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The Impact of City Anti-Contagion Policies (CAPs) on Air Quality Evidence from a Natural Experiment in China

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Abstract: In order to control the spread of the Coronavirus Disease 2019 (COVID-19), many countries around the world adopted aggressive anti-contagion policies (APs), the most common of which was to restrict people's transportation and economic activities, which not only curbed the spread of the epidemic but also improved urban air quality during the APs' implementation. However, the impact that these policies had in the post-AP period is unclear. Using daily air quality data for prefecture-level cities in China in early 2020 and the Difference-in-Differences (DiD) models, we measured the short-term (AP implementation period) and medium-term (post-AP period) impacts of the city APs (CAPs) on different kinds of air pollutants and considered the meteorological conditions. We found that the policies significantly reduced air pollution (i.e., particulate matter [PM2.5, PM10] and nitrogen dioxide [NO_2]) in the short term; although the medium-term impacts are in line with the short-term impacts, they are not significant. The effects were reduced in cities with higher incomes, larger populations, more industrial activities, and greater traffic volumes, and without a central heating system. Although the CAPs did not improve air quality in the long run, they improved air quality and health benefits in the short term. In addition, the policies' experiments verified the complexity of environmental governance.

Keywords: city anti-contagion policies; unsustainable impacts; DiD models; air quality

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1. Introduction

The public health incident COVID-19 affected more than 219 countries around the world and killed more than 6.3 million people (World Health Organization (WHO), Geneva, Switzerland, 2022). Faced with this sudden crisis, all countries adopted emergency policies to mitigate its impact. These policies aimed to reduce the spread of the virus by reducing personal contact within or between populations, such as, for example, increasing or extending holidays, restricting populations to their homes, closing restaurants or restricting travel, and delaying the resumption of housing construction and municipal infrastructure projects. Effective policies depend on people's social preferences and the government management capacity, and, on the other hand, on an accurate cost–benefit analysis of different anti-contagion policies (APs) [1]. When only focusing on the health benefits, which create huge costs for developing countries or regions, all countries consider whether the benefits of APs are worth the corresponding social and economic costs. These policies controlled the spread of the epidemic in a short period of time. However, little is known about the widespread impact of the APs.

An important component of evaluating the benefits of the APs' implementation is to measure non-negligible impacts on public benefits (e.g., air quality) in the short and long term. This special period was the "largest scale experiment ever" on air quality. In this context, it is possible to better measure the impact of human behavior on air quality [2]. Some studies have examined the short-term impact of government control measures on air quality. Scholars examined whether, how, and to what extent the policies affected air quality in different cities (e.g., Almaty, Barcelona, Bengaluru, Beijing, Brescia, Dhaka, Las Vegas, Lima, Madrid, Milan, Moscow, Mumbai, Quito, Rio de Janeiro, Rome, São Paulo, and Wuhan), regions (e.g., the Yangtze River Delta [YRD], the Pearl River Delta, California, and Western Europe, the world's 50 most polluted capital cities, and major cities across the globe), and countries (e.g., Canada, China, Ecuador, India, Iran, Nigeria, Poland, Portugal, Spain, Türkiye, the United Kingdom (UK), and the United States (US)). In 2020, a notable improvement in air quality was observed during the COVID-19 lockdown (implementing the APs) across the globe [3,4].

Developed economic regions: In Canada, the concentration levels of NO_2 and carbon monoxide (CO) were strongly correlated with the APs [5]. In the US, after the shutdown, PM2.5 and NO_2 concentration levels decreased significantly in New York, along with PM2.5, NO_2, and CO in California, but the ozone (O_3) concentration increased [2,6–8]. In Italy, PM10 and NO_2 concentrations were significantly reduced between 1 January and 27 March in Brescia [9]; from 9 March to 5 April, PM2.5, PM10, NOx, CO, black carbon (BC), and benzene concentrations were significantly reduced, but O_3 increased in Milan [10]. In Poland, five large cities showed a reduction in pollutant concentrations (PM2.5, PM10, and NO_2) in April and May compared to the same periods in 2018 and 2019 [11]. In Portugal, these reductions were observed for PM2.5, PM10, and NO_2 [12,13]. In Spain, at various time periods from February to April 2020, the concentration levels of PM10, SO_2, NO_2, CO, and BC were reduced, but O_3 increased in some cities [14–16]. In the UK, compared to the same period in the previous years, the PM2.5, NO_2, and nitrogen monoxide (NO) levels dropped substantially, but the O_3 levels increased [17–19].

Economies in transition regions: In Kazakhstan, from 19 March to 14 April, the concentration levels of PM2.5, NO_2, and CO were reduced, compared to the average in the same period in the previous two years, but O_3 increased in Almaty [20]. Developing economic regions: In Bangladesh, from 8 March to 15 May, there were nonuniform reductions in PM 2.5, SO_2, NO_2, O_3, and CO concentrations in Dhaka [21]. In Brazil, the concentrations of CO, NO_2, and PM10 decreased to varying degrees, but O_3 increased in Rio de Janeiro [22]; compared to the monthly mean for the last five years, there were drastic reductions in NO, NO_2, and CO concentrations, and O_3 increased in São Paulo [23]. In Ecuador, PM2.5 and NO_2 concentrations decreased significantly, and O_3 concentrations increased [24]; PM2.5, SO_2, NO_2, and CO concentrations decreased drastically, and the reduction in NO_2 induced an increase in O_3 in Quito [25]. In India, the AQI was improved in the mega cities [26], with decreases in PM2.5, PM10, NO_2, and CO compared to previous years and an increase in O_3 [27,28]. In Iran, from 21 March to 21 April in 2019 and 2020, concentrations of PM10, SO_2, NO_2, and CO decreased, and PM2.5 and O_3 increased [29]. In Nigeria, a substantial decline in fine aerosols was observed compared with pre-lockdown [30]. In Türkiye, the restrictions imposed (between 16 March and 15 April) in the 30 major cities significantly improved the air quality (PM2.5, PM10, and CO) [31].

In China, studies estimated and quantified the effects of the implementation of anti-contagion policies (e.g., travel restrictions, decreased human mobility, COVID-19 lockdown, and intracity mobility reductions) on concentrations of different kinds of air pollutants (e.g., PM2.5, PM10, SO_2, NO_2, CO, and O_3) during the COVID-19 outbreak at various time periods from January to April 2020. These studies, based on different sample cities (e.g., 44 cities in the north, 95 cities out of 324 sample cities, 30 cities in China, and the YRD Region) and different research methods, found similar conclusions, with significantly varying degrees of reduction in the concentration of air pollutants (i.e., PM2.5, PM10, SO_2, NO_2, and CO), but O_3 increased greatly [32–40]. In summary, most of the countries or regions mentioned above experienced a similar phenomenon that is, O_3 concentrations rose during this special period.

Although the link between APs and air quality has been widely discussed in the above studies based on different countries, compared to the pre-pandemic situation in 2020 or the same period in nearly five years, there was a significant reduction in different kinds of air pollutant concentrations (the highest frequency includes PM2.5, PM10, NO_2, and CO), but the O_3 level increased in the short term (during the APs' implementation). However, air pollution is not a short-term problem, and there is still a lack of research on how APs affect air quality in both the short term and the post-APs period. The effects should be tested over time to trace both the temporal dynamics and longer effects of the APs implementation. In China, the APs, in most cities, were issued directly by municipal governments, and a small number of policies were promulgated by the provincial governments, which can be broadly divided into two categories. One is defined as a restriction on the movement of people between different cities (city APs [CAPs]), and the other is defined as restricting mobility within the city (community APs [COAPs])) [1]. We focus on the impact of the CAPs on air pollution improvements. Therefore, first, we measure not only the short-term impact but also the post-policy (the medium-term) impact in China. Second, some studies only focused on the city's top pollutants and ignored changes in other air pollutants. This study included six common pollutants (i.e., PM2.5, PM10, SO_2, NO_2, and CO) and the Air Quality Index (AQI). Third, air pollution concentrations are closely related to meteorological changes [41]; the concentrations of different air pollutants are related to different meteorological variables (e.g., wind speed, air pressure, relative humidity, and duration of sunshine) [42]. For example, the temperature, air pressure, and wind speed have a direct impact on PM concentrations [43]. While some research measuring the impact during the period considered the weather conditions (e.g., rainfall, snowfall, and temperature), most of them ignored other meteorological indicators (e.g., the wind speed, air pressure, relative humidity, and duration of sunshine), which are considered in our research. Our findings will help researchers and policymakers in China and other countries understand the benefits and costs of the CAPs during COVID-19, which have important implications for current and future policy design.

2. Materials and Methods

2.1. Methodology

The exogenous shock time of APs was regarded as a natural experiment; we used the DiD model, an econometric model widely used to measure the causal effects of intervention methods, to examine the impact of the CAPs on air quality. This method overcomes the endogeneity problem and identifies the causal relationship by taking advantage of the heterogeneous effects of an exogenous shock on the treatment group (with CAPs) and the control group (without CAPs) before and after the policies were implemented.

2.1.1. Generalized DiD Model

In the first stage, we estimated the CAPs' short-term impacts from 1 January to 7 April 2020, using the generalized DiD Model, which measured the relative change in air quality between the two groups. We constructed the following econometric model for Difference-in-Differences testing:

$$Y_{it} = \alpha + \beta CAP_{it} + \gamma Met_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (1)$$

where i represents the city, and t represents the time (day). Y_{it} is the daily value of the air pollutant concentration or AQI in city i on day t. CAP_{it}, a dummy variable, denotes whether city i implemented CAPs on day t. CAP_{it} equals 1 if CAPs were implemented on date t, and 0 otherwise. Met_{it} is the daily value of meteorological indicators in city i at day t. μ_i and π_t are both vectors of dummy variables. μ_i is a set of dummy variables for a city and can control the mixed confounders for each city (e.g., conditions of geographical landscape, economic structure, and natural environment); π_t is a set of dummy variables for the date and can explain the shocks that occur collectively in all cities on a given day. ε_{it} is the error term.

