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The association between daily-diagnosed COVID-19 morbidity and short-term exposure to PM_1 is larger than associations with $PM_{2.5}$ and PM_{10}

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ABSTRACT

Exposure to particulate matter (PM) could increase both susceptibility to SARS-CoV-2 infection and severity of COVID-19 disease. Prior studies investigating associations between PM and COVID-19 morbidity have only considered $PM_{2.5}$ or PM_{10}, rather than PM_1. We investigated the associations between daily-diagnosed COVID-19 morbidity and average exposures to ambient PM_1 starting at 0 through 21 days before the day of diagnosis in 12 cities in China using a two-step analysis: a time-series quasi-Poisson analysis to analyze the associations in each city; and then a meta-analysis to estimate the overall association. Diagnosed morbidities and PM_1 data were obtained from National Health Commission in China and China Meteorological Administration, respectively. We found association between short-term exposures to ambient PM_1 with COVID-19 morbidity was significantly positive, and larger than the associations with $PM_{2.5}$ and PM_{10}. Percent increases in daily-diagnosed COVID-19 morbidity per IQR/10 PM_1 for different moving averages ranged from 1.50% (−1.20%, 4.30%) to 241% (95%CI: 80.7%, 545%), with largest values for exposure windows starting at 17 days before diagnosis. Our results indicate that smaller particles are more highly associated with COVID-19 morbidity, and most of the effects from $PM_{2.5}$ and PM_{10} on COVID-19 may be primarily due to the PM_1. This study will be helpful for implementing measures and policies to control the spread of COVID-19.

1. Introduction

The spread of COVID-19 has become one of the most important global health events since World War II and significantly impacts human life worldwide. The outbreak of COVID-19 was initially reported in Wuhan, China in December 2019 (Li et al., 2020; Huang et al., 2020; Wei et al., 2022). It was declared a pandemic and global public health emergency by the World Health Organization (WHO) in March 2020 due to its high infectivity and severe health threat, as well as rapid growth in morbidity and mortality. Globally, the COVID-19 pandemic has resulted in over 400 million confirmed cases with about 5.8 million confirmed deaths through early February 2022 (WHO, 2022).

People with COVID-19 were reported to have a wide range of mild to severe symptoms and clinical characteristics, including, but not limited to cough, shortness of breath or difficulty breathing, and acute respiratory failure (CDC, 2021; Guan et al., 2020). Main transmission pathways of respiratory viruses include inhalation of respiratory droplets between people in close contact (distance less than 6 feet), aerosol transmission in indoor and crowded spaces with poor ventilation, and physical contact with contaminated surfaces or with an infected person

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carrying the SARS-CoV-2 (CDC, 2021; Qian et al., 2021).

There is evidence that indoor and outdoor particulate matter (PM) short-term air pollution could impair the defense of the upper airways, weaken the immune response, and make humans more prone to be infected by the virus (Zhu et al., 2020; Chen et al., 2020). Some studies suggested labelling PM of air pollution as potential vectors of SARS-CoV-2 (Barakat et al., 2020; Cao et al., 2021; Shao et al., 2021a, 2021b). Thus, exposure to PM could increase both susceptibility to SARS-CoV-2 infection and severity of COVID-19 disease (Marquès et al., 2022). A cohort study in Milan, Italy showed a relationship between the ambient (outdoor) levels of $PM_{2.5}$ (particulate matter with aerodynamic diameter <2.5 μm) and PM_{10} (particulate matter with aerodynamic diameter <10 μm) and COVID-19 cases (Zoran et al., 2020). High historical $PM_{2.5}$ exposures in the United States are also found to be positively associated with higher county-level COVID-19 mortality rates, after accounting for many area-level confounders ($PM_{2.5}$, age, temperature, etc.), with an increase of just 1 μg/m^3 of $PM_{2.5}$ resulting in a 15% increase in COVID-19 deaths (Wu et al., 2020).

The aerosol particles with smaller sizes (less than 5 μm), such as those containing the SARS-CoV-2, are more dangerous to human health since they can suspend for longer periods and penetrate deeper into the lungs than those with larger sizes (Hinds, 1999; Meselson, 2020; Liu et al., 2020; Shao et al., 2021a, 2021b; Port et al., 2022). Marquès and Domingo (2022) systematically reviewed the research advances on the association between the outdoor air pollution and incidence of COVID-19, and pointed out that, the limitation of the prior studies is that

