A Health Impact and Economic Loss Assessment of O₃ and PM₂.₅ Exposure in China From 2015 to 2020

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Abstract
China is in a critical air quality management stage. Rapid industrial development and urbanization has resulted in non-ignorable air pollution, which seriously endangers human health. Assessment of the health impacts and economic losses of air pollution is essential for the prevention and control policy formulation. Based on ozone (O₃) and fine particulate matter concentration (PM₂.₅) monitoring data in 331 Chinese cities from 2015 to 2020, this study evaluated the health effects and the corresponding economic losses of O₃ and PM₂.₅ pollution on three health endpoints. The ratio of population exposed to O₃ levels that exceeded the Chinese Ambient Air Quality Standards (CAAQS) increased from 13.35% in 2015 to 14.15% in 2020, which resulted in 133,415 (2015) - 156,173 (2020) all-cause deaths, 88,941 (2015) - 104,051 (2020) cardiovascular deaths, and 28,614 (2015) - 33,456 (2020) respiratory deaths. The ratio of population exposed to PM₂.₅ levels that exceeded the CAAQS decreased, but in many regions, especially in North China and the Yangtze River Delta, the PM₂.₅ concentration remained high. By 2020, nearly half of the population in China was still exposed to PM₂.₅ levels that exceeded the CAAQS, and the corresponding economic losses reached CNY 3.46 and 3.05 billion, respectively. These results improved the understanding of the spatial-temporal variation trends of major air pollutants at city scale in China, and emphasize the continued coordination urgently needed for controlling O₃ and PM₂.₅ following the implementation of the 2013 policy to mitigate air pollution to protect human health.

Plain Language Summary
Based on ozone (O₃) and fine particulate matter concentration monitoring data in 331 Chinese cities from 2015 to 2020, this study adopted the health impact assessment model to evaluate the health effects of O₃ and PM₂.₅ pollution on three health endpoints: premature, cardiovascular, and respiratory mortality.

1. Introduction
In recent years, air pollution problems have become increasingly severe worldwide, having a negative influence on human health, the climate, and economic development (Fang et al., 2013; Leelieveld et al., 2015; Shang et al., 2013). Among atmospheric pollutants, the most commonly reported include particles matter with an aerodynamic diameter smaller than 2.5 microns (PM₂.₅) and 10 microns (PM₁₀), nitric dioxide, sulfur dioxide, and ozone (O₃; Shen et al., 2020). Notably, both long- and short-term atmospheric pollutants are related to acute and chronic impacts on human health (Jerrett et al., 2009; Philip et al., 2014; Shang et al., 2013).

In recent decades, rapid urbanization has been closely related to air pollution and human health worldwide (Ferreri et al., 2018; Guan et al., 2019; Lim et al., 2012; Wang et al., 2018). In China, rapid development of cities has created various environmental pollution problems (Huang et al., 2014; Zhang et al., 2020), which pose a notable threat to human health and cause substantial economic losses. The Chinese government has implemented a range of measures to improve air quality, such as the 2012 National Ambient Air Quality Standard and the 2013 Air Pollution Prevention and Control Action Plan (APPCAP). These efforts have realized great achievements, particularly in the remarkable reduction in PM₂.₅ pollution in many cities in China, as reported in several previous studies (Gui et al., 2019; Zhao et al., 2021). However, O₃ concentration exhibits an overall increasing trend, contrary to PM₂.₅ concentration. Zhao et al. (2021) demonstrated that the maximum daily 8-hr average O₃ concentration (MDA8 O₃) increased 3.4 μg m⁻³ per year from 2015 to 2018 in China. Maji and Sarkar (2020) reported that, in the summertime, the mean MDA8 O₃ value increased from 91.6 to 103.1 μg m⁻³ from 2015 to
2018 in China. Notably, studies have revealed that PM$_{2.5}$ reduction promotes O$_3$ enhancement (Li et al., 2019; Sicard et al., 2020).

O$_3$ poses increasingly adverse effects on human health and can cause systemic oxidative stress and harm to the cardiovascular and respiratory systems (Gabeheart et al., 2015; McDonnell et al., 1997; Salonen et al., 2018). Zhang et al. (2019) indicated that O$_3$ pollution can also cause a variety of diseases and social phenomena, including asthma emergencies, hospitalization, and absenteeism from school. Previous studies have provided valuable insights into O$_3$ risk assessment for protecting human health. On both regional and global scales, atmospheric chemistry models and remote sensing data have been adopted to estimate the potential health risks of O$_3$ exposure. Based on an atmospheric chemistry-general circulation model and satellite data, the global premature cardiovascular mortality and lung cancer attributable to O$_3$ and PM$_{2.5}$ pollution in 2005 were estimated to reach approximately 773 thousand/year, 186 thousand/year, and 2000 thousand/year, respectively (Lelieveld et al., 2013). Anenberg et al. (2010) used a global atmospheric chemical transport model to calculate the global mortality associated with O$_3$ in 2000, and found that the annual respiratory mortality attributable to O$_3$ was estimated to be 0.7 ± 0.3 million. In addition to negative effects on human health, O$_3$-related economic losses are greatly increasing. Several previous studies have estimated these losses. Feng et al. (2019) found that the costs of morbidity regarding respiratory diseases and nonaccidental mortality reached US$ 690.9 billion and US$ 7.5 billion, respectively. Previously, Maji et al. (2019) calculated that the national economic loss in 2016 due to exposure to O$_3$ was approximately US$ 7.6 billion.