Thus, in the Two-way Fixed Effects (TWFE) model, the coefficient β estimates the difference in air quality between the two groups before and after implementing the CAPs. The coefficient γ is a vector that estimates the impact of different meteorological indicators on air pollutant concentrations.

Second, most studies continued to implement the previous policies, and business activities were not fully recovered, even after the CAPs were lifted. Thus, based on the time interval for short-term impact measurements, datasets from 8 April to 31 July were defined as the post-CAPs period to measure the medium-term impacts on air quality. We reconstructed the following equation:

$$Y_{it} = \alpha + \beta_s CAP_{it} + \beta_m postCAP_{it} + \gamma Met_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (2)$$

where $postCAP_{it}$, a dummy variable, is an interactive term. When CAPs were implemented between 1 January and 7 April 2020, and the date t can be between 8 April and 31 July the $postCAP_{it}$ equals 1, and 0 otherwise. The coefficient β_s estimates the short-term impact of CAPs. The coefficient β_m estimates the medium-term impacts. The rest of the explanations are the same as in Equation (1).

2.1.2. Event Study

The basic assumption of the DiD model is that air quality trends are the same in both groups of cities without CAP intervention (i.e., the parallel trend assumption). Although the results show an improvement in air quality in the treated cities after implementation, the results may not be due to the effects of CAPs, but to systemic differences between the two groups. This hypothesis is impossible to test because we cannot observe counterfactuals about how air pollution concentrations in the experimental group of cities would change without these policies. However, before implementing CAPs, we must examine the air quality trends of the two groups and test whether they are comparable. Therefore, we used the following equation to test this comparability.

$$Y_{it} = \alpha + \sum_{m=k,\ m\neq -1}^{M} \beta^k \times D\_CAP_{it,k} + \gamma Met_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (3)$$

where $D\_CAP_{jt,k}$, a set of dummy variables, indicates the experimental status at different periods. We put 1 week into one bin (bin m∈M) in order to avoid the impact of high daily air pollution fluctuations on the trend testing [40]. The dummy value of m = −1 is omitted from Equation (3) so that the impact of CAPs is relative to the period of the week before the policies' implementation. m = −1 is used as a reference because the impact of CAPs may have been felt before they were implemented; for example, some people start personal protection by reducing travel and group activities before the government announces the CAPs, depending on the trend of new cases in the epidemic. During the prevention and control period, many cities in China used a seven-day observation period to observe the changes in new cases. β^k estimates the effects of CAPs m weeks after their implementation. We added leads of the experimental dummy to test whether the CAPs affect air pollutant concentrations before implementation. Intuitively, the coefficient β^k measures the difference in air quality between cities with CAPs and otherwise in period k, which is related to the difference one week before implementing CAPs. If the CAPs can mitigate air pollution, β^k is less than 0 when $k \geq 0$. The underlying assumption is satisfied; β^k is close to 0 when $k \leq -2$.

2.1.3. Heterogeneity Analysis

The above regression results, based on all sample cities, may ignore the potential differences in the impact of CAPs on air quality in different cities. We therefore further analyzed the heterogeneous impact of the policies on air quality, along with differences in socio-economic status, such as gross domestic product (GDP), industrial output, population, traffic, pollutant emissions, and other variables. The heterogeneity analyses were used to verify that the impacts of CAPs are universal and to enhance the validity of the final results. We fitted the following equation:

$$Y_{it} = \alpha + \beta CAP_{it} + \sum_{h \in H} \delta_h \cdot CAP_{it} \cdot hetero_h + \gamma Met_{it} + \mu_i + \pi_t + \varepsilon_{it} \quad (4)$$

where $hetero_h$ indicates the h characteristics of cities, and $CAP_{it} \cdot hetero_h$ is an interaction term between the CAP status and $hetero_h$ of city i on day t. The rest of the explanations are the same as Equation (1). It is important to note that there is no causal explanation for heterogeneity analysis; we compared the δ_h across interaction terms to analyze the channels whereby CAPs affect air pollutant concentrations.

2.2. Data

2.2.1. Air Pollution

Air pollution is a serious problem affecting billions of people worldwide, and the World Health Organization defines it as the pollution of the indoor or outdoor environment by any chemical, physical, or biological agent that alters the natural properties of the atmosphere. It is a complex mixture of particulate matter, gases, organic compounds, and metals. The composite level is measured by indexes (i.e., the Air Pollution Index (API) and the Air Quality Index (AQI)). The AQI is an API-based improvement that better characterizes ambient air quality conditions. The AQI, a comprehensive Air Quality Index evaluation, is used by government agencies to communicate real-time and future air quality to the public. A lower AQI value means better air quality.

This study includes six kinds of air pollutants along with the AQI. These data are obtained from the general environmental monitoring station of the Ministry of Ecology and Environment in China [44]. The original datasets consist of hourly records of the AQI values and common air pollutants concentrations from 1599 monitoring stations (from 1 January 2020, out-of-service monitoring stations were removed), covering 337 cities at the prefecture level and above. The pollutant concentrations are all mass concentrations, measured by the continuous automated monitoring system. The minimum requirement for the validity of the hourly pollutant concentration average data is at least 45 min of sampling time per hour. All valid data are included in statistics and evaluation. Adverse data and human intervention monitoring evaluation results cannot be selectively discarded, and air quality monitoring was carried out in accordance with the requirements of normative documents such as the Ambient Air Quality Monitoring Specification (Trial) [45].

In order to obtain daily data on air quality at the municipal level, first, we calculated the 24 h average as the current day value. Second, we worked out the distances between a city's population center (the location of the city government) and all monitoring stations within the city through latitude and longitude (data source: Baidu Map and AutoNavi Map), respectively. Finally, we used inverse distance weights to transform the station-level data into prefecture-level data [40].

2.2.2. City Anti-Contagion Policy (CAP) Data

We collected the epidemic-prevention policies of local governments (policies related to epidemic prevention and control) province by province and city by city using news media and official government websites. There are other expressions in existing studies, such as lockdowns, partial lockdowns, shutdowns, restricted activities, traffic restrictions, and traffic-free urban areas. They all have similar meanings (i.e., travel restrictions). In this study, a city was included in the treatment group when the city published the CAPs in the early stage of COVID-19 prevention and control. Considering the availability and validity of the data, the research sample in this study included 249 prefecture-level cities, of which 47 cities were included in the treatment group and the rest belonged to the control group. The specific distribution of cities is shown in Figure 1. Cities in the treatment group began implementing policies at different times, from late January to mid-February (see Table A1), mainly on 24 January; 4 and 5 February are shown in Figure 2. The policies were lifted between the last week of March and the first week of the following month in most prefecture-level cities. Among the cities in the treatment group, Wuhan was the last city to lift the CAPs on 8 April, so we treated 7 April as the last day of the CAP implementation period.

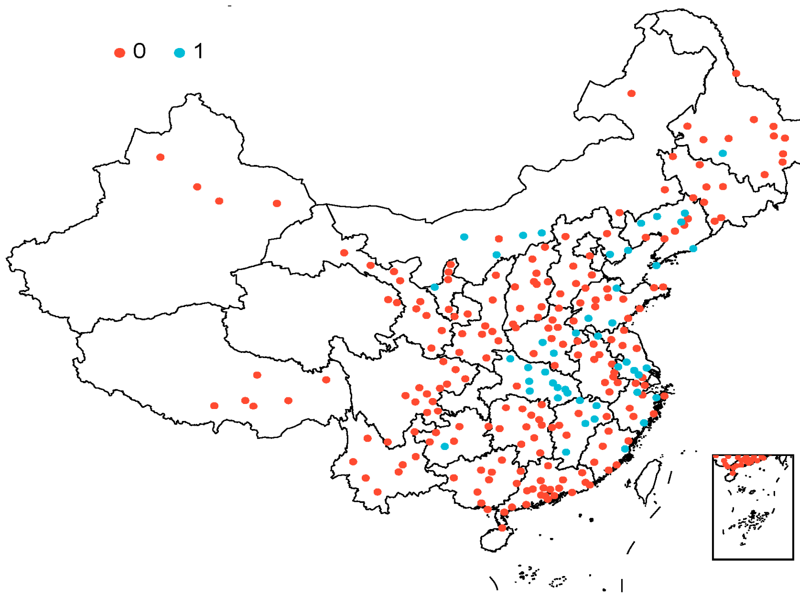

Figure 1. The distribution map of the sample cities. The value of 0 represents a city in the control group (202 cities), and 1 represents a city in the treatment group (47 cities).

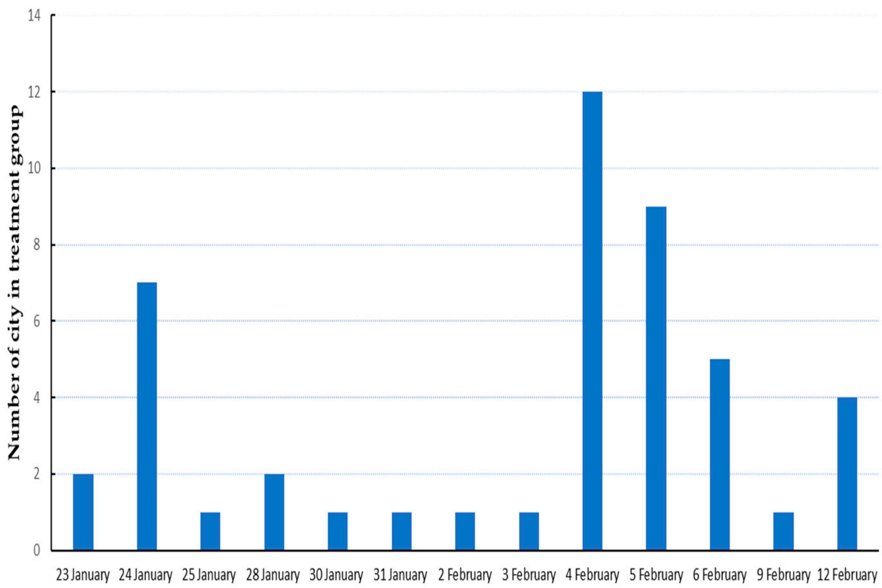

Figure 2. The start time of CAP implementation in the treatment group in 2020.

