine the relationship between COVID-19 lockdowns and air pollution using a fixed-effects panel data model. We then analyze the causal effect of lockdowns on air quality via a DID specification.

4.1. Fixed-Effects OLS Estimates

Table 3 presents the regression results on $PM_{2.5}$ based on Equation (1), with each column corresponding to a specific lockdown measure as the key predictor. The results indicate a strong negative correlation between lockdown measures and local air pollution levels, controlling for time-varying variables and fixed effects. Regarding meteorological factors, high humidity contributes to higher particulate matter concentrations [27], confirming the expected relationship for $PM_{2.5}$. However, the associations for temperature and wind do not align with our intuitive expectations. Specifically, high temperatures are associated with lower levels of air pollution, and high wind speed is associated with higher pollution levels. These counterintuitive findings may be attributed to sample selection.

Most observations are from cities in the northern hemisphere's mid-latitudes, which typically experience the highest levels of air pollution during winter. In such conditions, cold air circulates less, causing pollutants to persist in the atmosphere. Additionally, the need for heating during winter often leads to increased fine particulate matter emissions. Most sample cities adopted lockdown measures in March, a period in which temperature was beginning to rise. This temperature effect may explain the observed negative association between temperature and air pollution in the longer term. Similarly, the impact of wind may differ across time horizons: while wind may exacerbate air pollution in the short term, its long-term effects could diverge, especially when pollutant concentrations surpass certain thresholds.

Table 3. Impacts of COVID-19 lockdowns on air pollution: $PM_{2.5}$.

Dep. var. = / Measures:	(1) $PM_{2.5}$	(2) $PM_{2.5}$	(3) $PM_{2.5}$	(4) $PM_{2.5}$	(5) $PM_{2.5}$	(6) $PM_{2.5}$	(7) $PM_{2.5}$	(8) $PM_{2.5}$
C1	−1.889 ***							
	(0.071)							
C2		−1.791 ***						
		(0.081)						
C3			−2.266 ***					
			(0.105)					
C4				−0.760 ***				
				(0.054)				
C5					−3.115 ***			
					(0.125)			
C6						−1.878 ***		
						(0.088)		
C7							−1.696 ***	
							(0.099)	
C8								−2.301 ***
								(0.065)
Humidity	0.002	0.012 ***	0.011 **	0.017 ***	0.013 ***	0.013 ***	0.011 **	0.006
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
Temperature	−0.677 ***	−0.676 ***	−0.681 ***	−0.690 ***	−0.691 ***	−0.708 ***	−0.690 ***	−0.640 ***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Wind speed	0.159 ***	0.153 ***	0.158 ***	0.160 ***	0.162 ***	0.174 ***	0.163 ***	0.132 ***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.499	0.499	0.498	0.498	0.499	0.498	0.498	0.501
No. of cities	596	596	596	596	596	596	596	596
No. of countries	77	77	77	77	77	77	77	77
N	168,913	168,913	168,883	168,913	168,913	168,897	168,910	168,913
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the city-by-day level and are shown in parentheses; significance levels are ** 0.05, *** 0.01.

Table 4 presents results for additional air pollutants beyond $PM_{2.5}$. In columns (1) through (8), the key independent variable is the lockdown measure (C1 to C8), respectively. The estimates using Equation (1) indicate that except O_3, all pollutants are negatively correlated with lockdown measures. Specifically, lockdowns appear to reduce concentrations of most pollutants. However, O_3 showed a positive correlation with lockdown measures, aligning with the findings of Huang et al. [28] and Kroll et al. [29]. This positive association

can likely be explained by the nonlinear relationship between nitrogen oxides and ozone. When NO_2 concentrations decrease, ozone levels tend to rebound, as lower nitrogen oxide levels reduce the removal of ozone from the atmosphere.

Table 4. Main results using alternative air pollutants.

