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Screening Approach for Short-Term PM_{2.5} Health Co-Benefits: A Case Study from 15 Metropolitan Cities around the World during the COVID-19 Pandemic

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Abstract: Fifteen cities across the world have been selected to investigate the public health co-benefits of PM_{2.5} reduction, during a period when various non-pharmaceutical interventions (NPIs) were adopted in the COVID-19 pandemic. Through applying a public health model, AirQ+, substantial spatial variations of global public health co-benefits were identified. Differences in seasonal air quality and population baselines were key underlying factors. For cities in North America, NPIs were introduced during the low pollution season, generating no co-benefits. On the other hand, tremendous health co-benefits were observed for cities in India and China, due to the high PM_{2.5} background with a large population. Among all, New Delhi has received the largest co-benefits, which saved over 14,700 premature deaths. As the pollution level (i.e., 45 µg m⁻³) with NPIs still exceeded the air quality standard, more rigorous emission controls are urgently needed to protect the public's health in India. At last, a novel and practical tool for co-benefit screening was developed using data from one of the global measurement networks (i.e., IQAir).

Keywords: spatio-temporal dynamics of air pollution; COVID19; PM_{2.5}; pandemic lockdown; public health co-benefits; IQAir

1. Introduction

The rapid spread of COVID-19 has made the World Health Organization (WHO) declare the outbreak of the disease as a Public Health Emergency of International Concern on 30 January 2020, and a pandemic on 11 March 2020. In terms of the introduction of non-pharmaceutical interventions (NPIs), China has taken the earliest precaution in late January 2020, just before the lunar new year, to lockdown the affected cities (e.g., Wuhan), preventing the further spread of the virus within China [1]. With the continuous spread of COVID-19 and escalated confirmed cases globally, the world has taken the pandemic seriously and implemented a series of stringent policies to cut off its transmission routes. NPIs, such as restrictions on international travel, social distancing, work from home (WFH), and mandatory quarantine, were adopted. With surges in confirmed cases, some administrations have implemented massive city-wide or country-based emergency lockdowns [2]. These NPIs caused significant impacts on the local economy and industrial activities, in which travelling and gathering were suspended or heavily restricted [3]. It has been reported that traffic volumes in various US and European cities in the first three months of the pandemic were reduced by 48% to 86% [4]. In the UK, the reduction was about 41% to 55% [5]. In East Asia, limited reductions in traffic (i.e., 10–18%) and total passenger number (i.e., 41.4%) were also observed in cities, such as Hong Kong [4,6,7]. Apart from the absolute traffic volume reduction, decreases in traffic congestion (i.e., 14–20%) and total vehicle

number (i.e., 21.5%) were also reported [6,8]. These traffic reductions have resulted in a sharp decline in local air pollution and contributed to short-term public health co-benefits from pollution reduction [9–11]. Overall, reductions in global air pollution (excluding O_3) and values of the air quality index (AQI) were reported, ranging from -15 to -60% and -15.2 to -47% , respectively, with strong spatial heterogeneity [12–17]. Large pollution reductions (i.e., AQI from “Unhealthy” to “Moderate”) were observed in East and South Asia, while mild pollution reductions (i.e., AQI from “Moderate” to “Good”) were reported for Europe and North America [11,12,18]. A distinct pattern of global pollution reduction has emerged from the effect of NPIs. City-wide reductions in NO_2 , CO, PM_{10} , and $PM_{2.5}$, with an increase in O_3 , were generally observed during the lockdown. The increase in O_3 was attributed to the weakening of the titration effect from reducing NO_x ($NO + NO_2$) emissions. Keller et al. [19] reported that 18% to 60% reductions in NO_2 were observed in 46 countries between January to June 2020, when compared with the case of business as usual in 2019, while other studies reported drops in $PM_{2.5}$ or PM_{10} , between 4–32% in US cities, 24–60% in Chinese cities, 24% to 31% in European cities, and 19% to 54% in Indian cities [12,13,20–24]. In general, the percentage of reductions in roadside NO_2 and $PM_{2.5}$ were more significant than those observed in ambient stations, due to a substantial decrease in local vehicular traffic. In China, a strong correlation between NO_2 reduction and traffic volume was also reported for different cities [24]. Huang et al. [1] estimated that about 70–80% of the reduction in NO_x emission during the pandemic was attributable to the reduction in traffic; and every 1% drop in intra-city travel intensity (TI) contributed to about 2–4% NO_2 reduction [15]. Clearly, these studies have demonstrated that a reduction in traffic emissions can have substantial influence on air pollution during COVID-19. However, it should not be neglected that the level of pollution reduction in cities cannot solely be explained by the decline in vehicular emissions. Other factors, such as industrial emission in the region, change of local meteorology affecting pollution dispersion, urban and rural composition, level of lockdown, and seasonal pollution baselines, could also influence the pollution level observed during COVID-19 [24].