2.2.3. Meteorological Variables

We used relevant meteorological indicators (the atmospheric pressure (Pa), relative humidity (%), temperature (°C), wind speed (m/s), and sunshine duration (hour)) data recorded by the National Meteorological Information Center (NMIC) [46]. The NMIC is a public institution directly under the China Meteorological Administration, which integrates the Meteorological Data Center of the China Meteorological Administration, the National Meteorological Scientific Data Sharing Center, and the Global Information System Center of the World Meteorological Organization. The availability of the data is over 99.9%, and the accuracy rate is close to 100%. The original dataset consists of daily records from

2169 surface meteorological stations, covering 337 cities at the prefecture level and above. Since each prefecture-level city has multiple monitoring stations, the same method (i.e., the inverse distance weights) used for air quality measurement was used to determine the meteorological indicator data at the prefecture-level city.

2.2.4. Socio-Economic Status

The eleventh goal (i.e., make cities and human settlements inclusive, safe, resilient, and sustainable) of the Sustainable Development Goals (SDGs) includes 10 secondary objectives related to economic, social, cultural, and environmental aspects, and so on [47]. Sustainable cities and communities (indicators for city services and quality of life) (ISO 37120) includes 19 topics, such as the economy, energy, environment, health, wastewater, and so on [48]. New-type urbanization (an evaluation index system of city quality) (GB/T 39497-2020) includes five aspects: economic development, social culture, ecological environment, public services, and residents' lives [49].

The sources of air pollution can be divided into two main categories: natural factors (forest fires, volcanic eruptions, etc.) and human factors (such as industrial exhaust gases, domestic coal burning, and automobile exhaust gases). The latter is the main factor and is especially caused by industrial production and transportation. The CAPs restricted people's travel, but most industrial enterprises, such as urban housing construction and municipal infrastructure, began to resume work from 9 February to early March. Many industrial enterprises also operated normally during COVID-19 to ensure the normal life of residents, such as the heating system in Northern China's cities, so the level of industrialization of cities still affected the air quality in the region. In 2020, the number of motor vehicles reached 372 million in China, an increase of 6.9% over 2019 [50]. However, at the beginning of the year, due to the severe lockdown policy, the traffic of motor vehicles decreased significantly. The total emissions of the four pollutants (CO, hydrocarbon (HC), NOx, and PM from motor vehicles was 15.93 million tons, a decrease of only 0.69% compared with the previous year. In addition, the impact of emissions from non-road mobile sources (i.e., construction machinery, agricultural machinery, small general machinery, ships, aircraft, and railway locomotives) on air quality cannot be ignored, which emitted 163,000 tons of SO_2 (2.52%), 425,000 tons of HC (−2.30%), 4.782 million tons of NOx (−3.06%), and 237,000 tons of PM (−1.25%), NOx emissions were close to those of motor vehicles.

This study absorbed the connotations of the three evaluation systems, combined with the current sources of air pollution in China; we explored the socio-economic characteristics of cities from four dimensions, including the economy, population, environment, and infrastructure. Regional economic development was measured by GDP per capita (CNY); secondary industry as a percentage of GDP and the number of industrial enterprises; the population was measured by the registered household population at year-end (10,000 persons); the environment was measured by the volume of industrial wastewater discharged (10,000 tons), per capita emissions (t/person), and CO_2 emissions per GDP (t/104 RMB); infrastructure was measured by the number of buses and trolley buses under operation at year-end (unit), electricity consumption (10,000 kwh), and the central heating system. To explore the heterogeneity, we collected data from the "2020 China City Statistical Yearbook" [51], carbon emissions data from CEADS (Carbon Emission Accounts and Datasets) [52], and the "2020 China Population Census Yearbook" [53], which includes the most recent census data.

3. Results

3.1. The Short-Term Impact of CAPs

We estimated the short-term impact of CAPs on air quality using the Generalized DiD Model (Equation (1)); full results are shown in Table 1. During the implemented period, compared with control cities, we found that the policies implementation improved air quality. In rows (1) to (5) of Panel A, the AQI decreased by 8.398 (p = 0.066), and the concentrations of PM10, PM2.5, NO_2, and SO_2 dropped, respectively, by 8.884 $\mu g/m^3$

(p = 0.031), 6.951 μg/m^3 (p = 0.084), 3.345 μg/m^3 (p = 0.010), and 0.357 μg/m^3 (p = 0.736). The main content of the CAPs restricts people's travel, as well as transportation, so the associated air pollutants (particulate matter and NO_2) were significantly improved after implementing the policies. SO_2, although improved, was not significant. This is probably because industrial enterprises resumed work and production; according to related surveys, the resumption rate of large- and medium-sized manufacturing industries reached 85.6% as of the end of February. On the contrary, O_3 and CO increased, respectively, by 5.790 μg/m^3 (p = 0.000) and 0.001 mg/m^3 (p = 0.984). O_3 is formed by photochemical reactions of nitrogen oxides (NO_X) and hydrocarbons in the atmosphere when they are irradiated by the sun. The positive impact on O_3 was probably because of a lower concentration of NO_2, which resulted in constraints on the reaction of NO + O_3 [38], or was due to a minor NO concentration [10,14,17,18,27,32,35]. The CO concentration exhibited an insignificant minor increase. Although the short-term restrictions on transport travel can reduce CO emissions, the basic raw material industry and high-tech manufacturing industry maintained growth; for example, the output of medical protective consumables and daily necessities grew rapidly, with masks increasing by 127.5% and instant noodles increasing by 11.4%. It is likely that the above situation occurred due to the effects of both directions. In Panel B, including meteorological control variables, we obtained similar results, a slight difference in all the regression coefficients, but no change in significance, which reflects that the changes in air pollutant concentrations caused by CAPs are not strongly correlated with meteorological indicators [40].

Table 1. The short-term impact of CAPs on air quality.

	AQI	**PM2.5**	**PM10**	**SO_2**	**NO_2**	**O_3**	**CO**
(Panel A) short_t	−8.398 *	−6.951 *	−8.884 **	−0.357	−3.345 **	5.790 ***	0.001
	(4.541)	(4.000)	(4.087)	(1.059)	(1.291)	(1.054)	(0.048)
Observations	24,401	24,401	24,401	24,401	24,400	24,401	24,401
Adj R-squared	0.458	0.457	0.403	0.567	0.646	0.488	0.519
(Panel B) short_t	−7.557 *	−5.918 *	−8.723 **	−0.371	−3.295 ***	4.705 ***	0.010
	(4.073)	(3.382)	(3.781)	(0.850)	(0.954)	(0.879)	(0.039)
Meteorological control	Y	Y	Y	Y	Y	Y	Y
Observations	24,249	24,249	24,249	24,249	24,248	24,249	24,249
Adj R-squared	0.484	0.504	0.421	0.601	0.706	0.612	0.577
Number of cities	249	249	249	249	249	249	249
City fixed effects	Y	Y	Y	Y	Y	Y	Y
Date fixed effects	Y	Y	Y	Y	Y	Y	Y

Note: The above table can be divided into two parts (Panels A and B). The difference between the two parts is whether they include meteorological control variables. The meteorological control includes the atmospheric pressure, relative humidity, temperature, temp2 (temperature's square), wind speed, and sunshine duration. All the results of Panel B are detailed in Table A2. *** represents p < 0.01, ** represents p < 0.05, and * represents p < 0.1, applied to all of the following regression results.

We complemented the short-term impact results with testing for pre-treatment parallel trends. We adopted Equation (3) to analyze how the concentration of air pollutants between the experimental and control groups changed before and after the implementation of CAPs. We found that there was indeed a parallel trend in air pollutant concentration levels (except for O_3) in both groups of cities during the pre-treatment period (Figure 3 and Appendix A Table A8). For most outcome variables, we did not observe systematic pre-trends between the two groups before the CAPs; none of the estimation coefficients ($k \leq -2$) of the leading terms were statistically significant. The AQI decreased by about 15 percentage points in the two weeks following the CAPs' implementation, and in the subsequent periods, the results remained statistically significant. Figure 3B,C,E show similar results to Figure 3A. Detailed regressions results are shown in Appendix A Table A8.