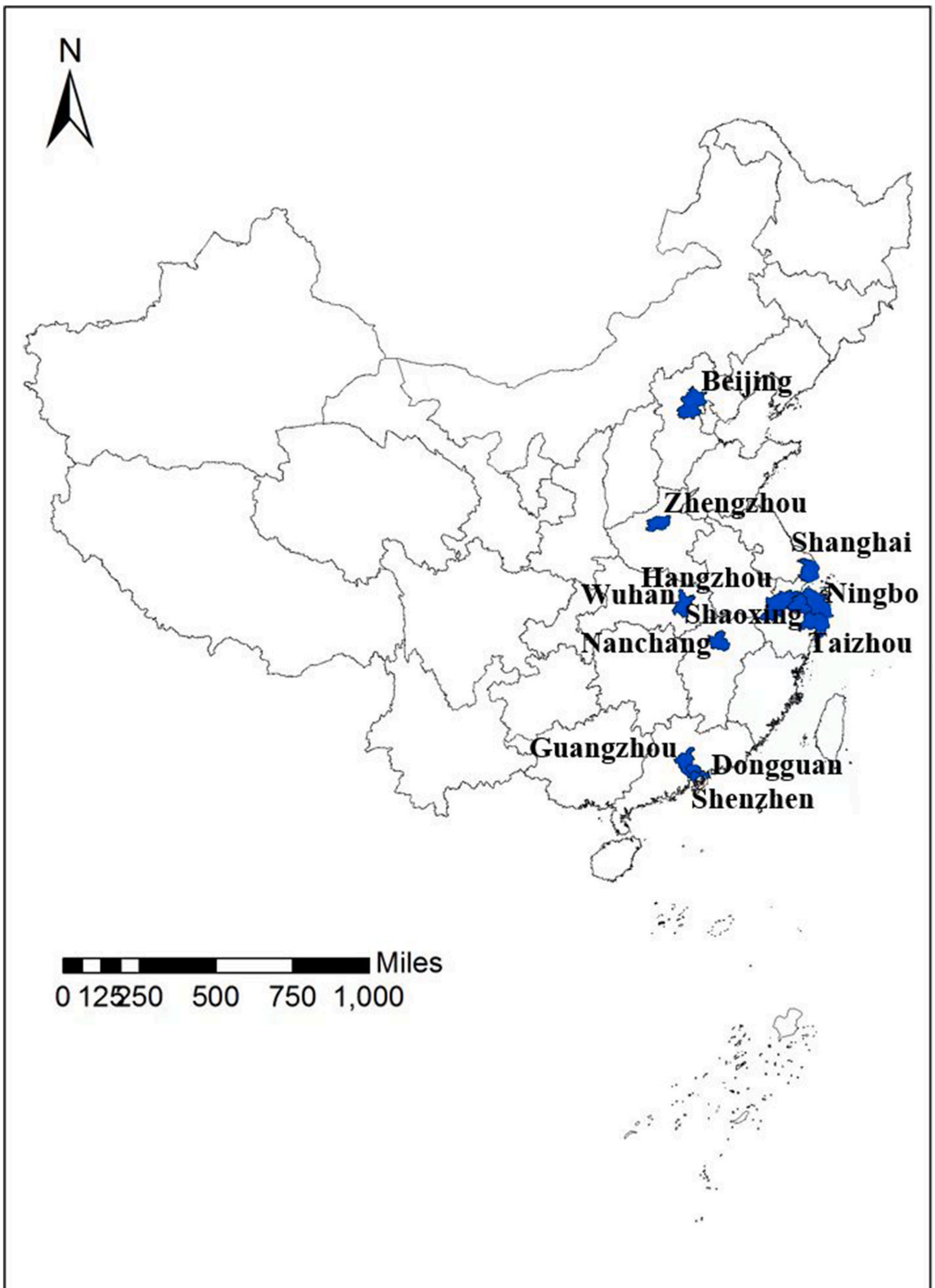

Fig. 1. The locations of 12 cities included in our study.

the examined pollutants are only confined to $PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2 and CO, and investigation on other important pollutants is urgently needed. At present, there have been no reports regarding PM_1 (particulate matter with aerodynamic diameter <1 μm) and COVID-19. PM_1 is composed of extremely fine particles. It has been reported that PM_1 is associated with a higher risk for emergency department visits (EDVs) than larger sizes of particulate matter (Liu et al., 2021).

This study aims to investigating the association between PM_1 and daily-diagnosed COVID-19 morbidity. Specifically, a two-step analysis (time-series quasi-Poisson analysis for each city and random-effects meta-analysis for overall association) was conducted based on data from 12 cities in China from January to June 2020 to assess the associations between ambient PM_1 and daily-diagnosed COVID-19 morbidity.

2. Methods

2.1. Data collection

Our investigation was based on data from 12 cities in China from Jan 13, 2020 to June 30, 2020 (Wuhan, Beijing, Guangzhou, Shanghai, Shenzhen, Nanchang, Hangzhou, Ningbo, Taizhou, Zhengzhou, Shaoxing, and Dongguan). Fig. 1 shows the locations of the 12 cities. The criteria for selecting the cities were: the total diagnosed morbidity of COVID-19 in the city was greater than 90 cases diagnosed during the study period; and the ambient PM_1 data was available from China Meteorological Administration. We excluded Feb 04, 2020 in Wuhan, because a large number of cumulative cases instead of the daily diagnosed morbidity was reported on that day (13436 cases).

Daily morbidities (cases with positive Polymerase Chain Reaction tests) were obtained from the daily published data (https://news.qq.com/zt2020/page/feiyan.htm#/global), which were gathered and reported by the National Health Commission in China. In order to minimize the interference of population flow, we only included the cases identified as local for each city and excluded the cases for those who traveled from abroad or other cities. Cases with positive PCR test were defined as diagnosed COVID-19 morbidity.

The PM_1 in situ measurements for the study period were collected from the China Atmosphere Watch Network (CAWNET) of the China Meteorological Administration (Wei et al., 2019). The detailed information for the PM_1 monitor stations used in this study is listed in Table S1 in Supplementary Material. PM_1 was measured using the GRIMM Model 1.180 Aerosol Spectrometer, which is an optical particle counter that measures and records particle number concentration (counts/cc) in multiple channels based on aerodynamic size and records 5-min average counts (5-min) for each channel. The 5-min values for each channel are used to calculate the mean 24h (daily) particle concentrations. For each size channel the particle number concentrations are converted to particle mass concentrations using the GRIMM protocols. PM_1 is then determined by adding the particle mass values for all channels for sizes up to 1 μm. The PM_1 determined this way is comparable to the $PM_{2.5}$ and PM_{10} measurements we used for this study, obtained from the China National Environmental Monitoring Centre (http://www.cnemc.cn/), measured using the tapered element oscillating microbalance (TEOM) or beta attenuation monitor (BAM), to determine compliance with China's National Ambient Air Quality Standard (Wei et al., 2021). It has been reported that the GRIMM-derived particle mass concentrations are highly consistent with those measured by the TEOM or BAM (Wei et al., 2019; Mukherjee et al., 2017). We assigned the average PM concentrations across all monitor stations in each city as exposure to the cases since we were unable to obtain the addresses of each case.

Daily meteorological data (including temperature and relative humidity) for each city were calculated from hourly data obtained from the NOAA Satellite and Information Service (http://www7.ncdc.noaa.gov/CDO/cdo).

2.2. Statistical analysis

We employed a two-step analysis to estimate the associations between ambient PM_1 and daily-diagnosed COVID-19 morbidity.