Moreover, although the concentration of PM$_{2.5}$ has declined in recent years, its impact on people's health and economic losses remains notable. Therefore, PM$_{2.5}$ pollution and related issues still receive global attention. The mortality, cardiovascular and respiratory mortality related to PM$_{2.5}$ in 2013 were estimated to be 763,595, 149,754, and 446,035, respectively, according to measured data (Song et al., 2016). Based on satellite data, Liu et al. (2017) examined the national deaths from stroke, lung cancer, and ischemic heart disease caused by PM$_{2.5}$ pollution, and the number increased from approximately 800 thousand in 2004 to over 1,200 thousand in 2012. With a global atmospheric chemical transport model, Anenberg et al. (2010) found that the annual global mortality due to PM$_{2.5}$ in 2000 was estimated to reach 3.5 ± 0.9 million cardiopulmonary deaths and 220 ± 80 thousand lung cancer deaths. Song et al. (2017) suggested that in 2015, PM$_{2.5}$ accounted for more than 40.3% of the total stroke deaths and 33.1%, 26.8%, and 15.5% of all acute respiratory system, ischemic heart disease, and all-cause deaths, respectively. With the use of monitoring data, the mortality related to PM$_{2.5}$ in China in 2016 was calculated to reach 964 thousand deaths, which accounted for 9.98% of the total deaths. Specifically, the morbidity of respiratory and cardiovascular diseases was 605 thousand and 364 thousand, respectively (Maji et al., 2018). More importantly, the PM$_{2.5}$-related economic losses remain very high, as X. Lu et al. (2017) revealed that the highest economic loss caused by PM$_{2.5}$ pollution in southern China occurred in 2012, at US$ 4.6 billion, which is approximately 6.1% of the local total gross domestic product. Xie et al. (2017) predicted that China will suffer economic losses of US$ 4.2 billion and equivalent life losses of US$ 285 billion due to PM$_{2.5}$ pollution in 2030 without a control policy.

Since 2013, the air conditions in China have shown a combined pollution characterized by high concentrations of PM$_{2.5}$ and O$_3$, it is a top issue to understand their adverse effects on human health in the atmospheric environment field. Due to a lack of data, many previous studies were mostly conducted based on atmospheric chemistry models or satellite products (Anenberg et al., 2010; Lelieveld et al., 2013; Lin et al., 2018; Xie et al., 2016; Zhao et al., 2017). In recent years, with the establishment of air quality monitoring sites, it becomes possible to quantify the health risks of PM$_{2.5}$ and O$_3$ based on monitoring data. However, it must be point out that, although some studies have used monitoring data to investigate the link between PM$_{2.5}$ and O$_3$ and their associated diseases, most of these studies have focused on either a region (e.g., Beijing-Tianjin-Hebei, Yangtze River Delta (YRD)) or a single pollutant (e.g., PM$_{2.5}$ or O$_3$; Maji & Namdeo, 2021; Maji et al., 2018; Song et al., 2016). Moreover, a recent study revealed that the decline in PM$_{2.5}$ in recent years has enhanced surface photochemical reactions, thereby exacerbated O$_3$ pollution (Li et al., 2019). Notably, it remains unclear whether the reduction in health risk due to decreased PM$_{2.5}$ is offset by the increase in health risk due to increased O$_3$ concentrations. Therefore, it is valuable to analyze the human health effects of PM$_{2.5}$ and O$_3$ simultaneously.

The objectives of this study are to (a) identify the long-term spatiotemporal variation trends and heterogeneity in O$_3$ and PM$_{2.5}$ pollution of 331 cities in China from 2015 to 2020 based on monitoring data, (b) quantify the
impacts of O3 and PM2.5 pollution on human health, and (c) estimate the economic losses related to O3 and PM2.5 pollution in China.

2. Data and Methods

2.1. Data

There are notable climatic variations in the eastern, western, southern, and northern areas of China due to geographical effects. Given these differences, six representative regions were divided, as follows: (a) North China (Beijing, Tianjin, Hebei, Shanxi, Henan, and Shandong); (b) Northeast China (Heilongjiang, Jilin, and Liaoning); Northwest China (Inner Mongolia, Ningxia, Gansu, Shaanxi, and Xinjiang); Southeast China (Jiangsu, Anhui, Shanghai, Hubei, Hunan, Jiangxi, Guangdong, Fujian, Zhejiang, and Hainan); Southwest China (Guangxi, Chongqing, Sichuan, Yunnan and Guizhou); and the Tibetan Plateau (Qinghai and Tibet; Figure 1).

Monitoring data on the MDA8 O3 and PM2.5 from 1 January 2015, to 31 December 2020, that pertain to 367 cities were collected from the China National Environmental Monitoring Centre, 2020 (https://quotsoft.net/air; Figure 1). Due to the acute lack of data in certain cities, 331 cities eventually participated in the following calculations. Moreover, considering the missing values and outliers in the data, a rigorous quality control of the data was performed using the method proposed by Barrero et al. (2015) to ensure the reliability of the study results. The annual mean values per city were calculated by averaging the daily data retrieved from all stations in this city.

Population data (>30 years for O3, all age groups for PM2.5) from the 6th Population Census in 2010 in each city were obtained from China’s economic and social big data research platform, 2020 (https://data.cnki.net/yearbook/Single/N2021050059). In recent decades, the population of China has grown slowly. Therefore, in this study, no further adjustments were applied to the obtained population data.
2.2. The Univariate Linear Regression Model

The slope calculated by the univariate linear regression model in this study was used to explore and test the long-term interannual variation rate of PM$_{2.5}$ and O$_3$ pollution. That indicates, how many units of PM$_{2.5}$ and O$_3$ are increasing or decreasing per year overall. The spatial patterns of the temporal variation trends (slope values) of the O$_3$ and PM$_{2.5}$ concentration were calculated for each city in China from 2015 to 2020 (Figure 2). The slope in the unitary linear regression model represents the annual rate of change, which has been analyzed by several previous studies (Hammer et al., 2020; Lu et al., 2020; Zhang et al., 2020). When the absolute value of the slope is larger, the increasing (positive slope values)/decreasing temporal trend (negative slope values) is stronger, which is a common method and the corresponding equation can be found in D. Lu et al. (2017).

2.3. Health Impacts

Log-linear (LL) exposure-response functions were used in this study, which were drawn from Hubbell et al. (2009). If the level of air pollutants exceeds the safe threshold, then the exposure-response coefficient can be used to calculate the change in health risk for one person with every 1 μg m$^{-3}$ increase in concentration (Liao et al., 2017). Furthermore, if the population of each city is known, then we can estimate the health effects.