In this study, 15 cities worldwide were selected to investigate the impact of $PM_{2.5}$ air quality and its associated short-term health co-benefits (measured as premature deaths) during the pandemic. The study examined the temporal and spatial variations of health co-benefits during the first few months of the COVID-19 pandemic. Owing to the influence of different meteorological conditions, four years (2017–2020) of ground-based $PM_{2.5}$ air quality data, obtained from various monitoring networks, were employed. Summaries of generalized location patterns and a discussion of mechanisms concerning the baseline pollution values with seasonal impact on the health co-benefits were performed. Through a comparative analysis, the study established the relationship between cities’ baseline concentration and level of premature deaths during the lockdown. The findings offer a unique explanation to the spatial heterogeneity observed in the global air pollution data. In addition, a novel screening method for public health co-benefits, using one of the global measurement networks (i.e., IQAir), was introduced. The rest of the paper is organized as follows. Section 2 covers data collection and analysis methodology. Section 3.1 examines the geospatial variations of air quality change around the world. Finally, Section 3.2 discusses $PM_{2.5}$ reductions and their associated public health co-benefits, along with the development of a co-benefit screening tool.

2. Data Collection, Observations, and Methodologies

2.1. Study Areas and Air Quality Data

Fifteen cities, from multiple air quality networks, were selected to investigate the geospatial variations of $PM_{2.5}$ and their associated short-term health effect before and during the pandemic, when NPIs were in place. Figure 1 shows the chosen cities from seven different air quality networks. Among them, three are in East Asia; four are in South or Southeast Asia; one is in the Middle East; one is in Africa; three are in America; and three are in Europe. Many of these cities, including Hong Kong, London, New York, Los

Angeles, Beijing, Tokyo, and Zurich, were listed as the top 50 smart cities [25]. The reasons for selecting these cities were mainly based on data availability, PM_{2.5} pollution level, and global spatial coverage.

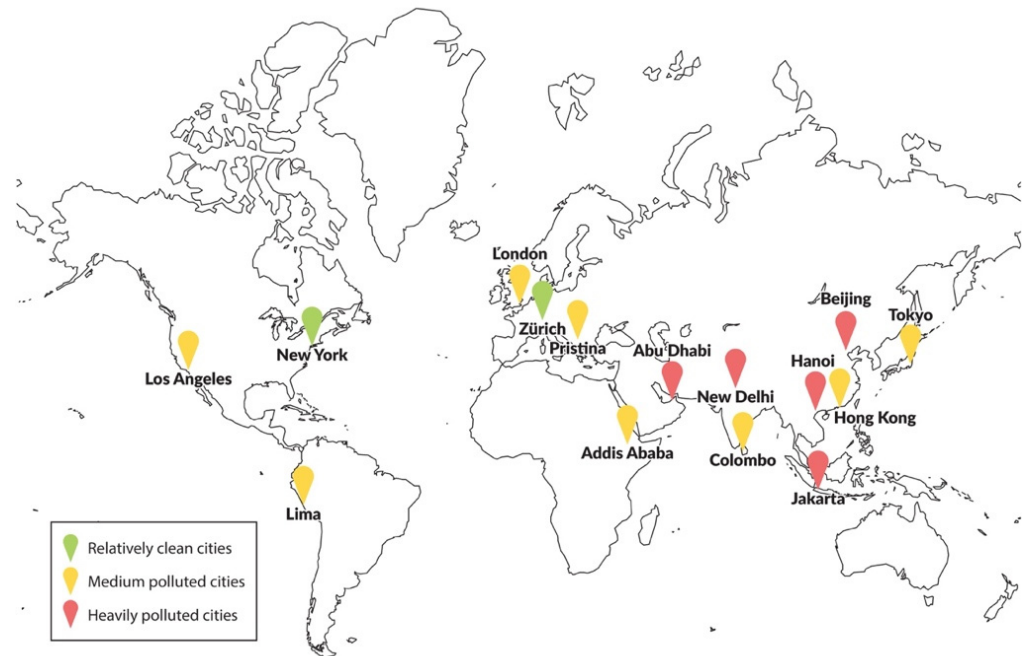


Figure 1. Selected cities for this air quality study.