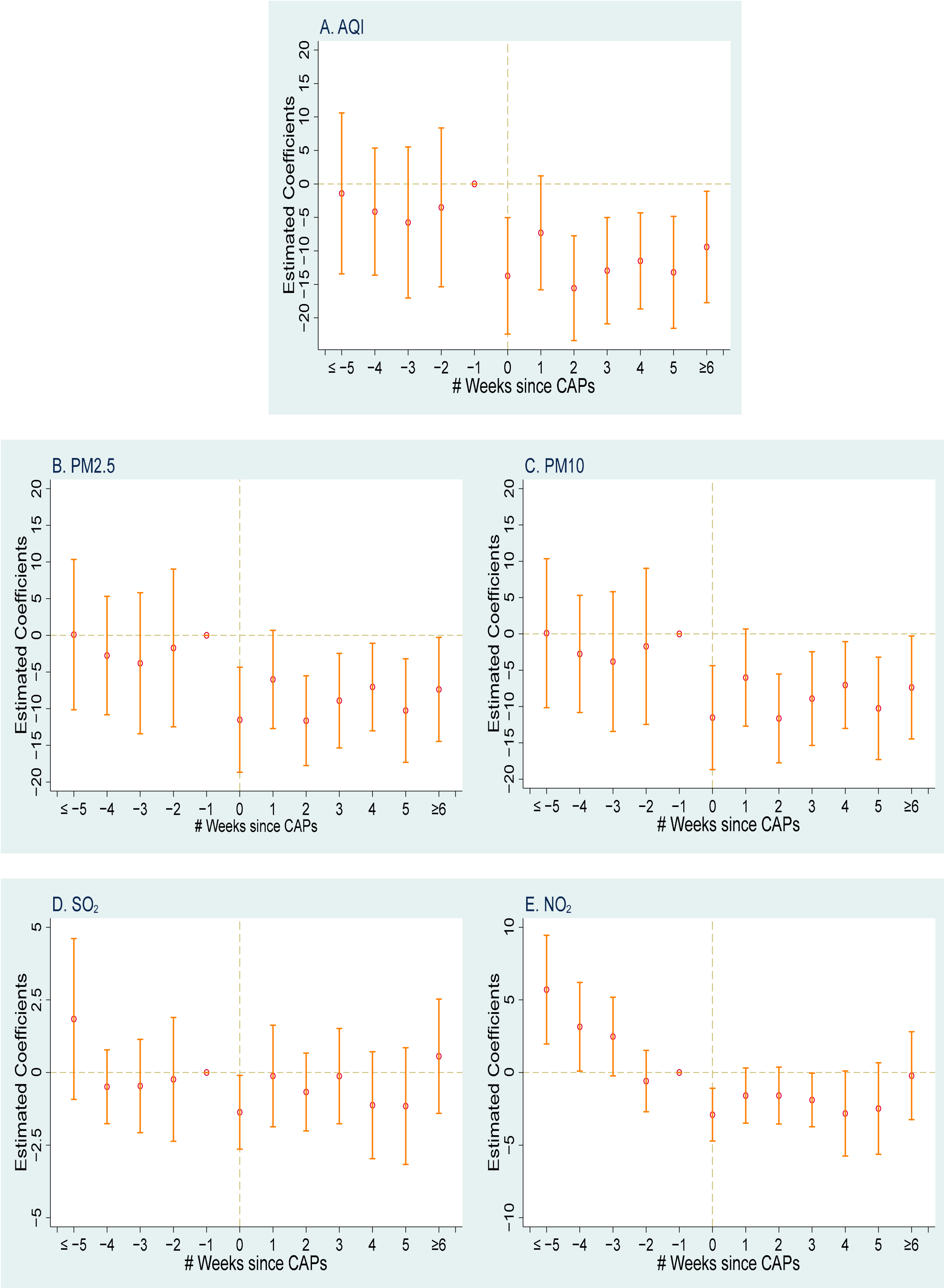

Figure 3. *Cont.*

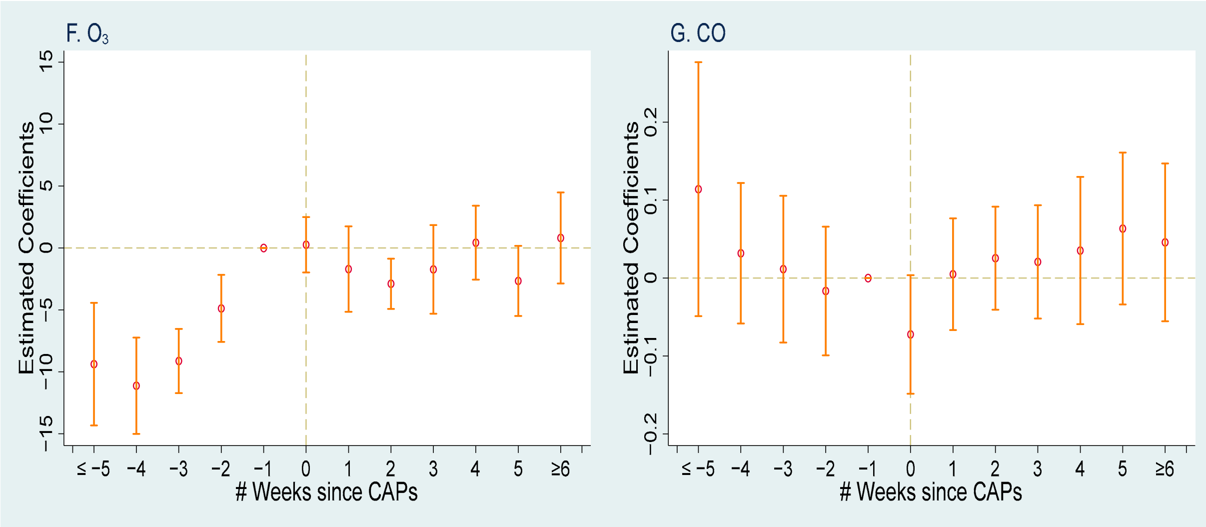

Figure 3. Event-study results. Separate regressions were performed for the AQI (Panel (**A**)) and air pollutants (Panels (**B**–**G**)) using the event-study method, illustrating the estimation coefficients and their 95% confidence intervals. The dotted longitudinal line represents the week in which CAPs were implemented. Meteorological control variables were included in regressions.

3.2. The Medium-Term Impacts of CAPs

There is continuity in the impact of policy implementation, even if they were lifted [1]; for example, the evolution of the urban form has long-term effects on PM2.5 [54]. When CAPs were loosened in China, although the epidemic was under control, previous habits were difficult to change in a short period of time. Given some unstable factors, most individuals still insisted on taking measures to protect themselves, such as avoiding unnecessary travel, and life and economic activities did not fully recover, especially in industries related to people gathering, such as tourism, catering, and entertainment. As a result, the short-term benefits of the CAPs are likely to persist for the first few months after the CAPs are canceled. Although the medium-term impacts align with the short-term impacts, they are insignificant (except for O_3) in the post-policy period. Compared to the estimates, the reduction in air quality became smaller when the policies were loosened (see Figure 4). The AQI was reduced by 5.281 ($p = 0.279$); the concentrations of PM2.5, PM10, SO_2, and NO_2 reduced, respectively, by 4.655 $\mu g/m^3$ ($p = 0.268$), 4.466 $\mu g/m^3$ ($p = 0.320$), 0.631 $\mu g/m^3$ ($p = 0.576$), and 1.932 $\mu g/m^3$ ($p = 0.136$); but O_3 and CO increased, respectively, by 8.50 $\mu g/m^3$ ($p = 0.000$), and 0.012 mg/m^3 ($p = 0.818$). Detailed regression results are shown in Appendix A Table A3. This situation is probably due to the rapid recovery of the industry after the CAPs were lifted, where industrial production turned from a decrease to an increase, and the growth rate of the manufacturing industry rebounded significantly in April 2020. Simultaneously, there was a major shift in how humans traveled, from public transport to private cars, and the pandemic encouraged travelers to avoid public transport, thus exacerbating air pollution [55].