Lockdown Measures:	**(1) C1**	**(2) C2**	**(3) C3**	**(4) C4**	**(5) C5**	**(6) C6**	**(7) C7**	**(8) C8**
Panel A: $PM_{2.5}$	−1.889 ***	−1.791 ***	−2.266 ***	−0.760 ***	−3.115 ***	−1.878 ***	−1.696 ***	−2.301 ***
	(0.071)	(0.081)	(0.105)	(0.054)	(0.125)	(0.088)	(0.099)	(0.065)
Panel B: PM_{10}	−1.420 ***	−1.241 ***	−1.423 ***	−0.555 ***	−2.337 ***	−1.388 ***	−1.239 ***	−1.368 ***
	(0.045)	(0.051)	(0.065)	(0.034)	(0.079)	(0.055)	(0.061)	(0.040)
Panel C: SO_2	−0.242 ***	−0.283 ***	−0.397 ***	−0.084 ***	−0.219 ***	−0.187 ***	−0.273 ***	−0.057 ***
	(0.014)	(0.016)	(0.021)	(0.011)	(0.024)	(0.017)	(0.019)	(0.013)
Panel D: NO_2	−1.031 ***	−1.023 ***	−1.128 ***	−0.423 ***	−1.314 ***	−0.847 ***	−0.910 ***	−0.549 ***
	(0.012)	(0.014)	(0.018)	(0.009)	(0.022)	(0.015)	(0.017)	(0.011)
Panel E: CO	−0.191 ***	−0.214 ***	−0.189 ***	−0.038 ***	−0.163 ***	−0.178 ***	−0.178 ***	−0.063 ***
	(0.015)	(0.018)	(0.024)	(0.012)	(0.027)	(0.019)	(0.022)	(0.014)
Panel F: O_3	1.189 ***	0.499 ***	0.564 ***	−0.132 ***	0.410 ***	0.220 ***	0.063 **	0.193 ***
	(0.020)	(0.024)	(0.030)	(0.016)	(0.037)	(0.025)	(0.028)	(0.019)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses are clustered at the city–day level; asterisks denote significance levels, ** $p < 0.05$, *** $p < 0.01$. The dependent variables are $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 emission levels in panels A to F, respectively. Control variables are daily temperature, wind speed, and humidity (unreported for brevity).

4.2. Difference-in-Differences Estimates

The estimates in Table 5, based on Equation (2), shows a similar pattern. Air pollution levels in cities with COVID-19 lockdown measures improve relative to those without. Specifically, the daily concentrations of NO_2, PM_{10}, $PM_{2.5}$, CO, and SO_2 decrease by 2.4~4.1, 3.7~5.9, 5.4~8.8, 0.4~0.7, and 0.2~0.9 units, respectively. This translates to percentage reductions of 21.3~35.1%, 13.6~26.2%, 9.4~18.2%, 5.9~15.6%, and 4.7~15.6% after controlling for meteorological variables and a range of fixed effects. Furthermore, nitrogen oxide levels generally decline more steeply than other pollutants, consistent with findings from Bauwens et al. [30] and Liu et al. [31] based on satellite data. This suggests that the pandemic-induced lockdowns, which reduced vehicle travel, led to decrease in nitrogen oxide emissions, a major byproduct of combustion. The positive correlation between lockdowns and O_3 concentrations remains significant using the DID approach.

Table 5. Difference-in-differences estimates of effect of COVID-19 lockdowns on air quality.

Lockdown Measures:	**(1) C1**	**(2) C2**	**(3) C3**	**(4) C4**	**(5) C5**	**(6) C6**	**(7) C7**	**(8) C8**
Panel A: $PM_{2.5}$	−8.777 ***	−7.971 ***	−8.343 ***	−7.698 ***	−7.315 ***	−5.403 ***	−6.583 ***	−8.073 ***
	(0.251)	(0.245)	(0.253)	(0.240)	(0.230)	(0.232)	(0.239)	(0.278)
	−5.855 ***	−5.287 ***	−5.406 ***	−5.245 ***	−5.053 ***	−3.726 ***	−4.523 ***	−4.609 ***
	(0.152)	(0.148)	(0.153)	(0.147)	(0.137)	(0.138)	(0.142)	(0.164)
Panel B: PM_{10}	−0.800 ***	−0.795 ***	−0.933 ***	−0.570 ***	−0.635 ***	−0.664 ***	−0.738 ***	−0.203 ***
	(0.061)	(0.059)	(0.062)	(0.044)	(0.055)	(0.055)	(0.057)	(0.069)
	−4.072 ***	−3.943 ***	−4.024 ***	−3.284 ***	−3.551 ***	−3.107 ***	−3.454 ***	−2.420 ***
Panel C: SO_2	(0.047)	(0.045)	(0.047)	(0.045)	(0.041)	(0.042)	(0.044)	(0.053)
	−0.693 ***	−0.693 ***	−0.641 ***	−0.490 ***	−0.407 ***	−0.418 ***	−0.552 ***	−0.520 ***