In this study, the LL method was adopted to evaluate the health impacts of O$_3$ and PM$_{2.5}$ pollution regarding three health endpoints, as:

\[ RR = \exp[\beta \times (C - C_0)] \]  \hspace{1cm} (1)

\[ E = f_p \times P \times ([RR - 1]/RR) \]  \hspace{1cm} (2)

Figure 2. Spatiotemporal variation trends of the annual mean MDA8 O$_3$ and PM$_{2.5}$ concentrations from 2015 to 2020 in China. BTH represents Beijing-Tianjin-Hebei region, YRD represents Yangtze River Delta, PRD represents Pearl River Delta.
where $\beta$ is the exposure-response coefficient indicating that, based on an increase of 1 $\mu$g m$^{-3}$ per pollutant, the percentage increase in the health impact (Liao et al., 2017) is derived from the relative risks. In this study, exposure-response coefficient ($\beta$) related O$_3$ pollution was estimated from the long-term epidemiological study by Turner et al. (2016) and cardiovascular and respiratory mortality from Lim et al. (2019), also a long-term study (Table 1). Meanwhile, $\beta$ related long-term PM$_{2.5}$ pollution was estimated from the previous studies (Aunan and Pan., 2004; Burnett et al., 2014; Kan and Chen., 2002; Xie et al., 2009, 2010) (Table 1).

2.4. Economic Impacts

The cost of illness (COI) model is applied to monetize the economic cost of each health endpoint, thereby estimating the socioeconomic loss caused by air pollution (Maji et al., 2018; Zhang et al., 2017).

The economic losses caused by O$_3$ and PM$_{2.5}$ pollution in this study are calculated with the COI method, which mainly refers to the additional health expenditures of residents attributed to air pollution, such as hospitalization and outpatient expenses. Based on the per capita medical expenses (MEs) in the China Health Statistics Yearbook (2015–2020), the economic loss in each city from 2015 to 2020 is estimated, as follows:

$$HE = \sum E_i \times RP_i$$

where $i$ denotes the health endpoint, and $RP_i$ denotes the per capita MEs for the category $i$ health endpoint, which was collected from the China Health Statistics Yearbook 2015–2020. The RP values for cardiovascular disease in 2015, 2016, 2017, 2018, 2019, and 2020 were CNY 23,997.56, 23,784.00, 24,949.80, 23,607.90, 27,579.12, and 27,579.12, respectively, and the RP values for respiratory disease were CNY 7,604.90, 7,663.60, 7,905.30, 7,975.60, 8,150.00, and 8,150.00, respectively.

3. Results

3.1. Annual Variations in the O$_3$ and PM$_{2.5}$

The slope values of the annual PM$_{2.5}$ concentration for 2015–2020 shows higher values in the more industrial and populated areas, such as NC and the YRD (Figure 2). PM$_{2.5}$ experienced a continuous and significant decrease

### Table 1

| Parameter       | All-cause | Cardiovascular | Respiratory |
|-----------------|-----------|----------------|-------------|
| $\beta$ (PM$_{2.5}$) | 0.00336 (0.00076, 0.00504) | 0.00068 (0.00043, 0.00093) | 0.00109 (0, 0.00221) |
| (Sources)       | 1, 2, 3, 4, 5 | 1, 4, 5 | 1, 4, 5 |
| RR (PM$_{2.5}$)  | 1.0342 (1.0076, 1.0517) | 1.0068 (1.0043, 1.0093) | 1.0110 (1.0000, 1.0223) |
| (Sources)       | 1, 2, 3, 4, 5 | 1, 5, 6 | 1, 5, 6 |
| $C_0$           | 10 $\mu$g/m$^3$ | 10 $\mu$g/m$^3$ | 10 $\mu$g/m$^3$ |
| $f_p$ (PM$_{2.5}$) | 0.00614 | 0.00546 | 0.01022 |
| $\beta$ (O$_3$) (Sources) | 0.00198 (0.001, 0.00392) | 0.00296 (0.001, 0.00583) | 0.00392 (0, 0.00862) |
| RR (O$_3$)      | 1.0200 (1.0100, 1.0400) | 1.0300 (1.0100–1.0600) | 1.0400 (1.0000–1.0900) |
| (Sources)       | Turner et al., 2016 | Lim et al., 2019 | Lim et al., 2019 |
| $C_0$           | 26.7 ppb | 26.7 ppb | 26.7 ppb |
| $f_p$ (O$_3$)   | 0.00654 | 0.00296 | 0.00072 |

Note. 1. Aunan & Pan, 2004; 2. Burnett et al., 2014; 3. Kan & Chen, 2002; 4. Xie et al., 2010; 5. Xie et al., 2009.
across China, and decreased from 48.7 μg/m³ in 2015 to 33.0 μg/m³ in 2020 at a rate of 3.11 μg/m³ from 2015 to 2020. The BTH, YRD and PRD regions showed a decreased trend in the annual PM_{2.5} concentrations, which decreased at rates of 6.28, 3.46, and 2.17, respectively (Figure 2).

The spatial distribution of O₃ concentration in China is similar to that of PM_{2.5}. However, different from PM_{2.5}, O₃ concentration shows a sustained increase at an average annual rate of 1.22 μg/m³ from 84.9 μg/m³ in 2015 to 90.1 μg/m³ in 2020, which indicates that humans suffer from more severe health risks associated with O₃ exposure. The increase was greater in BTH, YRD, and PRD regions (2.27 μg/m³, 2.02 μg/m³ and 1.79 μg/m³, respectively), than the national average of 1.22 μg/m³ (Figure 2).

3.2. Population Exposure to O₃ and PM_{2.5}

PM_{2.5} is decreasing and O₃ is increasing, which means China is currently experiencing complex and severe PM_{2.5} and O₃ pollution. In this study, according to the annual average O₃ and PM_{2.5} concentration and the population data of 331 cities in China and the above six representative regions, the cumulative population exposure level to O₃ and PM_{2.5} is calculated (Figures 3 and 4).