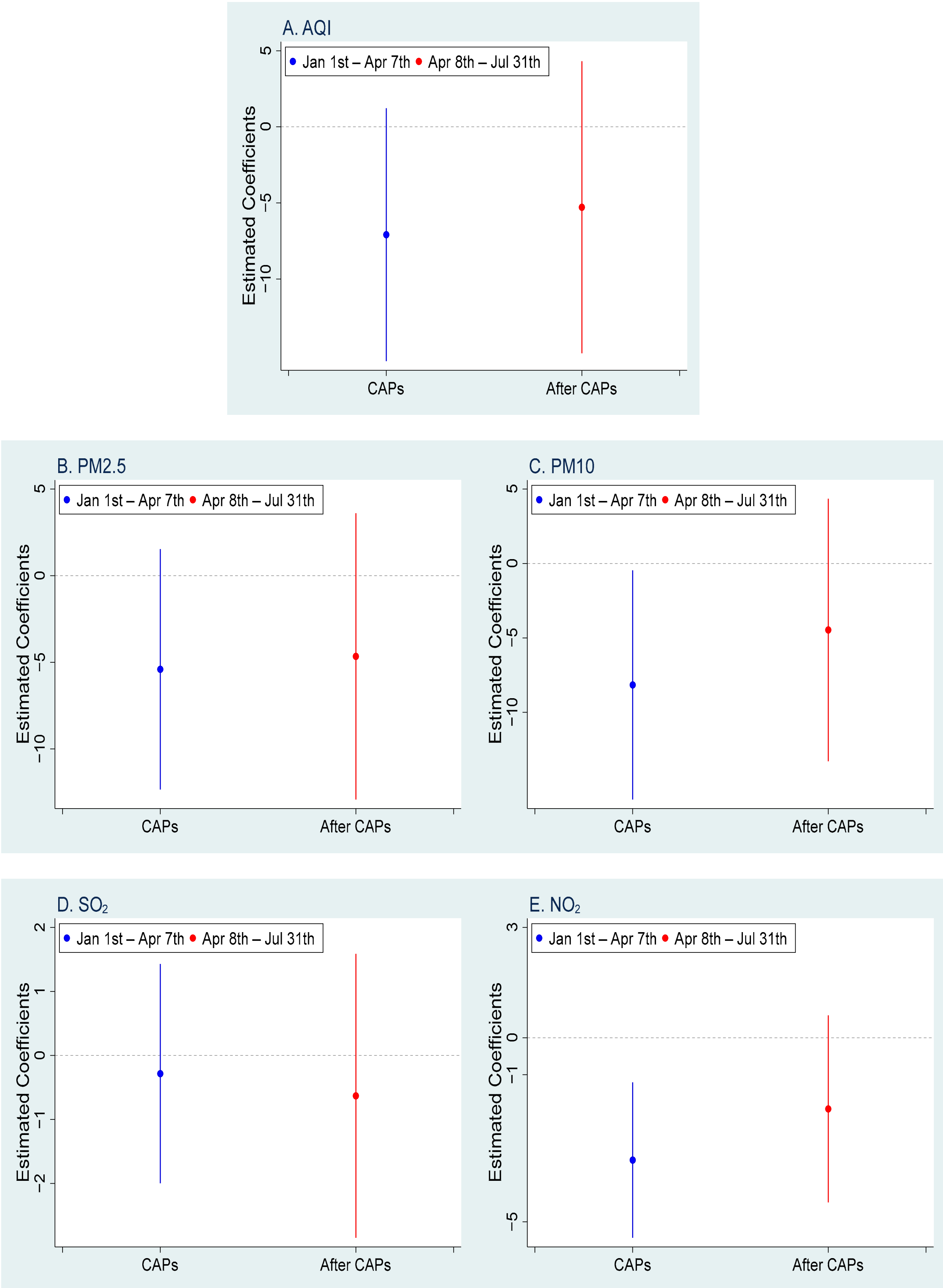

Figure 4. *Cont.*

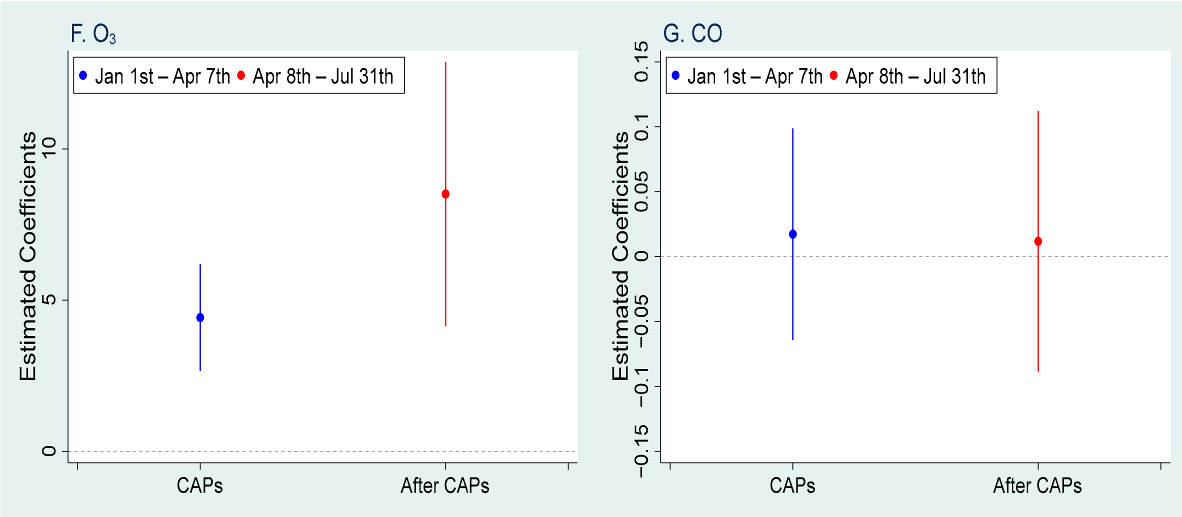

Figure 4. The impacts of CAPs on air quality. Separate regressions were performed for the AQI (Panel (**A**)) and air pollutants (Panels (**B**–**G**)) using Equation (2), illustrating the estimation coefficients and their 95% confidence intervals for the short-term (blue) and medium-term effects (red). Meteorological control variables were included in regressions.

3.3. Heterogeneity

In Figure 5, we measured the heterogeneity effect of the CAPs' implementation on air quality across the different types of cities (Equation (4)). For each pair of heterogeneity analysis, we divided all cities into two groups using the mean of the corresponding indicator, with those above the average being assigned to the high group (H) and the rest to the low group (L), except for the central heating system (0 indicates no, 1 indicates yes). The reference data of this classification are based on the values of various indicators released by the government in 2019 (except for the population). The Chinese government conducted its seventh population census in 2020, so the population data are the latest from this census.

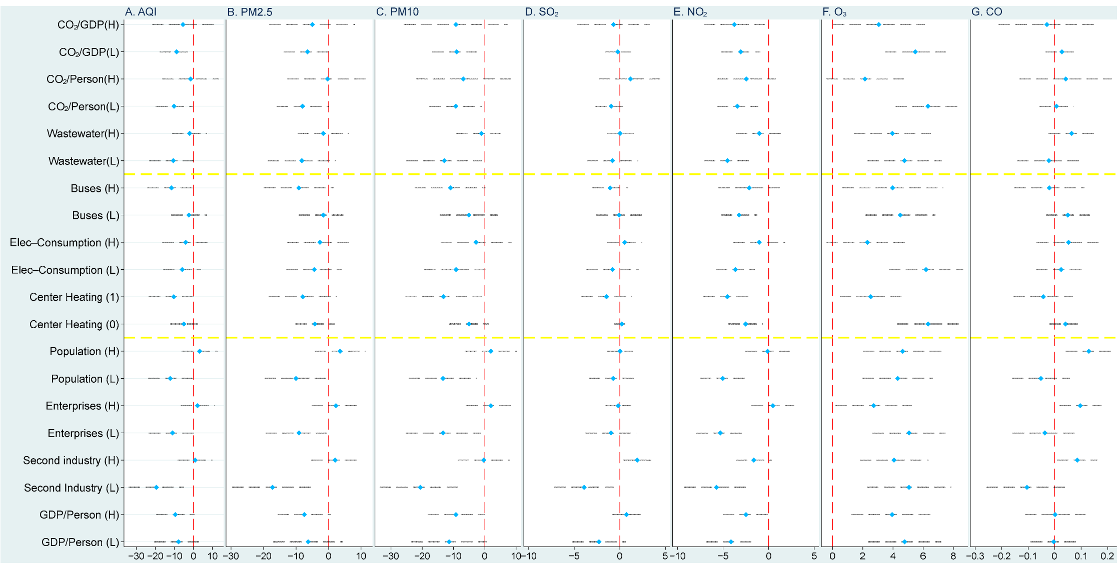

Figure 5. The heterogeneous impacts of CAPs on air quality illustrating the estimation coefficients (blue diamonds) and their 95% confidence intervals (dashed grey lines). Using a corresponding subsample, each row of (**A**–**G**) corresponds to a separate regression. The yellow horizontal dotted lines divide the heterogeneity analysis into three sections (from bottom to top): regional economic development, population, infrastructure, and environment. Meteorological control variables were included in regressions.

In the two classifications at the bottom of Figure 5, we examined the impact heterogeneity concerning regional economic development and population. This figure shows that the effect is bigger in cities with a lower GDP per capita, lower secondary industry as a percentage and number of industrial enterprises, and a lower population. With increasing industrial activities, the effect is less substantial, probably because industrial production declined while the production of important materials maintained growth. After 2 February 2020, work and production resumed. At the same time, investment in anti-epidemic related industries, such as the manufacturing of biological and pharmaceutical products, maintained growth, and the construction of key epidemic prevention projects was rapidly promoted. In order to maintain the normal order of life and production, the energy consumption in cities with a large population was still huge, which led to this situation. In the top section of Figure 5, we analyze the impacts of cities with different environmental conditions. We obtained similar results, where the larger impact was on the cities with lower carbon emissions and industrial wastewater discharged.

In the middle section of Figure 5 (the third classification), we compare the heterogeneity impacts of cities with different infrastructures. The impact of CAPs is greater in cities with a central heating system and more buses. During the implementation of CAP periods, cities with this heating system entered the heating season, which is mainly divided into the "extended heating season" implemented in individual areas (starting in mid-October and ending in mid-April of the following year) and the "standard heating season" implemented in most areas (which starts in mid-November and ends in mid-March of the following year). People rarely visited public places, such as schools, workplaces, and large shopping malls. The heating in these places was completely turned off, which reduced coal consumption. At the same time, there was no change in the number of dwellings with central heating in winter because heating companies in various cities must keep the system up and running during the heating season. The policies focused on restricting people's mobility, so the impact on cities with large passenger volumes was greater.

3.4. Robustness Check

In order to ensure the robustness of the benchmark regression results, we performed two robustness tests. First, in China, the first case of the new coronavirus infection appeared in Hubei Province and then spread to neighboring provinces centered on Hubei Province, which implemented the strictest and longest-lasting CAPs, so we excluded cities in Hubei Province. As reported in Table 2, compared with Tables 1 and A3, both short-term and medium-term effects were similar, proving that the results of this study are not driven by these cities in Hubei. Second, reduced air pollution in experimental groups may affect the air quality of neighboring cities due to the influence of meteorological control variables, leading to an underestimation of the treatment effect. In order to solve the spatial spillover effect, we removed the control group cities adjacent to the experimental group cities, which could be compared with a group of "clean" control cities. As reported in Table 3, compared with Tables 1 and A3, which confirms our conjectures that the impacts of CAPs were underestimated by the spillover issues. For example, in Panel E, the AQI decreased by 10.312 (p = 0.015), and the concentrations of PM10, PM2.5, NO_2, and SO_2 dropped, respectively, by 11.365 $\mu g/m^3$ (p = 0.005), 8.236 $\mu g/m^3$ (p = 0.019), 3.982 $\mu g/m^3$ (p = 0.000), and 0.665 $\mu g/m^3$ (p = 0.452). The effect on CO can be positive to negative, but the effect is still not significant (p = 0.765). In Panel F, in the medium term, the AQI decreased by 6.672 (p = 0.193); the concentrations of PM10, PM2.5, NO_2, SO_2, and CO dropped, respectively, by 5.563 $\mu g/m^3$ (p = 0.243), 5.894 $\mu g/m^3$ (p = 0.181), 2.596 $\mu g/m^3$ (p = 0.057), 0.981 $\mu g/m^3$ (p = 0.399), and 0.003 mg/m^3 (p = 0.984); only the medium-term effects of NO_2 became significant; and the effects of other air pollutants remained insignificant. We found similar results, showing that this spatial spillover effect is small.