Table 5. *Cont.*

Lockdown Measures:	**(1) C1**	**(2) C2**	**(3) C3**	**(4) C4**	**(5) C5**	**(6) C6**	**(7) C7**	**(8) C8**
Panel D: NO_2	(0.066) 4.565 *** (0.067)	(0.063) 4.288 *** (0.067)	(0.067) 5.009 *** (0.067)	(0.067) 3.760 *** (0.072)	(0.058) 3.183 *** (0.068)	(0.060) 3.881 *** (0.063)	(0.062) 3.756 *** (0.065)	(0.077) 2.647 *** (0.079)
Panel E: CO	−8.777 *** (0.251) −5.855 ***	−7.971 *** (0.245) −5.287 ***	−8.343 *** (0.253) −5.406 ***	−7.698 *** (0.240) −5.245 ***	−7.315 *** (0.230) −5.053 ***	−5.403 *** (0.232) −3.726 ***	−6.583 *** (0.239) −4.523 ***	−8.073 *** (0.278) −4.609 ***
Panel F: O_3	(0.152) −0.800 *** (0.061)	(0.148) −0.795 *** (0.059)	(0.153) −0.933 *** (0.062)	(0.147) −0.570 *** (0.044)	(0.137) −0.635 *** (0.055)	(0.138) −0.664 *** (0.055)	(0.142) −0.738 *** (0.057)	(0.164) −0.203 *** (0.069)
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country by Date Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses are clustered at the city-day level. Control variables are daily temperature, wind speed, and humidity (unreported for brevity). *** at 1% level. The dependent variables are $PM_{2.5}$, PM_{10}, SO_2, NO_2, CO, and O_3 emission levels in panels A to F, respectively.

Additionally, we document that the short-run impact implied by the DID estimates is substantially larger than the longer-term effects captured by the fixed-effects OLS estimates, suggesting potential downward bias in OLS estimates. Combing the DID and OLS estimations, the consistent results reinforce the conclusion that lockdowns have a significant positive impact on air quality, particularly in reducing NO_2 emissions.

4.3. Robustness Checks

To assess the robustness of our findings, we conducted a series of tests. As shown in Table 6, we first used the stringency index as the key independent variable to re-estimate Equation (1) (column 1). Second, we replicated the DID approach using the log of air quality index to account for potential outliers (column 2). Third, we employed an alternative estimation strategy to further test the causal relationship between lockdown and air pollution (column 3). Fourth, to address concern about expectation effects near the lockdown dates, we removed observations 5 and 10 days around the lockdown periods (columns 4 and 5). Fifth, given that some cities have only one monitoring station, which may not be fully representative of the entire city, we re-ran the DID approach excluding these cities (column 6). Finally, we repeated the DID specification using the full sample (column 7) and data at the country level (column 8). The estimation results remain robust across these various checks, with outcomes nearly identical to those reported earlier.

Table 6. Robustness test: $PM_{2.5}$.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Independent Variable:	**$PM_{2.5}$**	**log ($PM_{2.5}$)**	**The Dynamic Panel Data Model**	**Excluding Observations 5 Days Near the Lockdown Date**	**Excluding Observations 10 Days Near the Lockdown Date**	**Cities with More than One Monitoring Station Only**	**Full Sample**	**Country-Level Data**
Stringency index	−0.093 *** (0.003)							
C1		−0.109 *** (0.004)	−3.156 *** (0.198)	−5.610 *** (0.220)	−5.706 *** (0.229)	−5.422 *** (0.213)	−5.598 *** (0.214)	−9.390 *** (0.572)
C2		−0.101 *** (0.004)	−2.836 *** (0.192)	−4.812 *** (0.204)	−4.817 *** (0.211)	−4.613 *** (0.199)	−4.605 *** (0.199)	−7.697 *** (0.562)