2.2.1. Time-series quasi-Poisson analysis

For the first step, we used a time-series quasi-Poisson model (R package "mgcv") to estimate the association between ambient PM_1 and daily-diagnosed COVID-19 morbidity for each city. We included time as a variable to control for long-term trends (Hamilton, 1994). We also controlled for meteorological parameters, i.e., daily temperature (T) and relative humidity (RH) 5 days before diagnosis, and day of week (if the day is weekend or not), as previous studies found associations between these factors and morbidity (Ma et al., 2020). We selected T and RH 5 days before diagnosis as T and RH at this lag time had strongest associations with morbidity compared to associations for other lag times, according to our analysis as well as Ma et al.'s (2020) research. The model can be expressed as:

$$Log(E(Y)) = \beta_0 + \beta_1 \times PM_1 + \beta_2 \times lag5T + \beta_3 \times lag5RH + \beta_4 \times weekend + s(time, df = 2\, per - month) + e \quad (1)$$

where, $E(Y)$ is the daily-diagnosed COVID-19 morbidity; PM_1 is the PM_1 exposures for 22 different moving averages starting at 0 through 21 days before the day of diagnosis respectively; *lag5T* is the daily temperature 5 days before diagnosis; *lag5RH* is the daily relative humidity 5 days of diagnosis; *weekend* is a binary variable which equals to 1 for weekend and 0 for weekdays; $s(time, df = 2\ per\text{-}month)$ is a natural spline with 2 degrees of freedom per month, which represents time series; β_0 is the intercept; β_1, β_2, β_3, and β_4 are the regression coefficients; *e* is the standard error.

2.2.2. Random-effects meta-analysis

Subsequently, we applied meta-analysis (R package "metaphor") to evaluate the overall associations in all 12 cities. We used random-effects meta-analysis as there was significant heterogeneity between the results for different cities ($I^2 > 50\%$). The overall study error variance in a random-effects meta-analysis includes two components: within-study and between-study errors (Borenstein et al., 2009). The observed mean effect of city *i* (Θ_i) can be expressed as follows:

$$\Theta_i = \mu + \varepsilon_i + £_i \quad (2)$$

where, μ is the grand mean effect of PM_1 on daily-diagnosed COVID-19 morbidity; ϵ_i is the within-study error and $£_i$ is the between study error; *i* represents the city ID ($i = 1, 2, \ldots 12$).

The combined association between PM_1 and daily-diagnosed COVID-19 morbidity in all 12 Chinese cities (β) is given by weighted observed mean effects (Θ_i) for all cities. The weight for city *i* is the reciprocal of the error variance (Zanobetti and Schwartz, 2009).

We used equation (3) to calculate the relative percent changes (PC) of diagnosed morbidity per IQR/10 (IQR denotes interquartile range) increase of exposure to ambient PM_1:

$$PC = (\exp(\beta \times IQR/10) - 1) \times 100\% \quad (3)$$

where, β is the overall coefficient of PM_1 for the 12 cities.

2.2.3. Sensitivity analysis

As the daily-diagnosed COVID-19 morbidity cases in Wuhan were much higher than other cities, this may skew the overall results for the 12 studied cities. Therefore, we conducted a sensitivity analysis on the associations for other 11 cities to exclude the interference of high morbidity factors in Wuhan cases, and compared the results with the overall results for 12 cities.

All the above statistical analyses were performed using R software.

We consider results with $p < 0.05$ as significant and $0.05 \leq p < 0.1$ as marginally significant.

3. Results

3.1. Characteristics of daily-diagnosed morbidity and exposures

Our study included 170 days with daily-diagnosed COVID-19 morbidity and environmental data in 12 cities. The mean daily-diagnosed COVID-19 morbidity was 18 cases/day. The highest mean daily-diagnosed morbidity was found in Wuhan (196 cases/day), where COVID-19 was initially reported. Summary statistics of COVID-19 morbidities for all 12 cities together and for each city separately are shown in Table 1.

Table 2 shows the descriptive information of the environmental data on the day of diagnosis for all 12 cities together and for each city separately, including ambient exposures to PM_1, $PM_{2.5}$ and PM_{10}, temperature, and relative humidity. The Pearson correlations between PM_1, $PM_{2.5}$, and PM_{10} used in this study are shown in Fig. S1. The mean outdoor PM_1, $PM_{2.5}$ and PM_{10} exposure for all cities was 18.2, 29.8, and 49.1 μg/m^3, respectively. The mean PM_1, $PM_{2.5}$ and PM_{10} exposure for Wuhan was 17.5, 34.3, and 52.1 μg/m^3, respectively. Among the 12 cities, Zhengzhou had the highest PM exposure. The lowest PM_1 and PM_{10} levels were observed in Dongguan, while the lowest $PM_{2.5}$ level was observed in Guangzhou. The mean temperature for all cities was 18.0 °C and the mean relative humidity was 72%.

We presented the PM_1 exposure and daily-diagnosed COVID-19 morbidity by date in Wuhan, where the diagnosed morbidity was the highest, in Fig. S2 in Supplementary Material.

3.2. Associations between PM_1 exposures for different moving averages and daily-diagnosed morbidity

3.2.1. Overall associations for all 12 cities together

We assessed the associations between daily-diagnosed COVID-19 morbidity and ambient PM_1 starting with the day of diagnosis (day0) to moving averages through 21 days before diagnosis (day21), controlling for daily temperature and relative humidity 5 days before diagnosis, weekend/weekday, and long-time trends. Values of regression coefficients of PM_1 (β) and p-values for the 12 cities for different moving averages are presented in Table S2 in the Supplementary Material. We found that PM_1 exposures for moving averages starting from 21 days before the day of diagnosis were all positively associated with the increase of daily-diagnosed COVID-19 morbidity, and most of the associations were significant. Overall percent increases of daily-diagnosed COVID-19 morbidity with per IQR/10 PM_1 for different moving averages ranged from 1.50% (95%CI: −1.20%, 4.30%) to 241% (95%CI: 80.7%, 545%) as shown in Fig. 2. The largest association between diagnosed morbidity and PM_1 is for average exposure from 17 days before diagnosis.

Table 1
Summary of daily COVID-19 morbidities in the 12 study cities.

City	Total diagnosed morbidity	Daily range	Mean daily diagnosed
Wuhan	30706	0–1985	196
Beijing	864	0–121	5
Guangzhou	554	0–38	4
Shanghai	543	0–112	3
Shenzhen	457	0–60	3
Nanchang	225	0–21	1
Hangzhou	207	0–19	1
Ningbo	170	0–27	1
Taizhou	162	0–24	1
Zhengzhou	153	0–13	1
Shaoxing	109	0–13	1
Dongguan	96	0–9	1

Table 2
Descriptive information for environmental data on the day of diagnosis.