Table 1 shows the selected cities with their corresponding networks. For the AIRNow network, only one station per city was used due to data availability. All stations in the network are categorized as urban ambient (not urban traffic/roadside) stations. MET One BAM 1020 is used for continuous PM_{2.5} measurement [26]. For non-AIRNow stations, both urban ambient (hereinafter referred to as “ambient station”) and urban traffic/roadside stations (hereinafter referred to as “traffic station”) were selected. The inclusion of traffic stations allows one to gauge the influence of changes in local transport on PM_{2.5} from COVID-related NPIs. Depending on data availability, one to three stations were selected for each city. Details of the selected PM_{2.5} air quality stations and their station characteristics are listed in Table 1. For easy comparison among the stations, cities were divided into three groups based on their annual PM_{2.5} concentrations from the 2019 IQAir report, as shown in Figure 1 [27]. The IQAir report provides annual PM_{2.5} data from the top 100 most polluted cities, and the data were summarized from over 10,000 stations around the world. The first group is called “heavily polluted cities”, with an annual PM_{2.5} concentration greater than 40 $\mu\text{g m}^{-3}$. In our list, five cities fall into this category, including New Delhi (98.6 $\mu\text{g m}^{-3}$), Jakarta (51.7 $\mu\text{g m}^{-3}$), Beijing (42.1 $\mu\text{g m}^{-3}$), Abu Dhabi (42.4 $\mu\text{g m}^{-3}$), and Hanoi (46.9 $\mu\text{g m}^{-3}$). They were being ranked among the top 10 polluted cities in the report. The second group is called “medium polluted cities”, with an annual PM_{2.5} concentration between 10 $\mu\text{g m}^{-3}$ and 40 $\mu\text{g m}^{-3}$. These cities include Colombo (25.2 $\mu\text{g m}^{-3}$), Lima (23.7 $\mu\text{g m}^{-3}$), Pristina (23.5 $\mu\text{g m}^{-3}$), Vientiane (23.1 $\mu\text{g m}^{-3}$), Addis Ababa (20.1 $\mu\text{g m}^{-3}$), Los Angeles (12.7 $\mu\text{g m}^{-3}$), Hong Kong (20.3 $\mu\text{g m}^{-3}$), Tokyo (11.7 $\mu\text{g m}^{-3}$), and London (11.4 $\mu\text{g m}^{-3}$). The last group is referred to as “relatively clean cities”. These cities include New York and Zurich, with an annual PM_{2.5} concentration below 10 $\mu\text{g m}^{-3}$, which meets the annual standard of the WHO air quality guidelines (AQG). It should be noted that the optical-based PM_{2.5} measurements (i.e., using optical particle counter) taken from IQAir may be skewed toward the low-side of PM_{2.5}, compared to the measurement data gathered from official government networks (especially for groups in relatively heavily polluted cities), as some of their instruments may be situated in a semi-indoor environment

with a certain degree of PM_{2.5} removal from heating, ventilation, and air conditioning (HVAC) units or indoor filtration systems. Moreover, their instruments (those placed inside high-rise buildings) may be higher in station elevation than the official ambient air quality stations. Hence, the values reported in the IQAir report may not fully reflect the seriousness (i.e., maximum concentration) as the values reported from the official ambient air quality stations. Nevertheless, the IQAir still provides relatively reliable concentration data for the grouping and screening exercises.

Table 1. Selected cities with their air quality stations.