Table 6. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Independent Variable:	**$PM_{2.5}$**	**log ($PM_{2.5}$)**	**The Dynamic Panel Data Model**	**Excluding Observations 5 Days Near the Lockdown Date**	**Excluding Observations 10 Days Near the Lockdown Date**	**Cities with More than One Monitoring Station Only**	**Full Sample**	**Country-Level Data**
C3		−0.105 ***	−3.071 ***	−5.083 ***	−4.905 ***	−4.788 ***	−4.985 ***	−9.019 ***
		(0.004)	(0.200)	(0.214)	(0.221)	(0.209)	(0.209)	(0.577)
C4		−0.103 ***	−2.732 ***	−3.100 ***	−3.153 ***	−2.816 ***	−3.011 ***	−7.817 ***
		(0.004)	(0.187)	(0.210)	(0.216)	(0.204)	(0.204)	(0.554)
C5		−0.108 ***	−3.016 ***	−1.816 ***	−1.816 ***	−1.176 ***	−1.749 ***	−8.319 ***
		(0.004)	(0.179)	(0.179)	(0.179)	(0.175)	(0.175)	(0.536)
C6		−0.066 ***	−2.144 ***	−1.138 ***	−0.809 ***	−1.090 ***	−1.397 ***	−7.181 ***
		(0.004)	(0.182)	(0.178)	(0.181)	(0.174)	(0.174)	(0.537)
C7		−0.077 ***	−2.362 ***	−1.514 ***	−1.446 ***	−0.965 ***	−1.559 ***	−6.734 ***
		(0.004)	(0.186)	(0.180)	(0.184)	(0.177)	(0.177)	(0.539)
C8		−0.133 ***	−2.984 ***	−7.088 ***	−7.520 ***	−6.600 ***	−6.590 ***	−4.822 ***
		(0.005)	(0.223)	(0.245)	(0.258)	(0.233)	(0.234)	(0.632)

*** denote significance at the 10%, 5%, and 1% levels, respectively. After checking the original monitoring data in the aqicn.org database, 16 out of 596 cities reported readings only from one monitoring station. Control variables are the same as Table 5. Standard errors are clustered at the city–day level in parentheses for columns (1) to (7) and at the country–day level for column (8).

We also tested the robustness for our findings for other air pollutants, and estimates remain consistent with the main results in Table 5. Due to space limitations, the corresponding estimation results are not presented here but are available upon request.

5. Mechanism: Mobility Restriction

After establishing the causal effects of COVID-19 lockdowns on air pollution levels, it is important to realize the role of mobility restriction as a potential channel through which lockdown measures affect air pollution. Here, we further test this hypothesis from the perspective of transportation, since lockdown measures mainly affected traffic activities. We first employed the data on public transit from Google Maps to measure the variation in public transit use, then collected data on private vehicle use from the Apple Mobility Trends Reports.

Next, a mediating effect analysis was carried out to examine the effects of human travel by different modes on the relationship between mobility restriction and air quality improvement measured by $PM_{2.5}$ concentrations. Specifically, we report the estimates based on three-step regressions (Equations (4)–(6)) in Table 7 with human travel measured by public transit use (*lntransit*) and Table 8 with human travel measured by private vehicle use (*lndriving*). Columns (1), (4), (7), (10), (13), (16), (19), and (23) in Tables 7 and 8 show the effect of lockdowns on human travel measured by public transit use and private vehicle use, respectively, based on Equation (4), indicating that human travel has declined significantly where governments have imposed lockdown measures. In columns (2), (5), (8), (11), (14), (17), (20), and (23) of Table 7, we report the relationship between human mobility and air quality based on Equation (5); all coefficients are significantly negative at the 1% level, suggesting that more use of public transit was associated with better air quality. However, the corresponding estimate results in Table 8 show that private vehicle use contributes to air pollution, consistent with Chen et al.'s [32] findings that examine the causal relationship between private vehicle restriction and air pollution. The results using another individual air pollutant (PM_{10}) also provide similar evidence that human mobility measured by public transit use and by private vehicle use, respectively, are negatively and positively associated with air pollution. This distinction is not observed concerning other specific air pollutants (NO_2, SO_2, CO, and O_3). A potential explanation of this difference in