Table 2. The impact of CAPs on air quality (drop cities in Hubei Province).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
(Panel C) short_t	−8.151 *	−6.623 *	−10.009 **	−1.132	−3.232 ***	3.991 ***	−0.029
	(4.766)	(3.951)	(4.447)	(0.969)	(1.120)	(0.949)	(0.042)
Observations	23,173	23,173	23,173	23,173	23,172	23,173	23,173
Adj R-squared	0.484	0.504	0.420	0.602	0.705	0.612	0.583
(Panel D) short_t	−8.288 *	−6.616	−10.102 **	−1.047	−3.287 ***	3.692 ***	−0.022
	(4.885)	(4.066)	(4.525)	(0.971)	(1.240)	(0.978)	(0.045)
medium_t	−4.127	−4.135	−4.404	−1.401	−2.462	9.247 ***	−0.003
	(5.503)	(4.770)	(5.143)	(1.284)	(1.502)	(2.556)	(0.059)
Observations	48,333	48,335	48,335	48,335	48,332	48,335	48,335
Adj R-squared	0.480	0.467	0.381	0.520	0.657	0.555	0.567
Number of cities	238	238	238	238	238	238	238
Meteorological control	Y	Y	Y	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y	Y	Y	Y
Date fixed effects	Y	Y	Y	Y	Y	Y	Y

Note: The above table can be divided into two parts (Panels C and D). Panel C shows the impact (excluding cities in Hubei) using Equation (1). Panel D reflects the impacts (excluding cities in Hubei) using Equation (2). The meteorological control includes the atmospheric pressure, relative humidity, temperature, temp2 (temperature's square), wind speed, and sunshine duration. Detailed regression results are shown in Tables A4 and A5. *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

Table 3. The impact of CAPs on air quality (drop cities neighboring treatment cities).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
(Panel E) short_t	−10.312 **	−8.236 **	−11.365 ***	−0.665	−3.982 ***	5.928 ***	−0.012
	(4.211)	(3.485)	(3.975)	(0.882)	(0.994)	(0.948)	(0.040)
Observations	19,897	19,897	19,897	19,897	19,896	19,897	19,897
Adj R-squared	0.478	0.504	0.407	0.594	0.705	0.614	0.578
(Panel F) short_t	−9.739 **	−7.584 **	−10.683 ***	−0.536	−3.953 ***	5.536 ***	−0.003
	(4.352)	(3.624)	(4.086)	(0.896)	(1.110)	(0.964)	(0.042)
medium_t	−6.672	−5.894	−5.563	−0.981	−2.596 *	10.461 ***	−0.001
	(5.105)	(4.393)	(4.747)	(1.161)	(1.354)	(2.345)	(0.053)
Observations	42,069	42,070	42,070	42,070	42,069	42,070	42,070
Adj R-squared	0.471	0.463	0.367	0.509	0.660	0.552	0.566
Number of cities	204	204	204	204	204	204	204
Meteorological control	Y	Y	Y	Y	Y	Y	Y
City fixed effects	Y	Y	Y	Y	Y	Y	Y
Date fixed effects	Y	Y	Y	Y	Y	Y	Y

Note: The above table can be divided into two parts (Panels E and F). Panel E shows the impact (dropping the neighboring cities of treatment cities) using Equation (1). Panel F reflects the impacts (dropping the neighboring cities of treatment cities) using Equation (2). The meteorological control includes the atmospheric pressure, relative humidity, temperature, temp2 (temperature's square), wind speed, and sunshine duration. Detailed regression results are shown in Tables A6 and A7. *** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

4. Discussion

In this study, we examined the impact of the CAP implementation in prefecture-level cities in China on air quality in early 2020. Our study shows that CAPs create short-term benefits for air quality, and although they have a medium-term effect, this benefit is not significant; even though spatial spillovers are excluded, they only have a medium-term significant effect on NO_2 concentrations. The concentration of O_3 did not improve during the implementation of the policies and in the short term after they were lifted but became more severe instead, and the impact in the medium term was even greater than the impact of the short-term content. Next, we discuss our findings in depth.

First, our findings suggest that CAPs in China inadvertently create considerable environmental benefits. The treatment cities substantially improved the air quality, which led to greater health benefits, which is an important part of assessing the benefits of such policies. Our findings provide a benchmark for understanding the wider consequences of the CAPs.

Second, while the treatment cities featured drastically reduced air pollutant concentrations during the CAP implementation period, the impacts were not significantly long-lasting after the policies were lifted. In addition, the heterogeneity analysis reflects that the CAPs' impact on air quality is smaller in cities with a higher income, larger population, secondary sector activities, and buses, without central heating systems. Combined with a cost–benefit analysis, the high economic costs of such policies make them unsustainable options for tackling pollution problems.

Finally, different policies should be adopted for different air pollutants, but at the same time, the interaction between different pollutants should be considered. The O_3 concentration was unaffected by the policies; whether there is a policy in place or not, this concentration is more due to meteorological and climatic conditions. According to the parallel trend test, the effect was significant before the intervention but not after the intervention (see Figure 3F and Table A8), and the effect in the medium term was significantly greater than the impact in the short term. This is probably because this difference in O_3 concentrations between the two groups of cities before the intervention already existed, and the effect of policy interventions or changes during the CPAs' implementation was due not to the intervention but to seasons [30]. The total emissions of anthropogenic sources, natural sources of VOCs, and NOx in China were all above 2100×10^4 t, representing the main internal cause of O_3 pollution in China [56]. The results show that the generation of secondary pollutants (e.g., O_3) is affected by many factors [34]. Although the CAPs have more of a short-term impact on the environment, they are not without merit and once again proved that environmental governance is a comprehensive project, not just the treatment of specific pollutants.

Finally, we summarized some limitations of the study. First, data related to air quality and climate indicators at the smaller regional level (such as counties) are not available for the time being in China, and the impact cannot be more accurately measured because the policies in the later stage of the pandemic were specific to a town or even a small district. Second, the implementation time of the policy is based on the relevant policy documents issued by the government. Still, the relevant measures had been implemented sometime before the policy was promulgated. How to define the timing and extent of the implementation of the policies is a difficult point in research. Follow-up studies can quantify the extent of lockdowns by adding new cases every day and define the strictness of the policies according to the variables of new cases in the city because cities with a larger number of COVID-19 cases are more likely to enforce the APs [1]. For example, from the day a case of infection is discovered, the city will be closed and quarantined for 7 days, and if there are no new local cases within 7 days, it will slowly return to normal. Third, we focused on changes in air quality, and further research could expand the scope of the study, for example, measuring the changes in water quality during the special period. Finally, the scope of our study is limited to one country, similar to the currently existing research, and future research comparing the differences between countries or regions with different development models and atmospheric environmental conditions is necessary.

5. Conclusions

To improve COVID-19 prevention and control, we studied the externality of city anti-contagion policies (CAPs) and measured their impact on air pollutant concentrations. This study's contribution is that it measured not only the short-term (during the CAPs' implementation, 1 January to 7 April 2020) impact but also the medium-term (post-CAP implementation, 8 April to 31 July 2020) impact. We found that during the implementation period, air quality was improved significantly, but after the policies were lifted, the effect was insignificant. The impact of such policies on quality is not sustainable. In addition, in the short term, while the concentrations of most air pollutants (i.e., PM2.5, PM10, and NO_2) decreased significantly, there were still pollutant concentrations (i.e., O_3) that were on the rise. At the same time, these impacts also varied between different types of cities. Our findings show that such policies can only alleviate air pollution in the short term; the impact of such policies is not continuous. Urban air quality management is a complex project, and the formulation of policies should fully consider the types of pollutants and the related cities' characteristics.

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Data Availability Statement: The data presented in this study are available on request from the corresponding authors.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The start time of CAPs' implementation.