City	PM_1 (μg/m^3)				$PM_{2.5}$ (μg/m^3)				PM_{10} (μg/m^3)				Temperature (°C)				RH			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Wuhan	17.51	12.69	1.86	83.71	34.40	17.87	8.50	108.79	52.07	23.96	11.67	121.63	17.30	7.94	0.68	31.83	0.72	0.14	0.40	0.98
Beijing	23.18	21.58	2.13	118.98	40.85	36.22	4.00	206.38	61.78	37.53	8.63	223.17	13.34	10.39	−5.98	31.06	0.45	0.18	0.10	0.96
Guangzhou	14.31	7.52	1.91	36.55	20.85	10.84	3.50	63.04	38.53	18.56	5.58	116.71	22.56	5.56	9.28	31.70	0.73	0.12	0.39	0.93
Shanghai	17.08	9.57	3.72	58.13	35.03	21.65	8.29	127.96	42.68	20.16	6.96	103.96	16.20	7.03	2.74	29.37	0.72	0.15	0.37	0.96
Shenzhen	9.83	6.47	1.78	50.08	17.50	9.25	4.00	61.17	31.07	14.62	6.17	96.67	23.45	4.65	10.82	30.54	0.79	0.09	0.40	0.93
Nanchang	14.95	8.67	1.83	46.49	31.20	16.09	6.92	76.63	54.21	30.96	10.96	134.33	18.37	7.62	3.71	31.79	0.76	0.15	0.40	0.98
Hangzhou	19.64	10.28	5.10	80.25	29.47	15.68	6.75	114.46	53.52	26.80	10.33	167.75	16.32	7.76	2.63	31.36	0.73	0.16	0.35	0.99
Ningbo	15.46	9.35	3.25	54.89	24.22	14.72	3.79	95.46	40.06	21.55	7.38	120.29	15.86	6.39	2.61	27.91	0.82	0.13	0.35	1.00
Taizhou	17.34	10.39	3.65	55.86	26.61	14.74	2.88	84.21	46.61	23.46	8.50	124.79	16.02	5.85	3.91	26.25	0.86	0.11	0.42	1.00
Zhengzhou	41.89	30.44	3.53	157.73	47.80	34.98	8.79	238.96	90.01	40.34	13.58	255.79	16.06	9.12	−1.91	32.13	0.55	0.20	0.14	0.97
Shaoxing	18.49	7.87	5.65	48.77	27.23	11.61	6.17	71.47	45.34	20.74	10.00	116.67	17.01	7.42	2.56	31.79	0.73	0.17	0.27	0.98
Dongguan	8.24	5.16	0.95	25.99	22.20	13.11	1.29	74.96	33.05	16.08	3.29	98.21	23.51	4.64	10.82	30.54	0.79	0.10	0.27	0.93
All cities	18.17	15.79	0.95	157.73	29.79	21.58	1.29	238.96	49.09	29.78	3.29	255.79	17.99	7.88	−5.98	32.13	0.72	0.18	0.10	1.00

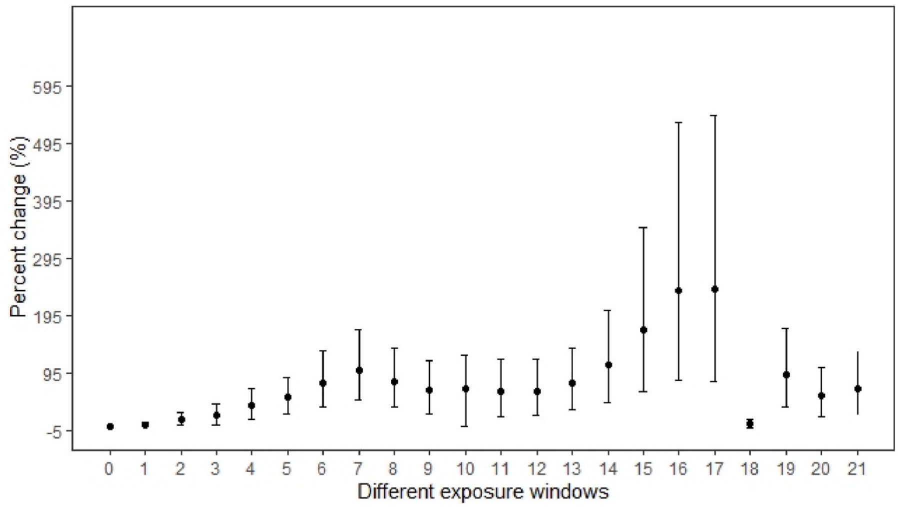

Fig. 2. Overall percent changes in daily-diagnosed COVID-19 morbidity per IQR/10 PM_1 for 12 cities for different exposure windows.

3.2.2. Associations for 11 cities excluding Wuhan

We excluded Wuhan and conducted analysis on the associations for other 11 cities for sensitivity analysis. Values of regression coefficients of PM_1 (β) and p-values for 11 cities for different moving averages are presented in Table S3 in the Supplementary Material. We found that the results were very similar with the associations for 12 cities as shown Fig. 3. It indicated that, though daily-diagnosed COVID-19 morbidity cases in Wuhan were much higher than other cities, including Wuhan in our meta-analysis did not skew the overall results for the 12 studied cities.

3.2.3. Associations for Wuhan

The regression coefficients for PM_1 (β_1) for Wuhan, the first outbreak site of COVID-19 and the most severely affected area in China, are shown in Table S4 in the Supplementary Material. Percent changes in daily-diagnosed COVID-19 morbidity per IQR/10 p.m.$_1$ for Wuhan for different moving averages are shown in Fig. 4. According to our results, the pattern of the associations was similar with the overall results. Percent changes were all positive except for the exposure on the diagnosis day. The percent changes of daily-diagnosed COVID-19 morbidity per IQR/10 PM_1 in Wuhan were larger than the overall values, ranging from −1.4% (95%CI: −3.1%, 0.4%) to 32.7% (95%CI: 20.7%, 45.8%). The values of percent changes were lower for Wuhan compared with the overall percent changes, because the IQR value in Wuhan was much lower.