For O₃, it is reported that at Level II of the CAAQS, the limits of MDA8 O₃ and the daily maximum 1 hr O₃ concentration are 160 μg/m³ (used in the study) and 200 μg/m³, respectively. In general, NC was the most severe region, followed by SE (including the YRD region), while the number of people exposed to excessive O₃ concentration in the TP was low (Figure 3). The proportion of people exposed to O₃ above the CAAQS in summer is higher than that in spring and autumn. In the summers of 2015, 2016, 2017, 2018, 2019 and 2020, 175.51 million (13.35%), 193.13 million (14.69%), 273.20 million (20.78%), 291.34 million (22.16%), 286.35 million (21.78%), and 186.03 million (14.15%) people in China were exposed to O₃ pollution that exceeded the CAAQS. All of these results indicate that in recent years, especially in the summer, the risk of O₃ exposure is high; therefore, it is necessary to analyze its impact on health.

For PM_{2.5}, the cumulative population exposed to PM_{2.5} above the CAAQS (15 and 35 μg/m³) decreases along with the decrease in PM_{2.5} from 2015 to 2020 (Figure 4). In 2015, 2016, 2017, 2018, 2019 and 2020, the number of people in China living with PM_{2.5} levels higher than 35 μg/m³ was 1,111.39 million, 1,034.52 million, 1,008.96 million, 880.27 million, 837.23 million, and 647.71 million, which accounted for approximately 84.53%, 78.69%, 76.74%, 66.95%, 63.68%, and 49.27%, respectively, of the total population. Notably, overall, NC was the most severely affected region, where approximately 90% of people lived in areas where concentrations of PM_{2.5} greater than 35 μg/m³. However, notably, in 2020, nearly 50% of the population still experienced air problems. Therefore, although PM_{2.5} has exhibited a downward trend in recent years, there remains a need to further reduce PM_{2.5} pollution.

3.3. Health Impacts of O₃ and PM_{2.5}

In this study, the spatiotemporal distributions of three health endpoints mortality in adults (>30 years) attributed to O₃ and PM_{2.5} exposure in 331 cities across China from 2015 to 2020 are shown in Figures S1-S4 in Supporting Information S1. For O₃, in China, the all-cause mortality was 133,415 [95% confidence interval (CI): 67,927–259,873] in 2015 and 156,173 (95% CI: 79,562–303,843) in 2020 at a threshold of 26.7 ppb (Table 2). In 2015, the estimated cardiovascular mortality was 88,941 (95% CI: 30,585–171,304), while respiratory mortality was 28,614 (95% CI: 0–49,278). These numbers increased to 104,051 (95% CI: 35,824–200,055) and 33,456 (95% CI: 0–70,548) in 2020. Cardiovascular and respiratory mortality accounted for 55.7% and 21.4% of all-cause mortality, respectively. From 2015 to 2020, all-cause, cardiovascular, and respiratory deaths attributable to O₃ exposure increased by 17.1%, 17.0%, and 16.9%, respectively (Figures S1 and S2 in Supporting Information S1). The cities with the highest six-year average all-cause mortality due to O₃ were Shanghai [4,101 (95% CI: 2,093–7,446)], Beijing [3,432 (95% CI: 1,750–6,668)], Linyi (Shandong) [1,887 (95% CI: 926–3,587)], Chengdu (Sichuan) [1,874 (95% CI: 954–3,648)], Chongqing [1,826 (95% CI: 926–3,587)] and Baoding (Hebei) [1,774 (95% CI: 906–3,436)] (Figure S1 in Supporting Information S1). The provinces with high health impacts from 2015 to 2020 at the three health endpoints were Shandong, Jiangsu, Henan, Guangdong, and Hebei, and these results suggest that the relevant authorities should focus on O₃ pollution control in these regions (Table 2). Overall,
the health impacts-related O₃ exposure are strongly correlated with the level of O₃ pollution and the size of the exposed population, such that several provinces, such as Shandong, Henan, Hebei, and Jiangsu, which have high O₃ levels, experience high numbers of premature deaths due to their large population. Guangdong has relatively low levels of O₃ pollution; however, it has the highest population in China, which caused the health effects attributed to long-term O₃ exposure to be higher than in other provinces (Figure S2 in Supporting Information S1).

It is estimated that approximately 920 million people (70% of the total population) are living in areas with a six-year average PM₂.₅ greater than 35 μg/m³. The cause-specific premature deaths and differences between 2016 and 2020 and 2015 due to long-term PM₂.₅ exposure in each city were therefore examined (Figures S3 and S4 in Supporting Information S1). Table 3 reports the details on three health endpoints in China and the five
provinces with high premature deaths from 2015 to 2020. In China, all-cause deaths decreased by 39.4%, from 1,105,089 (95% CI: 267,049–1,590,192) in 2015 to 669,555 (95% CI: 157,576–979,324) in 2020, and the highest value was found in 2015 (Figure S4 in Supporting Information S1). During the study period, cardiovascular and respiratory mortality decreased by 41.0%, from 212,917 (95% CI: 135,515–289,319) in 2015 to 125,529 (95% CI: 79,686–171,020) in 2020, and by 40.8%, from 632,101 (95% CI: 0–1,245,414) in 2015 to 374,265 (95% CI: 0–745,934) in 2020. From the provincial perspective, the number of all-cause premature deaths during the study period was higher in Henan (11.0%) [2015: 121,506; 2020: 76,673], Shandong (9.9%) [2015: 116,004; 2020: 69,265], and Hebei (8.4%) [2015: 94,543; 2020: 53,726] (Table 3). A larger decreasing trend in premature deaths was identified for the provinces of Zhejiang (55.9%), Hubei (46.4%), Guangdong (46.8%), Guizhou

Figure 4. Population exposure to PM$_{2.5}$ in six representative regions and China.
In 2015, five cities had the highest all-cause mortality, that is, Beijing [28,997 (95% CI: 7,154–41,180)], Chongqing [25,607 (95% CI: 6,130–37,050)], Shanghai [19,385 (95% CI: 4,638–28,056)], Baoding [18,770 (95% CI: 4,784–26,135)], and Tianjin [14,475 (95% CI: 3,945–20,691)]. By 2020, the all-cause mortality in Chongqing [14,212 (95% CI: 3,315–20,904)], Beijing [12,730 (95% CI: 2,985–18,658)], Shanghai [9,784 (95% CI: 2,275–14,419)], and Tianjin [9,710 (95% CI: 2,308–14,110)] remained the highest.