the human mobility–air pollution nexus under both modes of transport relates to public transit's role in improving air quality, particularly in reducing atmospheric particulate matter whose primary source is vehicular exhaust. Therefore, lockdown measures about closing public transport restrict people from traveling by it; moreover, someone may initiatively shift from public transit use to personal automobiles to reduce their chances of contracting COVID-19 [33]. Consequently, less public transit use leads to higher levels of $PM_{2.5}$ and PM_{10}. We next analyzed the results when introducing the mediator, as presented in columns (3), (6), (9), (12), (15), (18), (21), and (24) of Tables 7 and 8. The results show that the mediating role of mobility restriction in the relationship between lockdowns and air pollution exists. The coefficient of *lockdown* is still statistically significant but drops from −8.777 in column (1) of Table 5 to −5.696 in column (3) of Table 7 and −5.787 in column (3) of Table 8 after controlling the mediator. Other lockdown measures show analogous evidence with C1, suggesting the effects of lockdowns on the reduction in $PM_{2.5}$ are partially mediated by the mobility restriction. We also estimate the equations using data on other specific air pollutants (NO_2, CO, PM_{10}, SO_2, O_3). The results also confirm the role of mobility restrictions as a mechanism, which are not reported here to save space.

Table 7. Mediating analysis of public transit use.

LDM	**(1)**	**(2)** C1	**(3)**	**(4)**	**(5)** C2	**(6)**	**(7)**	**(8)** C3	**(9)**	**(10)**	**(11)** C4	**(12)**
	lnt	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnt**	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnt**	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnt**	**$PM_{2.5}$**	**$PM_{2.5}$**
LD	0.840 ***		−5.696 ***	−0.776 ***		−7.154 ***	−0.789 ***		−4.153 ***	−0.647 ***		−4.405 ***
	(0.005)		(0.407)	(0.004)		(0.360)	(0.005)		(0.405)	(0.004)		(0.320)
lnt		−1.468 ***	−3.850 ***		1.840 **	−5.627 ***		−1.605 ***	−3.072 ***		−2.531 ***	−4.435 ***
		(0.242)	(0.296)		(0.241)	(0.307)		(0.242)	(0.281)		(0.235)	(0.272)
N	56,754	46,618	46,618	60,645	50,137	50,137	56,121	46,139	46,139	64,307	53,694	53,694
R^2	0.524	0.558	0.559	0.572	0.550	0.554	0.473	0.564	0.565	0.503	0.548	0.550
LDM	**(13)**	**(14)** C5	**(15)**	**(16)**	**(17)** C6	**(18)**	**(19)**	**(20)** C7	**(21)**	**(22)**	**(23)** C8	**(24)**
	lnt	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnt**	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnt**	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnt**	**$PM_{2.5}$**	**$PM_{2.5}$**
LD	−0.580 ***		−7.273 ***	−0.632 ***		−0.849 ***	−0.705 ***		−4.551 ***	−0.402 ***		−2.663 ***
	(0.003)		(0.285)	(0.003)		(0.301)	(0.004)		(0.332)	(0.008)		(0.438)
lnt		−1.217 ***	−5.008 ***		1.855 ***	−2.335 ***		−2.063 ***	−4.518 ***		−1.434 ***	−1.713 ***
		(0.241)	(0.282)		(0.240)	(0.294)		(0.238)	(0.297)		(0.257)	(0.261)
N	74,015	62,220	62,220	61,728	51,101	51,101	60,586	49,973	49,973	45,725	37,710	37,710
R^2	0.535	0.535	0.539	0.548	0.534	0.534	0.563	0.558	0.559	0.348	0.567	0.568

, and * denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors in parentheses are clustered at the city–day level. Control variables are daily temperature, wind speed, and humidity (unreported for brevity). All regressions include date, country, and city fixed effects. The city–day and country–day interactions are also included to control for city-specific and country-specific time trends, respectively. LDM represents lockdown measures, *LD* represents $T_Lockdown^{n}_{mit}$, and *lnt* represents $ln(Human_mobility^{j}_{mit})$ measured by *lntransit*.

Table 8. Mediating analysis of private vehicle use.