3.3. Associations between $PM_{2.5}$ and PM_{10} and daily-diagnosed morbidity

In order to compare the effects of PM_1 with those of the two larger particle sizes, we applied the two-step method as described in the Methods section to examine the associations between daily-diagnosed COVID-19 morbidity with both $PM_{2.5}$ and PM_{10}. The time-series quasi-Poisson model for each city is:

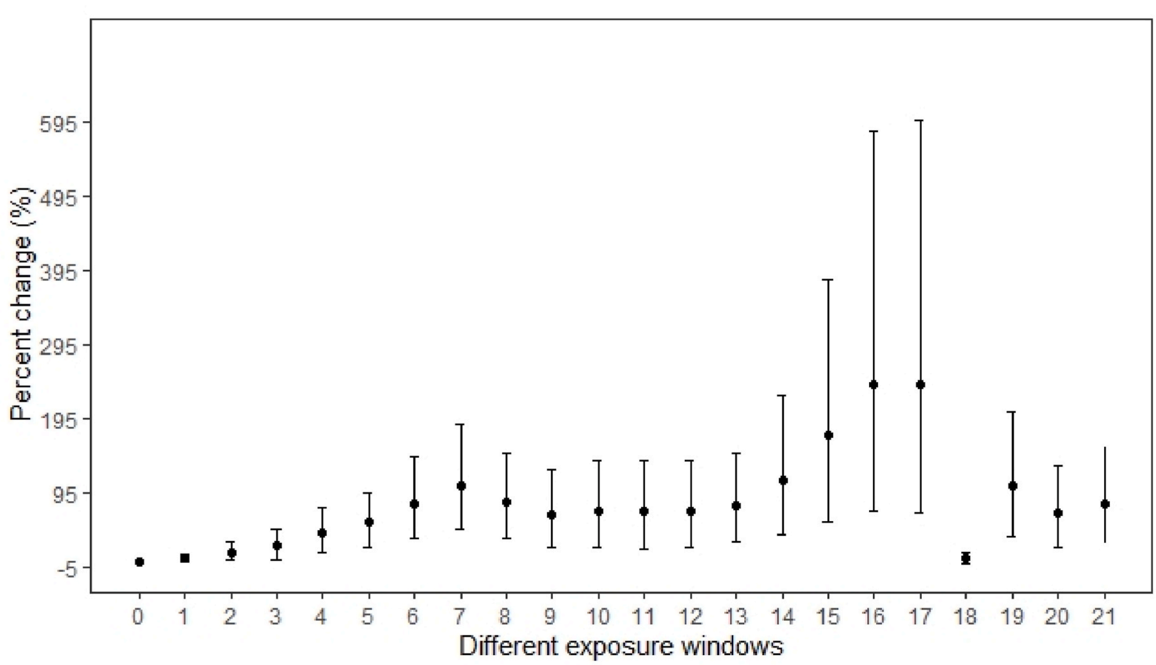

Fig. 3. Overall percent changes in daily-diagnosed COVID-19 morbidity per IQR/10 PM_1 for 11 cities excluding Wuhan for different exposure windows.

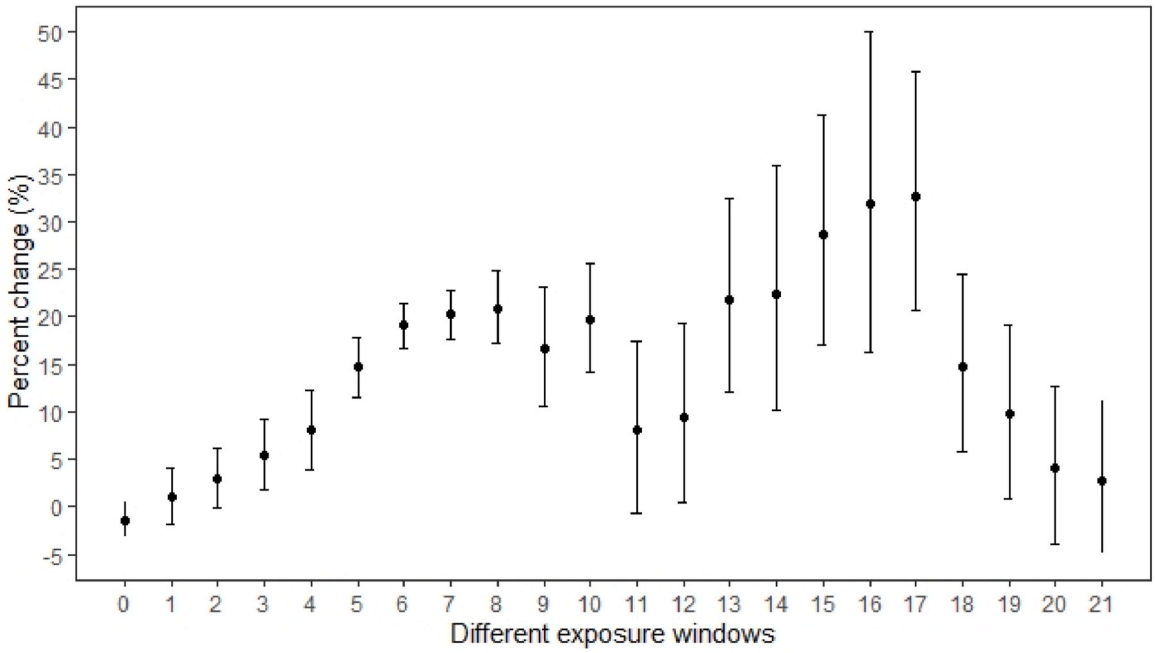

Fig. 4. Percent changes in daily-diagnosed COVID-19 morbidity per IQR/10 PM_1 for Wuhan with different exposure windows.

$$Log(E(Y)) = \beta_0 + \beta_1 \times Pollutant + \beta_2 \times lag5T + \beta_3 \times lag5RH + \beta_4 \times weekend + s(time, df = 2per - month) + e \quad (4)$$

where, *Pollutant* is the exposure of $PM_{2.5}$ or PM_{10} with different moving averages starting from 21 days before diagnosis.

Overall values of regression coefficients of PM_1 (β) for $PM_{2.5}$ and PM_{10} are presented in Table S5 and Table S6 in Supplementary Material. Overall percent changes in daily-diagnosed COVID-19 morbidity per IQR/10 $PM_{2.5}$ and PM_{10} with different moving averages are shown in Fig. S3 and Fig. S4 in the Supplementary Material, respectively. Compared with PM_1, the overall percent changes with $PM_{2.5}$ and PM_{10} per IQR/10 were smaller. Overall percent increases of daily-diagnosed COVID-19 morbidity per IQR/10 $PM_{2.5}$ for different moving averages ranged from 2.00% (95%CI: 0.300%, 3.80%) to 90.8% (95%CI: 36.3%, 167%), as shown in Fig. S3. For PM_{10}, the percent changes ranged from 2.80% (95%CI: 0.700%, 5.00%) to 52.7% (95%CI: 23.6%, 88.6%) (Fig. S4).