City	Province	CAPs	City	Province	CAPs
Fuzhou	Fujian	6 February 2020	Fuzhou	Jiangxi	4 February 2020
Anshun	Guizhou	5 February 2020	Jingdezhen	Jiangxi	4 February 2020
Qinhuangdao	Hebei	25 January 2020	Ganzhou	Jiangxi	6 February 2020
Tangshan	Hebei	28 January 2020	Jiujiang	Jiangxi	6 February 2020
Zhengzhou	Henan	4 February 2020	Yingtan	Jiangxi	6 February 2020
Zhumadian	Henan	4 February 2020	Chaoyang	Liaoning	5 February 2020
Xinyang	Henan	6 February 2020	Dalian	Liaoning	5 February 2020
Harbin	Heilongjiang	4 February 2020	Dandong	Liaoning	5 February 2020
Huanggang	Hubei	23 January 2020	Fushun	Liaoning	5 February 2020
Wuhan	Hubei	23 January 2020	Fuxin	Liaoning	5 February 2020
Huangshi	Hubei	24 January 2020	Shenyang	Liaoning	5 February 2020
Jingmen	Hubei	24 January 2020	Tieling	Liaoning	5 February 2020
Jingzhou	Hubei	24 January 2020	Bayannur	Inner Mongolia	12 February 2020
Shiyan	Hubei	24 January 2020	Ordos	Inner Mongolia	12 February 2020
Xianning	Hubei	24 January 2020	Hohhot	Inner Monglia	12 February 2020
Xiaogan	Hubei	24 January 2020	Ulanqab	Inner Mongolia	12 February 2020
Yichang	Hubei	24 January 2020	Yinchuan	Ningxia	31 January 2020
Xiangyang	Hubei	28 January 2020	Dongying	Shandong	30 January 2020
Changzhou	Jiangsu	4 February 2020	Jining	Shandong	3 February 2020
Nanjing	Jiangsu	4 February 2020	Linyi	Shandong	4 February 2020
Nantong	Jiangsu	4 February 2020	Wenzhou	Zhejiang	4 February 2020
Xuzhou	Jiangsu	4 February 2020	Hangzhou	Zhejiang	4 February 2020
Yangzhou	Jiangsu	5 February 2020	Ningbo	Zhejiang	4 February 2020
Wuxi	Jiangsu	9 February 2020			

Table A2. The short-term impact of CAPs on air quality (includes meteorological control variables).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
short_t	−7.557 *	−5.918 *	−8.723 **	−0.371	−3.295 ***	4.705 ***	0.010
	(4.073)	(3.382)	(3.781)	(0.850)	(0.954)	(0.879)	(0.039)
wind	−3.813 ***	−4.111 ***	−3.336 ***	−0.975 ***	−3.165 ***	2.940 ***	−0.047 ***
	(0.393)	(0.341)	(0.432)	(0.102)	(0.159)	(0.258)	(0.005)
airpressure	0.782 ***	0.552 ***	0.696 ***	−0.159 ***	−0.252 ***	0.780 ***	−0.009 ***
	(0.155)	(0.136)	(0.160)	(0.041)	(0.053)	(0.088)	(0.002)
temperature	0.669 ***	0.462 ***	0.692 ***	−0.278 ***	−0.271 ***	1.119 ***	−0.008 ***
	(0.180)	(0.158)	(0.203)	(0.049)	(0.064)	(0.100)	(0.003)
temper2	0.053 ***	0.0435 ***	0.0639 ***	0.014 ***	0.020 ***	0.021 ***	0.0003 ***
	(0.008)	(0.007)	(0.008)	(0.002)	(0.002)	(0.003)	(8.04×10^{-5})
humidity	0.216 ***	0.371 ***	−0.122	−0.030 ***	0.008	−0.161 ***	0.005 ***
	(0.063)	(0.048)	(0.096)	(0.008)	(0.013)	(0.024)	(0.0005)
sunduration	−0.725 ***	−0.454 ***	−1.088 ***	0.020	−0.023	0.938 ***	0.0004
	(0.161)	(0.118)	(0.293)	(0.026)	(0.037)	(0.06)	(0.0014)
Observations	24,249	24,249	24,249	24,249	24,248	24,249	24,249
Adj R-squared	0.484	0.504	0.421	0.601	0.706	0.612	0.577
Number of cities	249	249	249	249	249	249	249
City fixed effects	Y	Y	Y	Y	Y	Y	Y
Date fixed effects	Y	Y	Y	Y	Y	Y	Y

*** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

Table A3. The short-term and medium-term impacts of CAPs on air quality.

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
(Panel C) short_t	−8.192 *	−6.874 *	−8.808 **	−0.570	−3.675 ***	6.105 ***	0.001
	(4.681)	(4.132)	(4.222)	(1.085)	(1.342)	(1.157)	(0.050)
medium_t	−6.727	−6.368	−5.782	−0.666	−2.259	11.109 ***	0.002
	(5.401)	(4.862)	(4.826)	(1.444)	(1.560)	(2.500)	(0.060)
Observations	53,029	53,031	53,031	53,031	53,028	53,031	53,031
Adj R-squared	0.447	0.426	0.360	0.461	0.599	0.452	0.510
(Panel D) short_t	−7.086 *	−5.403	−8.158 **	−0.284	−3.323 ***	4.424 ***	0.017
	(4.219)	(3.524)	(3.910)	(0.870)	(1.073)	(0.898)	(0.041)
medium_t	−5.281	−4.655	−4.466	−0.631	−1.932	8.509 ***	0.012
	(4.873)	(4.194)	(4.480)	(1.126)	(1.291)	(2.218)	(0.051)
wind	−2.180 ***	−2.742 ***	−1.733 ***	−0.772 ***	−3.049 ***	2.245 ***	−0.039 ***
	(0.281)	(0.233)	(0.369)	(0.088)	(0.153)	(0.277)	(0.003)
airpressure	0.934 ***	0.755 ***	0.901 ***	−0.037	0.069	0.283 ***	−0.003 **
	(0.128)	(0.117)	(0.133)	(0.042)	(0.044)	(0.097)	(0.001)
temperature	0.081	−0.067	0.085	−0.358 ***	−0.138 ***	1.345 ***	−0.007 ***
	(0.152)	(0.132)	(0.167)	(0.047)	(0.051)	(0.153)	(0.002)
temper2	0.052 ***	0.041 ***	0.054 ***	0.012 ***	0.013 ***	0.036 ***	0.0004 ***
	(0.006)	(0.005)	(0.007)	(0.002)	(0.002)	(0.004)	(6.98×10^{-5})
humidity	0.038	0.207 ***	−0.247 ***	−0.036 ***	−0.021 *	−0.054	0.004 ***
	(0.040)	(0.033)	(0.061)	(0.009)	(0.012)	(0.034)	(0.0004)
sunduration	−0.496 ***	−0.415 ***	−0.965 ***	−0.007	−0.060 *	0.679 ***	−0.0004
	(0.106)	(0.087)	(0.202)	(0.023)	(0.032)	(0.097)	(0.001)
Observations	50,671	50,673	50,673	50,673	50,670	50,673	50,673
Adj R-squared	0.481	0.469	0.384	0.519	0.658	0.558	0.566
Number of cities	249	249	249	249	249	249	249
City fixed effects	Y	Y	Y	Y	Y	Y	Y
Date fixed effects	Y	Y	Y	Y	Y	Y	Y

*** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

Table A4. The robustness check (drop cities in Hubei Province) (1).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
short_t	−8.151 *	−6.623 *	−10.01 **	−1.132	−3.232 ***	3.991 ***	−0.0285
	(4.766)	(3.951)	(4.447)	(0.969)	(1.120)	(0.949)	(0.0423)
wind2	−3.847 ***	−4.162 ***	−3.371 ***	−0.990 ***	−3.223 ***	2.973 ***	−0.0470 ***
	(0.410)	(0.356)	(0.449)	(0.106)	(0.166)	(0.268)	(0.005)
airpressure	0.766 ***	0.546 ***	0.656 ***	−0.163 ***	−0.266 ***	0.769 ***	−0.008 ***
	(0.158)	(0.139)	(0.161)	(0.0413)	(0.0541)	(0.0897)	(0.002)
temperature	0.609 ***	0.416 ***	0.627 ***	−0.285 ***	−0.280 ***	1.118 ***	−0.009 ***
	(0.180)	(0.157)	(0.204)	(0.0494)	(0.0649)	(0.102)	(0.003)
temper2	0.0527 ***	0.0427 ***	0.0631 ***	0.0137 ***	0.0207 ***	0.0196 ***	0.0002 ***
	(0.00783)	(0.00687)	(0.00753)	(0.00196)	(0.00214)	(0.00302)	(8.03×10^{-5})
humidity	0.219 ***	0.375 ***	−0.123	−0.0321 ***	0.00790	−0.154 ***	0.005 ***
	(0.0641)	(0.0483)	(0.0981)	(0.00854)	(0.0127)	(0.0240)	(0.0005)
sunduration	−0.745 ***	−0.469 ***	−1.125 ***	0.00827	−0.0178	0.941 ***	−0.0001
	(0.168)	(0.123)	(0.308)	(0.0270)	(0.0390)	(0.0652)	(0.002)
Observations	23,173	23,173	23,173	23,173	23,172	23,173	23,173
Adj R-squared	0.492	0.511	0.428	0.608	0.709	0.617	0.589

*** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

Table A5. The robustness check (drop cities in Hubei Province) (2).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
short_t	−8.288 *	−6.616	−10.10 **	−1.047	−3.287 ***	3.692 ***	−0.022
	(4.885)	(4.066)	(4.525)	(0.971)	(1.240)	(0.978)	(0.045)
medium_t	−4.127	−4.135	−4.404	−1.401	−2.462	9.247 ***	−0.003
	(5.503)	(4.770)	(5.143)	(1.284)	(1.502)	(2.556)	(0.059)
wind2	−2.225 ***	−2.798 ***	−1.754 ***	−0.781 ***	−3.071 ***	2.253 ***	−0.039 ***
	(0.289)	(0.239)	(0.382)	(0.0901)	(0.159)	(0.287)	(0.003)
airpressure	0.916 ***	0.743 ***	0.877 ***	−0.0427	0.0687	0.266 ***	−0.003 **
	(0.130)	(0.118)	(0.135)	(0.0421)	(0.0450)	(0.0982)	(0.001)
temperature	0.0333	−0.107	0.0418	−0.362 ***	−0.136 ***	1.343 ***	−0.007 ***
	(0.153)	(0.133)	(0.170)	(0.0475)	(0.0519)	(0.155)	(0.002)
temper2	0.0521 ***	0.0408 ***	0.0533 ***	0.0115 ***	0.0130 ***	0.0368 ***	0.0004 ***
	(0.00613)	(0.00514)	(0.00743)	(0.00162)	(0.00152)	(0.00359)	(7.11×10^{-5})
humidity	0.0367	0.205 ***	−0.249 ***	−0.0378 ***	−0.0191	−0.0478	0.004 ***
	(0.0410)	(0.0340)	(0.0625)	(0.00919)	(0.0123)	(0.0348)	(0.0004)
sunduration	−0.509 ***	−0.428 ***	−0.985 ***	−0.00965	−0.0487	0.663 ***	−0.0005
	(0.112)	(0.0904)	(0.212)	(0.0238)	(0.0327)	(0.101)	(0.001)
Observations	48,333	48,335	48,335	48,335	48,332	48,335	48,335
Adj R-squared	0.484	0.472	0.387	0.525	0.660	0.559	0.571

*** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

Table A6. The robustness check (drop cities neighboring lockdown cities) (1).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
short_t	−10.31 **	−8.236 **	−11.36 ***	−0.665	−3.982 ***	5.928 ***	−0.012
	(4.211)	(3.485)	(3.975)	(0.882)	(0.994)	(0.948)	(0.040)
wind2	−3.855 ***	−4.165 ***	−3.210 ***	−0.897 ***	−3.116 ***	3.064 ***	−0.046 ***
	(0.431)	(0.339)	(0.490)	(0.0989)	(0.170)	(0.268)	(0.004)
airpressure	0.649 ***	0.421 ***	0.609 ***	−0.169 ***	−0.289 ***	0.848 ***	−0.009 ***
	(0.173)	(0.151)	(0.183)	(0.0431)	(0.0573)	(0.104)	(0.002)
temperature	0.745 ***	0.494 ***	0.774 ***	−0.276 ***	−0.258 ***	1.130 ***	−0.008 ***
	(0.182)	(0.159)	(0.219)	(0.0527)	(0.0686)	(0.114)	(0.003)
temper2	0.0456 ***	0.0380 ***	0.0564 ***	0.0135 ***	0.0185 ***	0.0231 ***	0.0002 ***
	(0.00754)	(0.00660)	(0.00770)	(0.00221)	(0.00221)	(0.00354)	(8.16×10^{-5})
humidity	0.175 **	0.335 ***	−0.169	−0.0298 ***	0.00164	−0.154 ***	0.005 ***

Table A6. *Cont.*

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
	(0.0698)	(0.0521)	(0.109)	(0.00909)	(0.0131)	(0.0271)	(0.0005)
sunduration	−0.880 ***	−0.565 ***	−1.319 ***	0.00975	−0.0333	0.979 ***	−0.001
	(0.181)	(0.129)	(0.343)	(0.0300)	(0.0396)	(0.0716)	(0.002)
Constant	−563.1 ***	−377.3 **	−503.4 ***	178.0 ***	308.6 ***	−771.3 ***	9.709 ***
	(167.9)	(147.0)	(173.1)	(41.60)	(55.72)	(100.8)	(1.760)
Observations	19,897	19,897	19,897	19,897	19,896	19,897	19,897
Adj R-squared	0.486	0.511	0.416	0.600	0.710	0.620	0.584

*** represents $p < 0.01$, ** represents $p < 0.05$, applied to all of the following regression results.

Table A7. The robustness check (drop cities neighboring lockdown cities) (2).

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
short_t	−9.739 **	−7.584 **	−10.68 ***	−0.536	−3.953 ***	5.536 ***	−0.003
	(4.352)	(3.624)	(4.086)	(0.896)	(1.110)	(0.964)	(0.042)
medium_t	−6.672	−5.894	−5.563	−0.981	−2.596 *	10.46 ***	−0.001
	(5.105)	(4.393)	(4.747)	(1.161)	(1.354)	(2.345)	(0.053)
wind2	−2.060 ***	−2.641 ***	−1.463 ***	−0.746 ***	−3.006 ***	2.235 ***	−0.038 ***
	(0.320)	(0.248)	(0.419)	(0.0933)	(0.169)	(0.293)	(0.003)
airpressure	0.915 ***	0.734 ***	0.895 ***	−0.0435	0.0528	0.394 ***	−0.003 **
	(0.145)	(0.132)	(0.151)	(0.0455)	(0.0490)	(0.104)	(0.002)
temperature	0.182	−0.000457	0.140	−0.364 ***	−0.108 **	1.434 ***	−0.007 ***
	(0.158)	(0.140)	(0.177)	(0.0516)	(0.0520)	(0.168)	(0.002)
temper2	0.0445 ***	0.0360 ***	0.0453 ***	0.0117 ***	0.0117 ***	0.0352 ***	0.0003 ***
	(0.00626)	(0.00529)	(0.00801)	(0.00183)	(0.00158)	(0.00380)	(7.57×10^{-5})
humidity	0.0192	0.193 ***	−0.267 ***	−0.0374 ***	−0.0203 *	−0.0462	0.004 ***
	(0.0424)	(0.0336)	(0.0684)	(0.00876)	(0.0117)	(0.0373)	(0.0004)
sunduration	−0.547 ***	−0.454 ***	−1.071 ***	−0.0171	−0.0661 **	0.667 ***	−0.0013
	(0.117)	(0.0911)	(0.235)	(0.0245)	(0.0323)	(0.105)	(0.0011)
Constant	−827.1 ***	−682.8 ***	−786.0 ***	57.48	−21.21	−350.8 ***	3.879 **
	(140.1)	(127.5)	(142.3)	(44.00)	(47.36)	(101.4)	(1.531)
Observations	42,069	42,070	42,070	42,070	42,069	42,070	42,070
Adj R-squared	0.476	0.468	0.373	0.514	0.664	0.556	0.570

*** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

Table A8. The event-study estimation results.

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
Lead_D5	−5.549	−4.570	−3.712	1.020	4.249 **	−8.092 ***	0.062
	(5.958)	(5.051)	(5.782)	(1.327)	(1.719)	(2.100)	(0.074)
Lead_D4	−5.732	−4.660	−3.154	−0.780	2.489 *	−8.857 ***	0.007
	(4.392)	(3.680)	(4.301)	(0.591)	(1.430)	(1.674)	(0.042)
Lead_D3	−7.197	−5.746	−4.724	−0.551	1.871	−6.721 ***	−0.014
	(5.459)	(4.615)	(5.371)	(0.743)	(1.271)	(1.245)	(0.045)
Lead_D2	−4.893	−3.240	−0.991	0.0630	−0.249	−4.183 ***	−0.023
	(5.802)	(5.297)	(5.978)	(1.095)	(1.019)	(1.187)	(0.043)
D0	−14.671 ***	−12.611 ***	−12.291 ***	−1.196 *	−2.621 ***	−0.032	−0.079 **
	(4.291)	(3.519)	(4.060)	(0.620)	(0.853)	(0.955)	(0.039)
D1	−7.581 *	−6.707 **	−5.038	0.197	−1.322	−1.379	−0.010
	(4.280)	(3.404)	(4.398)	(0.861)	(0.939)	(1.351)	(0.037)
D2	−15.856 ***	−12.207 ***	−14.56 ***	−0.476	−1.466	−2.921 ***	0.015
	(3.884)	(3.006)	(3.821)	(0.614)	(0.940)	(1.068)	(0.032)
D3	−12.771 ***	−8.978 ***	−12.61 ***	0.057	−1.740 **	−0.617	0.016
	(3.918)	(3.165)	(3.709)	(0.748)	(0.859)	(1.411)	(0.037)

Table A8. *Cont.*

	AQI	PM2.5	PM10	SO_2	NO_2	O_3	CO
D4	−11.930 ***	−7.589 **	−15.75 ***	−0.964	−2.658 **	0.455	0.032
	(3.575)	(2.936)	(3.725)	(0.767)	(1.276)	(1.323)	(0.046)
D5	−11.855 ***	−9.611 ***	−11.33 ***	−1.132	−2.661 **	−0.840	0.050
	(3.994)	(3.192)	(3.602)	(0.836)	(1.277)	(1.403)	(0.045)
D6	−9.897 **	−7.569 **	−8.539 **	0.052	−1.349	0.481	0.037
	(4.110)	(3.402)	(3.765)	(0.808)	(1.369)	(1.527)	(0.046)
wind2	−3.792 ***	−4.094 ***	−3.315 ***	−0.972 ***	−3.160 ***	2.953 ***	−0.046 ***
	(0.392)	(0.339)	(0.431)	(0.102)	(0.159)	(0.260)	(0.005)
airpressure	0.797 ***	0.564 ***	0.708 ***	−0.158 ***	−0.250 ***	0.782 ***	−0.008 ***
	(0.156)	(0.137)	(0.160)	(0.041)	(0.053)	(0.089)	(0.002)
temperature	0.669 ***	0.461 ***	0.690 ***	−0.279 ***	−0.268 ***	1.118 ***	−0.008 ***
	(0.179)	(0.157)	(0.203)	(0.050)	(0.064)	(0.100)	(0.003)
temper2	0.053 ***	0.044 ***	0.0640 ***	0.0141 ***	0.020 ***	0.021 ***	0.0003 ***
	(0.008)	(0.00684)	(0.008)	(0.002)	(0.002)	(0.003)	(8.08×10^{-5})
humidity	0.219 ***	0.374 ***	−0.120	−0.030 ***	0.008	−0.158 ***	0.005 ***
	(0.063)	(0.0480)	(0.096)	(0.008)	(0.012)	(0.024)	(0.0004)
sunduration	−0.726 ***	−0.453 ***	−1.091 ***	0.020	−0.024	0.938 ***	0.0004
	(0.161)	(0.118)	(0.294)	(0.026)	(0.037)	(0.064)	(0.001)
Observations	24,249	24,249	24,249	24,249	24,248	24,249	24,249
Adj R-squared	0.485	0.504	0.421	0.602	0.706	0.617	0.578

*** represents $p < 0.01$, ** represents $p < 0.05$, and * represents $p < 0.1$, applied to all of the following regression results.

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