LDM	**(1)**	**(2)** C1	**(3)**	**(4)**	**(5)** C2	**(6)**	**(7)**	**(8)** C3	**(9)**	**(10)**	**(11)** C4	**(12)**
	lnd	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnd**	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnd**	**$PM_{2.5}$**	**$PM_{2.5}$**	**lnd**	**$PM_{2.5}$**	**$PM_{2.5}$**
LD	−0.725 ***		−5.787 ***	−0.691 ***		−5.205 ***	−0.711 ***		−5.190 ***	−0.691 ***		−5.205 ***
	(0.004)		(0.306)	(0.004)		(0.283)	(0.004)		(0.304)	(0.004)		(0.283)
lnd		2.869 ***	−0.076		2.000 ***	−0.515 **		2.779 ***	0.241		2.000 ***	−0.515 **
		(0.212)	(0.262)		(0.200)	(0.241)		(0.212)	(0.258)		(0.200)	(0.241)
N	65,898	54,320	54,320	71,493	59,566	59,566	65,272	53,860	53,860	71,493	59,566	59,566
R^2	0.513	0.519	0.522	0.523	0.509	0.512	0.495	0.522	0.525	0.523	0.509	0.512

Table 8. *Cont.*

LDM	(13)	(14) C5	(15)	(16)	(17) C6	(18)	(19)	(20) C7	(21)	(22)	(23) C8	(24)
	lnd	$PM_{2.5}$	$PM_{2.5}$	lnd	$PM_{2.5}$	$PM_{2.5}$	lnd	$PM_{2.5}$	$PM_{2.5}$	lnd	$PM_{2.5}$	$PM_{2.5}$
LD	−0.624 ***		−7.138 ***	−0.647 ***		−1.158 ***	−0.702 ***		−3.291 ***	−0.469 ***		−4.726 ***
	(0.004)		(0.267)	(0.003)		(0.269)	(0.003)		(0.288)	(0.005)		(0.306)
lnd		2.834 ***	−0.184		2.079 ***	1.477 ***		2.270 ***	0.471 *		2.721 ***	1.632 ***
		(0.202)	(0.230)		(0.206)	(0.249)		(0.208)	(0.260)		(0.220)	(0.231)
N	78,902	66,091	66,091	70,161	58,113	58,113	69,211	57,176	57,176	55,239	45,655	45,655
R^2	0.506	0.503	0.508	0.512	0.501	0.501	0.539	0.513	0.514	0.333	0.543	0.546

*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city–day level and are reported in parentheses. Control variables are daily temperature, wind speed, and humidity (unreported for brevity). All regressions include the date, country, and city fixed effects. The city–day and country–day interactions are also included to control for city-specific and country-specific time trends, respectively. LDM represents lockdown measures, *LD* represents $T_Lockdown^{n}_{mit}$, and *lnd* indicates $ln(Human_mobility^{j}_{mit})$ measured by *lndriving*.

6. Discussion

Our findings underscore the significant environmental benefits of COVID-19-induced lockdown measures, particularly regarding air quality improvements. The pronounced decline in NO_2 levels, which is directly linked to vehicular emissions, highlights the transportation sector as a primary driver of urban air pollution [34,35]. The mechanism analysis sheds light on how mobility restrictions mediate the relationship between lockdowns and air quality improvements. The significant reductions in both public transit and private vehicle use during lockdowns emphasize the critical role of human mobility in shaping air pollution dynamics. Notably, our findings reveal a duality: while reduced private vehicle use contributed positively to air quality improvements, the decline in public transit use had an unintended adverse effect, particularly on particulate matter concentrations ($PM_{2.5}$ and PM_{10}). This distinction can be attributed to the efficiency of public transit systems in reducing emissions per passenger compared to private vehicles [36]. The observed shift from public transit to private vehicle use during lockdowns, likely driven by health concerns, underscores the need for strategies that prioritize safe and environmentally friendly public transportation options even during public health crises. The heterogeneity in the impacts across specific air pollutants provides critical insights. While nitrogen oxides experienced the steepest declines due to reduced vehicular emissions, the positive correlation between lockdowns and O_3 concentrations requires careful interpretation. This phenomenon likely stems from complex photochemical reactions where reductions in NO_2 limit ozone scavenging, resulting in higher ozone levels in certain areas [37]. These findings highlight the intricate interplay between different pollutants and stress the importance of considering secondary effects when designing air quality interventions.

Furthermore, the significant short-term effects captured by the DID estimates suggest that temporary, localized interventions, such as vehicle-free zones or "green weeks", could provide immediate environmental benefits during periods of poor air quality or elevated health risks. Our findings also underscore the value of high-resolution, real-time data in understanding the relationship between human mobility and environmental outcomes. By leveraging datasets such as those from OxCGRT, GCMR, and AMTR, policymakers can identify specific mobility patterns and sectors driving emissions. This evidence-based approach could enable more precise and effective interventions tailored to local contexts, rather than one-size-fits-all measures.