4. Discussion

This study investigated the associations between short-term exposure to ambient PM_1 and daily-diagnosed COVID-19 morbidity based on the data from 12 cities in China using a two-step analysis. Prior studies of the associations between PM and COVID-19 morbidity generally focused on $PM_{2.5}$ or PM_{10} (Zoran et al., 2020; Wu et al., 2020; Zhou et al., 2020a, 2020b; Conticini et al., 2020; Travaglio et al., 2021; Liang et al., 2020). To the best of our knowledge, our study provides the first attempt to examine the association between PM_1 and COVID-19 morbidity.

Our results show, for the 12 investigated cities together, daily-diagnosed COVID-19 morbidity was significantly associated with PM_1 exposures for different moving averages starting from 1 day before diagnosis (day1) to day21 (p-values < 0.05), except for day18. While for Wuhan city, daily-diagnosed COVID-19 morbidity was significantly associated with ambient PM_1 exposures starting from day3 to day19 (p-values < 0.05), except for day11. Specifically, with per IQR/10 increase of PM_1 concentration for day17, the overall percent change of daily-diagnosed COVID-19 morbidity was 241% (95%CI: 80.7%, 545%) for the 12 cities together, and the percent change was 32.7% (95%CI: 20.7%, 45.8%) for Wuhan. This is a remarkable increase, indicating that PM_1 exposure is highly correlated with daily-diagnosed COVID-19 morbidity.

Our results also indicate that the associations between PM_1 and daily-diagnosed COVID-19 morbidity increased with the length of exposure windows for exposure windows starting from day0 to day17, and then decreased. For PM_1 exposure starting from day17, the percent change (PC) of daily-diagnosed COVID-19 morbidity increases about 160-fold compared to PC for exposure on diagnosis day. While for Wuhan city, the PC for exposure starting from day17 increases about 29-fold compared to PC for day1. The main reason may be that for longer exposure windows, the coronavirus can transmit wider and farther, resulting in more significant cumulative impact. Under the exposure condition of longer time, people have more possibility and chance to be infected by the virus via various pathways, e.g., inhalation of respiratory droplets or aerosols or direct touch, which makes the morbidity rate rise rapidly. In addition, the possibility of a lag between exposure and when there is sufficient response to infection to test positive also contributes the higher morbidity in longer time.

Since many studies attempted to analyze the impact of $PM_{2.5}$ and PM_{10} on the COVID-19 morbidity, it is necessary to make a comparison among the contributions for particles of different sizes (i.e., PM_1, $PM_{2.5}$ and PM_{10}), to identify which size of particles shows the highest effect. Therefore, we also examined associations of diagnosis of COVID-19 with $PM_{2.5}$ and PM_{10}. We found that the association between diagnosis of COVID-19 and PM_1 exposure was larger than the associations with $PM_{2.5}$ and PM_{10} exposures. For example, at moving average starting from day17, the PC of $PM_{2.5}$ (90.8% (95%CI: 36.3%, 167%)) and PM_{10} (29.5% (95%CI: 16.6%, 43.8%)) for the 12 cities together were about 62%–88% lower than that of PM_1 (241% (95%CI: 80.7%, 545%)). This analysis suggests that PM_1 concentration may contribute more significantly than $PM_{2.5}$ and PM_{10} concentrations, which have been used as exposure indices in prior studies. Because PM_1 has a smaller size range, it may travel farther and suspend longer than $PM_{2.5}$ and PM_{10}, and it can penetrate deeper into the lungs, and lead to more severe health effects. This indicates that future studies of PM health effects should include this size range. In order to examine which size range of the particles may influence the COVID-19, we included PM_1 together with two residuals: the residual of $PM_{2.5}$ and PM_1 (represents PM from 1 μm to 2.5 μm), and the residual of PM_{10} and PM_1 (represents PM from 1 μm to 10 μm), respectively, in our models. However, no significant associations were found between either of these residuals and diagnosed morbidity. This result suggests that most of the effects from $PM_{2.5}$ and PM_{10} on COVID-19 may be primarily due to the PM_1.

A possible feature of the PM_1 that may be responsible for the higher effects per μg/m^3 (or IQR) is that each μg of PM_1 particles has a far greater number of particles than for the same mass for either $PM_{2.5}$ or PM_{10}. This suggests that part of why there are higher effects from PM_1 than the other two is that the particle number concentration influences the outcome, rather than the mass concentration of each of these size ranges, since each individual particle will cause cell damage (See and Balasubramanian, 2008). Table 2 shows that for all 12 cities, the mean mass concentration (μg/m^3) increases with increasing size range going between PM_1 and PM_{10}. So it is clear that the differences in effects are not related to mass concentrations for these three sizes. This reason suggests that future studies should include direct measurements of particle number concentration, using the conventional condensation nuclei counter (CNC) method (McMurry, 2005).

For $PM_{2.5}$ and PM_{10}, the percent increases of daily-diagnosed COVID-19 morbidity in the present study are higher than the results in a prior study. Zang et al. (2022) applied the meta-analysis to quantitatively explore the association between the short-term exposure to air pollutants and COVID-19 risk. They obtained that, with a 1 μg/m^3 increment in the $PM_{2.5}$ and PM_{10} concentrations, the COVID-19 morbidity increases 0.3% and 0.5%, respectively. The reasons for the difference are probably due to that: (1) the present study uses a different index, i.e., the percent change of daily-diagnosed COVID-19 morbidity per IQR/10; (2) we perform calculation and analysis under different moving averages from day0 to day21. However, the present results are comparable to the results in Lu et al. (2021)'s study based on data of 41 Chinese cities, which indicated that, a 10 μg/m^3 increase in the $PM_{2.5}$ concentrations was positively associated with a 5% percent change in the COVID-19 morbidity.