| Region      | Year | All-cause          | Cardiovascular | Respiratory |
|-------------|------|--------------------|----------------|-------------|
| China       | 2015 | 133,415 (67,927–259,873) | 88,941 (30,585–171,304) | 28,614 (0–60,511) |
|             | 2016 | 145,188 (73,933–282,711) | 96,773 (33,290–186,295) | 31,116 (0–65,774) |
|             | 2017 | 175,735 (89,315–340,091) | 116,570 (40,215–223,500) | 37,445 (0–78,603) |
|             | 2018 | 172,845 (88,132–335,707) | 115,060 (39,683–220,670) | 36,964 (0–77,633) |
|             | 2019 | 171,249 (87,316–332,630) | 114,002 (39,315–218,661) | 36,625 (0–76,934) |
|             | 2020 | 156,173 (79,562–303,843) | 104,051 (35,824–200,055) | 33,456 (0–70,548) |
| Shandong    | 2015 | 14,887 (7,598–28,859) | 9,901 (3,421–18,934) | 3,178 (0–6,643) |
|             | 2016 | 15,308 (7,814–29,663) | 10,178 (3,519–19,455) | 3,266 (0–6,822) |
|             | 2017 | 17,964 (9,184–34,707) | 11,927 (4,135–22,697) | 3,821 (0–7,926) |
|             | 2018 | 18,072 (8,732–32,955) | 11,329 (3,932–21,533) | 3,629 (0–7,510) |
|             | 2019 | 18,533 (9,479–35,776) | 12,299 (4,268–23,376) | 3,939 (0–8,153) |
|             | 2020 | 17,460 (8,924–33,754) | 11,596 (4,018–22,087) | 3,717 (0–7,720) |
| Jiangsu     | 2015 | 11,358 (5,797–22,017) | 7,553 (2,610–14,445) | 2,424 (0–5,068) |
|             | 2016 | 11,053 (5,639–21,442) | 7,353 (2,539–14,078) | 2,361 (0–4,944) |
|             | 2017 | 12,324 (6,297–23,838) | 8,187 (2,835–15,607) | 2,625 (0–5,459) |
|             | 2018 | 11,146 (5,688–21,613) | 7,414 (2,561–14,184) | 2,380 (0–4,978) |
|             | 2019 | 12,085 (6,172–23,403) | 8,033 (2,779–15,338) | 2,577 (0–5,573) |
|             | 2020 | 11,347 (5,791–22,004) | 7,548 (2,607–14,441) | 2,423 (0–5,069) |
| Henan       | 2015 | 10,502 (5,348–20,451) | 7,000 (2,408–13,477) | 2,252 (0–4,758) |
|             | 2016 | 13,259 (6,763–25,737) | 8,824 (3,045–16,907) | 2,834 (0–5,942) |
|             | 2017 | 15,674 (8,009–30,319) | 10,413 (3,606–19,849) | 3,338 (0–6,943) |
|             | 2018 | 16,093 (8,226–31,109) | 10,687 (3,704–20,354) | 3,425 (0–7,113) |
|             | 2019 | 15,976 (8,165–30,889) | 10,611 (3,676–20,214) | 3,401 (0–7,066) |
|             | 2020 | 14,185 (7,240–27,498) | 9,434 (3,260–18,041) | 3,028 (0–6,330) |
| Guangdong   | 2015 | 9,561 (4,865–18,647) | 6,378 (2,190–12,307) | 2,053 (0–4,355) |
|             | 2016 | 8,957 (4,553–17,498) | 5,980 (2,050–11,568) | 1,927 (0–4,103) |
|             | 2017 | 11,709 (5,963–22,792) | 7,803 (2,685–15,015) | 2,510 (0–5,298) |
|             | 2018 | 11,888 (6,056–23,132) | 7,921 (2,727–15,232) | 2,547 (0–5,372) |
|             | 2019 | 12,852 (6,552–24,971) | 8,557 (2,950–16,420) | 2,749 (0–5,779) |
|             | 2020 | 10,276 (5,229–20,037) | 6,854 (2,355–13,220) | 2,206 (0–4,676) |
| Hebei       | 2015 | 8,164 (4,157–15,897) | 5,442 (1,872–10,475) | 1,750 (0–3,698) |
|             | 2016 | 9,074 (4,623–17,655) | 6,046 (2,082–11,624) | 1,944 (0–4,099) |
|             | 2017 | 12,015 (6,137–23,258) | 7,985 (2,763–15,237) | 2,561 (0–5,335) |
|             | 2018 | 12,544 (6,411–24,253) | 8,331 (2,887–15,872) | 2,670 (0–5,549) |
|             | 2019 | 11,718 (5,984–22,693) | 7,789 (2,694–14,874) | 2,499 (0–5,211) |
|             | 2020 | 10,813 (5,517–20,978) | 7,194 (2,484–13,774) | 2,310 (0–4,837) |
3.4. Economic Loss Attributable to O₃ and PM₂.₅ Pollution