7. Conclusions

This study examines the relationship between COVID-19 lockdown measures and air pollution reduction using high-quality datasets covering the January to December 2020 period. Employing fixed effects OLS and DID methodologies, we provide robust cross-national evidence of how pandemic-induced restrictions have influenced air quality. The results demonstrate a significant reduction in key air pollutants during lockdowns, with NO_2 concentrations decreasing by 21–35%, followed by reductions in PM_{10} (14~26%), $PM_{2.5}$ (9~18%), CO (6~16%), and SO_2 (5~16%). In contrast, O_3 concentrations increased by 15~29%, potentially due to complex atmospheric chemistry processes triggered by reduced NO_2 levels. Human mobility is identified as a potential channel through which lockdown measures impact air pollution. Our findings reveal that lockdowns result in decreased utilization of both public transit and private vehicles. However, the reduction in public transit usage is associated with elevated concentrations of $PM_{2.5}$ and PM_{10}, whereas diminished automobile use correlates with reductions across all observed air pollutants.

These findings highlight the practical applicability of our methodologies, particularly the ability to quantify air quality improvements in response to reduced human mobility. Policymakers could leverage these insights to design targeted interventions. For instance, strategies such as teleworking policies, promotion of remote services, and urban designs that encourage walking and cycling could provide long-term environmental benefits. Moreover, the role of public transit systems is critical. Our results suggest that while reduced car usage leads to overall improvements in air quality, declines in public transit ridership can offset these gains by contributing to increased particulate matter concentrations. Governments and urban planners should prioritize investment in cleaner, safer, and more efficient public transit systems, especially during public health crises, to maintain both environmental and health benefits [38].

This study also makes a notable scientific contribution by identifying human mobility as a crucial channel through which lockdowns influence air pollution. The nuanced findings—such as the differential impacts of reduced public transit versus private vehicle use—highlight the complex mechanisms through which mobility restrictions influence pollution dynamics. This research not only enriches our understanding of short-term policy impacts but also lays the groundwork for examining structural changes that could arise from shifts in travel behavior and industrial activity. Moreover, the observed variations in air quality improvements across countries highlight the importance of contextual factors, such as urban density, industrial composition, and the stringency of lockdown measures. For example, countries with more extensive public transit networks experienced differing impacts compared to those with higher reliance on private vehicles. These cross-country differences emphasize the need for localized policy responses rather than one-size-fits-all solutions [39].

However, several limitations should be acknowledged. First, the reliance on station-based air pollution data may introduce biases, including low update frequencies and non-random placement of monitoring stations, which may not fully capture spatial variations. The integration of satellite-based data could mitigate these issues, providing more comprehensive coverage and higher temporal resolution. Second, the absence of detailed, city-level data on government policy responsiveness limits the ability to assess localized impacts of lockdown measures. Addressing these limitations in future research could significantly enhance the robustness of findings.

Future studies could extend the scope of this research in several ways. First, exploring the long-term health benefits associated with improved air quality could provide valuable insights into the public health implications of mobility restrictions. Understanding how cleaner air affects respiratory and cardiovascular outcomes would offer

compelling evidence for integrating air quality goals into broader public health policies. Second, investigating the medium- and long-term economic impacts of air quality improvements—particularly on human capital and productivity—could deepen our understanding of the broader socioeconomic consequences. Third, leveraging alternative data sources, like mobile phone location data and satellite imagery, could improve the precision of analyses on human mobility and its environmental impacts. Lastly, future research could explore the role of technological innovations, such as electric vehicles and smart city infrastructure, in mitigating air pollution while accommodating economic growth. By addressing these gaps, future research can deepen our understanding of the nexus between air pollution, human activity, and policy interventions, offering valuable insights for achieving both environmental and public health objectives in a post-pandemic world.

The COVID-19 pandemic has inadvertently demonstrated how swift and significant changes in human behavior can lead to environmental benefits. However, these benefits must be contextualized within the broader trade-offs between economic activity and environmental sustainability. Policymakers must carefully design strategies to achieve a balance, ensuring that environmental objectives are met without imposing undue economic hardship. The lessons from this study highlight the urgent need to rethink urban mobility and energy systems in ways that align with global climate goals while fostering resilient economies.

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