Region	Cities	Sites	Sources
SEA, SA, EA, SAM, ME, NA, and AF	New Delhi, India; Jakarta, Indonesia; Beijing, China; Hanoi, Vietnam; Colombo, Sri Lanka; Lima, Peru; Pristina, Kosovo; Addis Ababa, Ethiopia, and Abu Dhabi, UAE		AIRNow, Department of State, USA: https://www.airnow.gov/international/us-embassies-and-consulates/ (accessed on 26 May 2020)
NA	Los Angeles, USA	Long Beach ¹ , LA-North, and Riverside-Rubidoux	South Coast Air Quality Management District: https://www.arb.ca.gov/aqmis2/aqdselect.php (accessed on 26 May 2020)
NA	New York, USA	PS314 ¹ , Queens Near Road ¹ , and Maspeth ¹	New York State Department of Environmental Conservation: http://www.nyaqinow.net (accessed on 26 May 2020)
EA	Hong Kong, China	Shum Shui Po, Mongkok ¹ , Shatin and Yuen Long	Hong Kong Environmental Protection Department https://cd.epic.epd.gov.hk/EPICDI/air/station/?lang=en (accessed on 26 May 2020)
EA	Tokyo, Japan	Daiichi Keihin Takanawa ¹ , Takanawa, Minato-ku, and Daiba, Minato-ku	Minato City Council, Tokyo: https://www.city.minato.tokyo.jp/kankyoushidouasesutan/2016date.html (accessed on 26 May 2020)
EU	London, UK	Marylebone Road ¹ , Kensington, Haringey Park ¹ , and Camden Kerbside ¹	Department for Environment Food & Rural Affairs https://uk-air.defra.gov.uk/data/data_selector (accessed on 26 May 2020)
EU	Zurich, Switzerland	Zürich-Kaserne (only station in Zurich)	National Air Pollution Monitoring Network, Switzerland https://www.bafu.admin.ch/bafu/en/home/topics/air/state/data/historical-data.html (accessed on 26 May 2020)

¹ Roadside/urban traffic station; SEA—Southeast Asia; SA—South Asia; EA—East Asia; East; AF—Africa; NA.—North America; ME.—Middle East; EU—Europe; SAM—South America.

In this study, the hourly air quality data in the first two months (about 60 days) after the announcement of the COVID-19 pandemic were collected. The common period of 1 April to 15 May 2020 (45 days), when all cities have implemented some forms of NPIs, was adopted for the analysis. For evaluating the short-term co-benefits of air pollution reduction during the study period, air quality data from 2017 to 2019 on the same calendar period were also collected. All data (2017–2020) were processed to obtain a uniform format to analyze the influence of emission change on air quality. The selection of three earlier historical years allows a better reflection on the effect of meteorological variations in air quality comparison. It is common to evaluate air quality changes in such a way for the observation comparison [6,12,14,17]. After the air quality evaluation, the processed data was then further applied to a public health model, AirQ+, to estimate the potential short-term health benefit from the pandemic. As multiple cities were considered, spatial variations of health co-benefits and how background pollution concentration influences the health co-benefits were investigated. Details of AirQ+ are discussed in the next section. At last, with the case studies of New Delhi, London, Hong Kong, New York, and Zurich, the relationship of local traffic change and PM_{2.5} air quality were examined. Data from TomTom vehicular

GPS network, which contains the nearly real-time hourly congestion level for individual streets, was used to evaluate traffic reduction and the change in congestion level during the pandemic [28]. The proposed analysis with local air quality data provides insights into how the COVID-related NPIs affect the local traffic and subsequently influence the temporal and spatial patterns of air pollution around the world.

2.2. The Health Co-Benefit Model, AirQ+

AirQ+ quantifies the health burden and impact of air pollution. It was developed by the WHO regional office for Europe. The model utilizes regional public health data with a pollutant exposure methodology to assess the health effects from air pollutant exposure. The health-related outcomes, including mortality and morbidity, can be determined through the model. The model has been validated and used in various air quality and health-related studies [29–31]. In this study, the 24-h $\text{PM}_{2.5}$ data from 2017 to 2020 (1 April to 15 May) in the selected cities (i.e., 15) was used as inputs. Simulations of pre-COVID cases (i.e., 2017, 2018, and 2019) were performed independently for individual years. The multiple-year observations allow us to evaluate the impact of meteorological variations on air quality and health related impacts. The COVID-19 situation was simulated based on data in 2020. The differences between the pre-COVID and COVID-19 situations were then used to estimate the short-term health co-benefits during the pandemic. To calculate the air quality health impact (i.e., mortality rate) from the model, city-level population data obtained from the United Nations [32] was applied. The default value of $25 \mu\text{g m}^{-3}$ (24-h mean) was applied as the cut-off concentration, aligning with the WHO AQG for the 24-h $\text{PM}_{2.5}$ standard [33]. Based on the data obtained from Western Europe and North American studies, a relative risk (RR) value of 1.0123 for all-cause mortality was used [34].