Our study has some limitations. Firstly, confirmed cases may not capture all morbidity and the number of observation days is limited (170 days), which will result in some bias and reduce the precision and power. However, previous study indicates that the precision and power depend only in the useable variation of exposure and the total number of disease events, instead of the number of the days (Armstrong et al., 2020). Secondly, the official report of morbidity is the number of cases with positive PCR tests and the test capacity varies greatly at the beginning or end of the pandemic, which will impact the number of cases reported each day. Thirdly, some potential confounding factors in our statistical models may be missing, such as public health-related policies, the shifting populations between cities, or UV radiation (Chaudhry et al., 2020; Hopman et al., 2020; Badr et al., 2020; Zhou et al., 2020a, 2020b; Ianevski et al., 2019). We tried to include some policies such as "the Wuhan lockdown" in our model, but did not find significant results. Moreover, the present study doesn't include analysis on individual-level features (age, gender, etc.) of morbidity. Despite the above limitations, our present study is the first to incorporate PM_1 exposure as an important factor for the morbidity of COVID-19 and may be helpful for implementing measures and policies related to community mitigation and personal protection (e.g., use of masks that could capture small particles $<$1 μm efficiently) to control the spread of COVID-19.

5. Conclusions

This is the first study to identify a significantly positive association between short-term exposure to PM_1 and daily-diagnosed COVID-19 morbidity. Our results also indicate that smaller particles are more highly associated with COVID-19 morbidity, and most of the effects from $PM_{2.5}$ and PM_{10} on COVID-19 may be primarily due to the PM_1. Therefore, researchers and policy makers should account for PM_1 as a potential risk factor of COVID-19.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2022.113016.

References

Armstrong, B.G., Gasparrini, A., Tobias, A., Sera, F., 2020. Sample size issues in time series regressions of counts on environmental exposures. BMC Med. Res. Methodol. 20, 15.

Badr, H.S., Du, H., Marshall, M., Dong, E., Squire, M.M., Gardner, L.M., 2020. Association between mobility patterns and COVID-19 transmission in the USA: a mathematical modelling study. Lancet Infect. Dis. 20, 1247–1254.

Barakat, T., Muylkens, B., Su, B.L., 2020. Is particulate matter of air pollution a vector of Covid-19 pandemic? Matter 3, 977–980.

Borenstein, M., Hedges, L.V., Higgins, J.P.H., Rothstein, H.R., 2009. Introduction to Meta-Analysis. John Wiley & Sons, Ltd., West Sussex, United Kingdom.

Cao, Y.X., Shao, L.Y., Jones, T., Oliveira, M.L.S., Ge, S.Y., Feng, X.L., et al., 2021. Multiple relationships between aerosol and COVID-19: a framework for global studies. Gondwana Res. 93, 243–251.

CDC, 2021. Centers for Disease Control. https://www.cdc.gov/coronavirus/2019-ncov/index.html.

Chaudhry, R., Dranitsaris, G., Mubashir, T., Bartoszko, J., Riazi, S., 2020. A country level analysis measuring the impact of government actions, country preparedness and socioeconomic factors on COVID-19 mortality and related health outcomes. EClinicalMedicine 25, 25100464.

Chen, N., Zhou, M., Dong, X., Qu, J., Gong, F., Han, Y., Qiu, Y., Wang, J., Liu, Y., Wei, Y., Xia, J., Yu, T., Zhang, X., Zhang, L., 2020. Epidemiological and clinical characteristics of 99 cases of 2019 novel coronavirus pneumonia in Wuhan, China: a descriptive study. Lancet 395, 507–513.

Conticini, E., Frediani, B., Caro, D., 2020. Can atmospheric pollution be considered a cofactor in extremely high level of SARS-CoV-2 lethality in Northern Italy? Environ. Pollut. 261, 114465.

Guan, W., Ni, Z., Hu, Y., Liang, W., Ou, C., He, J., Liu, L., Shan, H., Lei, C., Hui, D.S.C., Du, B., Li, L., Zeng, G., Yuen, K.-Y., Chen, R., Tang, C., Wang, T., Chen, P., Xiang, J., Li, S., Wang, J., Liang, Z., Peng, Y., Wei, L., Liu, Y., Hu, Y., Peng, P., Wang, J., Liu, J., Chen, Z., Li, G., Zheng, Z., Qiu, S., Luo, J., Ye, C., Zhu, S., Zhong, N., 2020. Clinical characteristics of coronavirus disease 2019 in China. N. Engl. J. Med. 382, 1708–1720.

Hamilton, J.D., 1994. Time Series Analysis. Princeton University Press, Princeton, New Jersey.

Hinds, W.C., 1999. Aerosol Technology: Properties, Behavior, and Measurement of Airborne Particles, second ed. John & Wiley Sons.

Hopman, J., Allegranzi, B., Mehtar, S., 2020. Managing COVID-19 in low- and middle-income countries. JAMA 323, 1549–1550.

Huang, C., Wang, Y., Li, X., Ren, L., Zhao, J., Hu, Y., Zhang, L., Fan, G., Xu, J., Gu, X., 2020. Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. Lancet 395, 497–506.

Ianevski, A., Zusinaite, E., Shtaida, N., Kallio-Kokko, H., Valkonen, M., Kantele, A., Telling, K., Lutsar, I., Letjuka, P., Metelitsa, N., Oksevch, V., Dumpis, U., Vitkauskiene, A., Stašaitis, K., Öhrmalm, C., Bondeson, K., Bergqvist, A., Cox, R.J., Tenson, T., Merits, A., Kainov, D.E., 2019. Low temperature and low UV indexes correlated with peaks of influenza virus activity in Northern Europe during 2010-2018. Viruses 1, 207.

Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., Ren, R., Leung, K.S.M., Lau, E.H.Y., Wong, J.Y., Xing, X., Xiang, N., Wu, Y., Li, C., Chen, Q., Li, D., Liu, T., Zhao, J., Liu, M., Tu, W., Chen, C., Jin, L., Yang, R., Wang, Q., Zhou, S., Wang, R., Liu, H., Luo, Y., Liu, Y., Shao, G., Li, H., Tao, Z., Yang, Y., Deng, Z., Liu, B., Ma, Z., Zhang, Y., Shi, G., Lam, T.T.Y., Wu, J.T., Gao, G.F., Cowling, B.J., Yang, B., Leung, G.M., Feng, Z., 2020. Early transmission dynamics in Wuhan, China, of novel coronavirus–infected pneumonia. N. Engl. J. Med. 382, 1199–1207.