For the convenience of calculation, we assume that the population incurs no per capita MEs related to premature deaths. This study estimates only the economic losses associated with cardiovascular and respiratory diseases caused by O₃ and PM₂.₅. Figure S5 in Supporting Information S1 shows city-specific economic loss associated with cardiovascular and respiratory diseases attributable to O₃ and PM₂.₅ pollution in China by using the COI method with different C₀ values (for O₃: 26.7 ppb; for PM₂.₅: 10 μg/m³). Economic losses attributable to the O₃

| Region  | Time | All-cause | Cardiovascular | Respiratory |
|---------|------|-----------|----------------|-------------|
| China   | 2015 | 1,105,089 (267,049–1,590,192) | 212,917 (135,515–289,319) | 632,101 (0–1,245,414) |
|         | 2016 | 999,538 (239,961–1,444,093) | 191,280 (121,664–260,087) | 568,472 (0–1,123,254) |
|         | 2017 | 939,871 (224,650–1,361,527) | 179,050 (113,835–243,563) | 532,504 (0–1,054,194) |
|         | 2018 | 810,276 (192,155–1,179,521) | 153,112 (97,269–208,443) | 455,945 (0–905,723) |
|         | 2019 | 774,314 (183,241–1,128,637) | 146,001 (92,731–198,802) | 434,914 (0–864,733) |

| Shandong | 2015 | 116,004 (28,681–164,567) | 22,884 (14,598–31,026) | 67,687 (0–132,047) |
|          | 2016 | 100,613 (24,551–143,880) | 19,580 (12,474–26,581) | 58,039 (0–113,876) |
|          | 2017 | 85,792 (20,692–123,568) | 16,496 (10,497–22,420) | 53,991 (0–96,610) |
|          | 2018 | 72,971 (17,419–105,774) | 13,883 (8,825–18,887) | 44,297 (0–81,804) |

| Jiangsu  | 2015 | 71,576 (17,216–164,567) | 13,724 (8,730–31,026) | 40,776 (0–132,047) |
|          | 2016 | 60,361 (14,379–143,880) | 11,459 (7,283–26,581) | 34,100 (0–113,876) |
|          | 2017 | 57,377 (13,658–123,568) | 10,884 (6,917–22,420) | 32,392 (0–96,610) |
|          | 2018 | 55,884 (13,278–105,774) | 10,580 (6,723–18,887) | 31,498 (0–81,804) |

| Henan    | 2015 | 121,506 (30,059–172,276) | 23,984 (15,300–32,516) | 70,936 (0–138,352) |
|          | 2016 | 108,689 (26,618–155,063) | 21,231 (13,531–28,813) | 62,899 (0–123,216) |
|          | 2017 | 98,023 (23,805–140,574) | 18,982 (12,087–25,782) | 56,311 (0–110,717) |
|          | 2018 | 92,623 (22,385–133,223) | 17,847 (11,359–24,252) | 52,986 (0–104,398) |

| Guangdong | 2015 | 48,942 (11,423–71,954) | 9,097 (5,770–12,404) | 27,160 (0–54,327) |
|           | 2016 | 44,751 (9,956–100,614) | 9,097 (5,770–12,404) | 27,160 (0–54,327) |
|           | 2017 | 46,860 (9,956–100,614) | 9,097 (5,770–12,404) | 27,160 (0–54,327) |
|           | 2018 | 41,678 (9,956–100,614) | 9,097 (5,770–12,404) | 27,160 (0–54,327) |

| Hebei    | 2015 | 94,543 (11,423–133,319) | 18,841 (15,300–25,750) | 55,641 (0–108,080) |
|          | 2016 | 86,279 (10,420–122,381) | 17,023 (13,531–28,813) | 50,351 (0–98,219) |
|          | 2017 | 80,695 (10,923–114,925) | 15,812 (12,087–25,782) | 50,351 (0–98,219) |
|          | 2018 | 67,270 (9,956–96,720) | 12,972 (9,097–22,420) | 44,297 (0–81,804) |

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Table 3

The Estimated Three Premature Deaths Related to Long-Term Exposure to PM₂.₅ in China and Provinces With High Premature Deaths From 2015 to 2020
increased from 2015 to 2020 and reached a maximum at different times in different cities. There was an increasing trend of economic losses from cardiovascular and respiratory mortality, which increased from 2.13 billion CNY (95% CI: 0.73–4.11 billion) in 2015 to 2.87 billion CNY (95% CI: 0.99–5.52 billion) in 2020 and from 0.22 billion CNY (95% CI: 0–0.46 billion) in 2015 to 0.27 billion CNY (95% CI: 0–0.57 billion) in 2020 (Table 4 and Figure S5 in Supporting Information S1). In 2020, the cities with the highest economic losses from cardiovascular diseases due to long-term O₃ exposure were Shanghai [66.52 (95% CI: 22.93–127.64 million)], Beijing [57.52 (95% CI: 19.80–110.63 million)], Tianjin [37.19 (95% CI: 12.83–71.27 million)], Linyi (Shandong) [36.49 (95% CI: 12.66–69.42 million)], and Chengdu (Sichuan) [30.63 (95% CI: 10.52–59.14 million)]. In contrast, Nuijiang (Yunnan) [161,471 (95% CI: 54,751–317,418)] and Linzhi (Tibet) [205,143 (95% CI: 70,068–398,992)] had the lowest economic losses, which were approximately 0.28% and 0.36% of those in Beijing, respectively. Economic losses in 2020 due to cardiovascular mortality accounted for approximately 91.3% of the total economic losses attributable to O₃ exposure, which is much higher than those due to respiratory mortality.

The economic losses of cardiovascular and respiratory mortality related to long-term PM₂.₅ exposure decreased from 5.11 billion CNY (95% CI: 3.25–6.94) in 2015 to 3.46 billion (95% CI: 2.20–4.71) in 2020 and from 4.81 billion CNY (95% CI: 0–9.47) in 2015 to 3.05 billion CNY (95% CI: 0–6.08) in 2020 (Table 4 and Figure S5 in Supporting Information S1). In 2015, the cities with the highest economic loss of cardiovascular diseases—related to long-term PM₂.₅ exposure were Beijing [136.96 (95% CI: 87.34–185.74) million], Chongqing [117.24 (95% CI: 74.55–159.47) million], Shanghai [88.71 (95% CI: 56.41–120.67) million], Baoding (Hebei) [91.5–352 thousand), 112 thousand (95% CI: 38.1–214 thousand) and 33.8 (95% CI: 0–71.4 thousand), respectively based on atmospheric chemistry models or satellite data (Lelieveld et al., 2013; Lin et al., 2018). Because the accuracy of health impact assessments attributable to O₃ can be greatly influenced by the O₃ data source, the monitoring data can help to obtain a more accurate result. Maji and Namdeo. (2021) reported the impact of long-term O₃ exposure on human health by using a model consistent with this study (LL model) in which data from 2015 to 2019 were examined. Their results showed that in 2019, when 26.7 ppb was used as the threshold (Cₒ) for MDA8 O₃, the mortality for the all-cause, cardiovascular, and respiratory was 181 thousand (95% CI: 91.5–352 thousand), 112 thousand (95% CI: 38.1–214 thousand) and 33.8 (95% CI: 0–71.4 thousand), respectively, which is generally consistent with the results of this study; however, when the (Cₒ) for MDA8 O₃ was set to 0 ppb, the mortality was 487 thousand (95% CI: 249–922 thousand), 298 thousand (95% CI: 104–552 thousand), and 89,000 (95% CI: 0–178,000), respectively, which is much larger than the results of this study; these differences suggest that the selection of the O₃ threshold results in widely varying estimates of long-term