Liang, D., Shi, L., Zhao, J., et al., 2020. Urban air pollution may enhance COVID-19 case-fatality and mortality rates in the United States. Innovation 1, 100047.

Liu, L., Zhang, J., Du, R.G., Teng, X.M., Li, W.J., 2020. Chemistry of atmospheric fine particles during the COVID pandemic in a megacity of eastern China. Geophys. Res. Lett. 48, e2020.

Liu, L., Song, F., Fang, J., Wei, J., Ho, H.C., Song, Y., Zhang, Y., Wang, L., Yang, Z., Hu, C., Zhang, Y., 2021. Intraday effects of ambient PM1 on emergency department visits in Guangzhou, China: a case-crossover study. Sci. Total Environ. 750, 142347.

Lu, B., Wu, N., Jiang, J., Li, X., 2021. Associations of acute exposure to airborne pollutants with COVID-19 infection: evidence from China. Environ. Sci. Pollut. Res. Int. 28, 50554–50564.

Ma, Y.L., Zhao, Y.D., Liu, J.T., He, X.T., Wang, B., Fu, S.H., Yan, J., Niu, J.P., Zhou, J., Luo, B., 2020. Effects of temperature variation and humidity on the death of COVID-19 in Wuhan, China. Sci. Total Environ. 724, 138226.

Marquès, M., Domingo, J.L., 2022. Positive association between outdoor air pollution and the incidence and severity of COVID-19. A review of the recent scientific evidences. Environ. Res. 203, 111930.

Marquès, M., Correig, E., Ibarretxe, D., Anoro, E., Arroyo, J.A., Jericó, C., et al., 2022. Long-term exposure to PM_{10} above WHO guidelines exacerbates COVID-19 severity and mortality. Environ. Int. 158, 106930.

McMurry, P.H., 2005. The history of condensation nucleus counters. Aerosol Sci. Technol. 33, 297–322.

Meselson, M., 2020. Droplets and aerosols in the transmission of SARS-CoV-2. N. Engl. J. Med. 382, 2063.

Mukherjee, A., Stanton, L.G., Graham, A.R., Roberts, P.T., 2017. Assessing the utility of low-cost particulate matter sensors over a 12-week period in the Cuyama valley of California. Sensors 17, 1805.

Port, J.R., Yinda, C.K., Avanzato, V.A., Schulz, J.E., Holbrook, M.G., van Doremalen, N., et al., 2022. Increased small particle aerosol transmission of B.1.1.7 compared with SARS-CoV-2 lineage A in vivo. Nat. Microbiol. 7, 213–223.

Qian, H., Miao, T., Liu, L., Zheng, X., Luo, D., Li, Y., 2021. Indoor transmission of SARS-CoV-2. Indoor Air 31, 639–645.

See, S., Balasubramanian, R., 2008. Chemical characteristics of fine particles emitted from different gas cooking methods. Atmos. Environ. 42, 8852–8862.

Shao, L.Y., Ge, S.Y., Jones, T., Santosh, M., Silva, L.F.O., Cao, Y.X., et al., 2021a. The role of airborne particles and environmental considerations in the transmission of SARS-CoV-2. Geosci. Front. Times 12, 101189.

Shao, L., Cao, Y., Jones, T., Santosh, M., Silva, L.F.O., Ge, S., da Boit, K., Feng, X., Zhang, M., BéruBé, K., 2021b. COVID-19 mortality and exposure to airborne PM2.5: a lag time correlation. Sci. Total Environ. 806, 151286.

Travaglio, M., Yu, Y., Popovic, R., Selley, L., Leal, N.S., Martins, L.M., 2021. Links between air pollution and COVID-19 in England. Environ. Pollut. 268, 115859.

Wei, J., Li, Z., Guo, J., Sun, L., Huang, W., Xue, W., Fan, T., Cribb, M., 2019. Satellite-derived 1-km-Resolution PM1 concentrations from 2014 to 2018 across China. Environ. Sci. Technol. 53, 13265–13274.

Wei, J., Li, Z., Li, K., Dickerson, R., Pinker, R., Wang, J., Liu, X., Sun, L., Xue, W., Cribb, M., 2022. Full-coverage mapping and spatiotemporal variations of ground-level ozone (O_3) pollution from 2013 to 2020 across China. Remote Sens. Environ. 270, 112775 https://doi.org/10.1016/j.rse.2021.112775.

Wei, J., Li, Z., Lyapustin, A., Sun, L., Peng, Y., Xue, W., Su, T., Cribb, M., 2021. Reconstructing 1-km-resolution high-quality PM2.5 data records from 2000 to 2018 in China: spatiotemporal variations and policy implications. Remote Sens. Environ. 252, 112136.

WHO, 2022. World Health Organization. https://www.who.int/emergencies/diseases/novel-coronavirus-2019.

Wu, X., Nethery, R.C., Sabath, M.B., Braun, D., Dominici, F., 2020. Air pollution and COVID-19 mortality in the United States: strengths and limitations of an ecological regression analysis. Sci. Adv. 6, eabd4049.

Zang, S.T., Luan, J., Li, L., Yu, H.X., Wu, Q.J., Chang, Q., Zhao, Y.H., 2022. Ambient air pollution and COVID-19 risk: evidence from 35 observational studies. Environ. Res. 204, 112065.

Zanobetti, A., Schwartz, J., 2009. The effect of fine and coarse particulate air pollution on mortality: a national analysis. Environ. Health Perspect. 117, 898–903.

Zhou, F., Yu, T., Du, R., et al., 2020a. Clinical course and risk factors for mortality of adult inpatients with COVID-19 in Wuhan, China: a retrospective cohort study. Lancet 395, 1054–1062.

Zhou, Y., Xu, R., Hu, D., Yue, Y., Li, Q., Xia, J., 2020b. Effects of human mobility restrictions on the spread of COVID-19 in Shenzhen, China: a modelling study using mobile phone data. Lancet Digit. Health 2, E417–E424.

Zhu, Y., Xie, J., Huang, F., Cao, L., 2020. Association between short-term exposure to air pollution and COVID-19 infection: evidence from China. Sci. Total Environ. 727, 138704.

Zoran, M.A., Savastru, R.S., Savastru, D.M., Tautan, M.N., 2020. Assessing the relationship between surface levels of PM2.5 and PM10 particulate matter impact on COVID-19 in Milan, Italy. Sci. Total Environ. 738, 139825.