| Pollutants | Time | Cardiovascular (billion) | Respiratory (billion) |
|-----------|-----|-------------------------|----------------------|
| O₃        | 2015 | 2.13 (0.73–4.11)         | 0.22 (0–0.46)        |
|           | 2016 | 2.30 (0.79–4.43)         | 0.24 (0–0.50)        |
|           | 2017 | 2.91 (1.00–5.58)         | 0.30 (0–0.62)        |
|           | 2018 | 2.72 (0.94–5.21)         | 0.29 (0–0.62)        |
|           | 2019 | 3.14 (1.08–6.03)         | 0.30 (0–0.63)        |
|           | 2020 | 2.87 (0.99–5.52)         | 0.27 (0–0.57)        |
| PM₂.₅     | 2015 | 5.11 (3.25–6.94)         | 4.81 (0–9.47)        |
|           | 2016 | 4.55 (2.89–6.18)         | 4.35 (0–8.61)        |
|           | 2017 | 4.47 (2.84–6.07)         | 4.21 (0–8.33)        |
|           | 2018 | 3.61 (2.30–4.92)         | 3.64 (0–7.22)        |
|           | 2019 | 4.03 (2.56–5.48)         | 3.54 (0–7.05)        |
|           | 2020 | 3.46 (2.20–4.71)         | 3.05 (0–6.08)        |

4. Discussion

This study assessed the health impacts and economic loss-related long-term exposure to MDA8 O₃ and PM₂.₅ in China during the study period of 2015–2020. This study showed that the O₃ concentration and the deaths of three health endpoints and economic loss cause by long-term O₃ exposure increased significantly in China, which is similar to the results of other studies (Lu et al., 2020; Maji & Namdeo, 2021). At the same time, the PM₂.₅ concentration and corresponding premature mortality decreased significantly in most cities; however, they still exceed the CAAQS in many regions. China is facing new challenges from the complex and increasing mix of O₃ and PM₂.₅ pollution.

Some prior studies examined the health effects attributed to O₃ exposure from a national perspective predominantly based on atmospheric chemistry models or satellite data (Lelieveld et al., 2013; Lin et al., 2018). Because the accuracy of health impact assessments attributable to O₃ can be greatly influenced by the O₃ data source, the monitoring data can help to obtain a more accurate result. Maji and Namdeo. (2021) reported the impact of long-term O₃ exposure on human health by using a model consistent with this study (LL model) in which data from 2015 to 2019 were examined. Their results showed that in 2019, when 26.7 ppb was used as the threshold (Cₒ) for MDA8 O₃, the mortality for the all-cause, cardiovascular, and respiratory was 181 thousand (95% CI: 91.5–352 thousand), 112 thousand (95% CI: 38.1–214 thousand) and 33.8 (95% CI: 0–71.4 thousand), respectively, which is generally consistent with the results of this study; however, when the (Cₒ) for MDA8 O₃ was set to 0 ppb, the mortality was 487 thousand (95% CI: 249–922 thousand), 298 thousand (95% CI: 104–552 thousand), and 89,000 (95% CI: 0–178,000), respectively, which is much larger than the results of this study; these differences suggest that the selection of the O₃ threshold results in widely varying estimates of long-term
premature mortality. Recently, Guan et al. (2021) conducted a nationwide study of 338 cities in China which generated much higher estimated health risks from O₃ than did our study. The difference between the results of these two studies may be that this study used exposure-response coefficient (β) from Lim et al. (2019) and Turner et al. (2016), whereas the study by Guan et al. (2021) used β from Jerrett et al. (2009). Notably, the selection of β also has a significant impact on the assessment of health impacts. Malley et al. (2017) used different RR values, from Jerrett et al. (2009) and Turner et al. (2016) to estimate mortality caused by O₃ pollution in China, with large differences in the results. The differences among these studies indicate that the health impact assessment-related O₃ is primarily related to the O₃ threshold (Cₒ₃), exposure-response coefficient (β), and the data source of O₃. Additionally, the selection of the O₃ indicator has a great impact on the health assessment-related to O₃ exposure (Feng et al., 2019).

Recently, Burnett et al. (2018) and Yin et al. (2020) estimated that there were 1.11 million in 2015 and 850,000 in 2017 deaths from all-cause deaths due to long-term PM₂.₅ exposure, respectively, and our results were slightly lower than that reported in Burnett et al. (2018), but higher than that reported in Yin et al. (2020). Notably, the factors which influenced O₃-related health risk assessment can also affect that of PM₂.₅. For example, Song et al. (2016) reported that there were 763,595 all-cause, 149,754 cardiovascular, and 446,035 respiratory deaths caused by PM₂.₅ pollution in 2013, which were slightly lower than that in this study. One possible reason is that their study region contains only 190 cities, which is far less than this study. Furthermore, there is a significant decrease in PM₂.₅ concentration in recent years. According to the study of Kuerban et al. (2020), in 2015, PM₂.₅ pollution caused 436,260, 149,755, and 94,397 deaths from all-cause, respiratory, and cardiovascular diseases, and the three health endpoints death numbers in 2018 are 344,177, 109,326, and 70,982, respectively using LL model with much lower estimated health risks than our results. The differences may because the selection of the exposed population, this study used the all population as the exposed population, but Kuerban et al. (2020) considered only the population of cities with monitoring stations, which resulted in a lower value. Based on LL model, Maji et al. (2018) showed that the total all-cause deaths attributed to PM₂.₅ in China was 1.258 (95% CI: 1.053, 1.420) million in 2016, which were slightly higher than our results. The reason for the difference may lie in the different selection of coefficients: this study used β and fₛ from the previous studies (Aunan and Pan, 2004; Burnett et al., 2014; Kan and Chen, 2002; Xie et al., 2009, 2010), whereas the study by Maji et al. (2018) used β and fₛ from Li et al. (2013), Qiu et al. (2013) and NBSC (2016). Although these studies used the same LL model, the number of deaths related to PM₂.₅ were different, indicating that the PM₂.₅-related health impact assessment is also influenced by the exposed population, coefficients (fₛ and β), and number of cities.

According to previous studies (Burnett et al., 2015; Yin et al., 2017), the estimated RRs with LL and IER models are relatively consistent. Maji et al. (2018) demonstrated that the number of all-cause deaths attributed to PM₂.₅ in China was 0.964 (95% CI: 0.447, 1.355) million using IER model (the sum of four type of mortality: cerebrovascular, chronic obstructive pulmonary, ischemic heart disease, and lung cancer), whereas the all-cause deaths was 1.258 (95% CI: 1.053, 1.420) million based on LL model (the sum of five health endpoints: hospital admission due to cardiovascular disease, hospital admission due to respiratory disease, asthma attack, chronic bronchitis and emergency room visits for respiratory disease). It indicates that the LL model results have a slightly higher value of PM₂.₅-related deaths due to the different coefficients and selection of health endpoints. Moreover, IER were employed to estimate limited health endpoints during PM₂.₅ related exposure-response assessment (Yin et al., 2017), which is not suitable for our aims to directly obtain the mortality corresponding to the three health endpoints (all-cause, cardiovascular, and respiratory diseases) caused by PM₂.₅ and O₃ pollution. Furthermore, there are no robust cohort studies to suggest which risk model is more appropriate for China (Maji et al., 2018). A recent cohort study showed that the RR values estimated in areas of high PM₂.₅ concentration in China were not consistent with those specified in the IER model. The China-specific cohort studies contribute to narrow the gap in RR values in the high concentration areas, but are not appropriate for IER, suggesting that IER may underestimate the effect of high PM₂.₅ levels in China (Pope et al., 2018). Therefore, considering reasons mentioned above, this study applied the LL model to estimate the number of deaths from the three health endpoints, which has been widely adopted by many other studies (Kuerban et al., 2020; Maji & Namdeo, 2021; Yin et al., 2017).

We applied the COI method to quantify the medical expenditure of each city by considering each health endpoint attributable to O₃ and PM₂.₅ pollution from 2015 to 2020. High O₃- and PM₂.₅-related economic losses were found in Beijing, Tianjin, Hebei, Anhui, Henan, Shandong, Jiangsu, Sichuan, Guangdong and Zhejiang Provinces. Some studies have shown that the adverse health effects of air pollution can cause significant economic losses...
(Nansai et al., 2020; World Bank, 2016). Maji et al. (2019) used the value of a statistical life (VSL) model to assess the economic loss caused by O3 pollution in 338 cities in China, and the results showed that there was an economic loss of US$7.6 billion in 2016. Wang et al. (2021) estimated the MEs and the VSL caused by the health burden of PM2.5 and O3 in 31 Chinese provinces from 2010 to 2050, and their results indicated that the MEs due to PM2.5 and O3 was approximately US$ 6.3 billion and that the VSL was approximately US$ 112.1 billion in 2010. The results of these two studies are higher than those of this study, and the differences may lie in the selection of the models and the sources of pollutant data, which may lead to dramatic differences in the results. Moreover, Lanzi et al. (2018) predicted that PM2.5 pollution will cause US$ 2.26 trillion economic loss in 2030 without any control. Xie et al. (2017) showed that if there is no control policy, China will suffer US$ 4.2 billion in economic losses and US$ 285 billion in human loss in 2030. Therefore, we should continue to give more attention to air quality improvement, especially coordinated control for O3 and PM2.5 pollution.

Several uncertainties are involved in this study. First, we assumed that the total population of each city is exposed to the same average O3 and PM2.5 concentrations, although the exposure environment of each person varies greatly in space and time (Maji et al., 2018). Second, the air quality monitoring stations are mainly distributed in urban areas, but the population of each city is not located only across these areas, which can introduce some uncertainty. Studies have revealed that the O3 is significantly higher in suburban areas than in urban areas (Sicard et al., 2016). Therefore, in this study, the health effects estimated using the average concentration over all areas in each city may smaller than the actual effects.

5. Conclusions

This study analyzed the temporal and spatial heterogeneity of long-term O3 and PM2.5 pollution in 331 cities across China from 2015 to 2020. It was found that PM2.5 concentrations continued to decrease in almost all Chinese cities, especially in cities located in NC and the YRD; conversely, O3 showed an overall increasing trend. The population exposed to high PM2.5 decreased from 2015 to 2020, but notably, although there was a substantial reduction in PM2.5 due to the implementation of the APPCAP in recent years, it was still high in many cities. By 2020, approximately half of the population lived in areas where PM2.5 exceeded the CAAQS; therefore, further control of PM2.5 pollution will still be necessary in the future. Meanwhile, the ratio of the population exposed to O3 continued to increase from 13.35% in 2015% to 14.15% in 2020; it peaked at 22.16% in 2018 and caused all-cause, cardiovascular, and respiratory mortality of 156,173 [95% CI: 79,562–303,843], 104,051 (95% CI: 35,824–200,055), and 33,456 (95% CI: 0–70,548) in 2020, respectively. According to these increases and the results of this study, it is imperative to urgently propose and adopt strict measures to control the continued rise of O3 pollution in the future.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Data sets for this study are publicly available. Data on ozone concentration are available via the China National Environmental Monitoring Centre (https://quotsoft.net/air/), and Population data (>30 years and all age group) obtained from the 6th Population Census (https://data.cnki.net/yearbook/Simple/N2021050059).

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