3. Results and Discussion

3.1. Geospatial Variations of Air Quality Change before and during the Pandemic

The NPIs were more popular among countries and cities in America, Europe, and East Asia at the beginning of the pandemic. The intention was to break the transmission pathways of COVID-19, aiming to lower the rising trend and ease the shortage of resources (i.e., physicians and surgical masks) in the public health sector. As many cities suffered from a strong hit in the first wave of the pandemic, the large number of confirmed cases, combined with a lack of medical resources, forced governments to implement NPIs to curb the spread of the virus. Table 2 summarizes the average $\text{PM}_{2.5}$, as well as the percentage change of pollutant concentrations between the pandemic and business-as-usual condition (BAU) situation in 2017–2019, for the same calendar period. The grey color highlights cities with a full lockdown, which restricted people from leaving their homes freely, and “#” indicates cities with non-lockdown NPIs, where policies such as school closure, suspension of public services, or social distancing were in force. As reflected in the table, the full lockdown (cities with grey color) has resulted in appreciable $\text{PM}_{2.5}$ reductions (shown as negative) on both ambient and traffic air quality stations, regardless of their regions. The percentage change in $\text{PM}_{2.5}$ from cities with lockdown ranged from -12% to -49% in the ambient stations, with Beijing, New Delhi, London, Los Angeles, Lima, and New York being -28% , -49% , -12% , -14% , -48% , and -24% on 3-year averaging (2017–2019), respectively. For traffic stations, the range of change was between -18% and -25% . The observed low value of the change at the top range (-25%) among traffic stations may create a misconception of less drastic reductions at traffic stations than ambient stations. However, when we carefully analyzed the traffic station data, the low value at the top range was caused by data missing for some cities with heavy $\text{PM}_{2.5}$ reductions. Excluding those cities that did not have data from traffic stations in calculating the percentage change in the ambient stations, the upper range has become -24% , which is comparable with that of traffic stations.

Table 2. Summary of PM_{2.5} air quality for selected cities.

Group	Reg. ¹	City	St. Type ²	Average PM _{2.5} Conc. (µg m ⁻³)				% Change from 2020			
				2020	2019	2018	2017	2019	2018	2017	2017–2019
Heavily polluted city	EA	Beijing, CN	Amb.	43	51.9	65.9	61.8	−17	−35	−30	−28
	SEA	Jakarta, Indonesia ²	Amb.	50.4	46.5	51.8	32.2	8	−3	57	16
	SEA	Hanoi, Vietnam	Amb.	42.4	-	33.3	-	-	27	-	-
	SA	New Delhi, India	Amb.	42.2	91	70.8	88.1	−54	−40	−52	−49
Medium polluted city	ME	Abu Dhabi, UAE ²	Amb.	20.1	42.7	48.9	-	−53	−59	-	−56
	EA	Hong Kong, CN ²	Tra.	19.3	21.2	23.4	29.6	−9	−18	−35	−22
			Amb.	15.6	14.9	19.6	21.8	5	−20	−28	−17
	EA	Tokyo, Japan	Tra.	13.5	12.2	15.3	14.7	11	−12	−8	−4
			Amb.	10.5	11.8	17.7	14.3	−11	−41	−27	−28
	SA	Colombo, Sri Lanka	Amb.	14.6	21.7	22	-	−33	−34	-	−33
	AF	Addis Ababa, Ethiopia	Amb.	19.4	19.2	22.2	19.1	1	−13	2	−4
	EU	Pristina, Kosovo	Amb.	18.3	16.3	15.3	16.3	12	20	12	15
	EU	London, UK	Tra.	12.7	20.5	14.8	15.1	−38	−14	−16	−24
			Amb.	11.7	16.5	11.3	12.2	−29	4	−4	−12
Relatively clean city	NA	LA, USA	Tra.	9.9	11.4	12.9	11.9	−13	−23	−17	−18
			Amb.	11.1	11.1	15.5	11.9	0	−28	−7	−14
	SAM	Lima, Peru	Amb.	15	24.4	29.8	32	−39	−50	−53	−48
	EU	Zurich, Switzerland ²	Amb.	8.5	10.4	9	8.6	−18	−6	−1	−9
	NA	New York, USA	Tra.	3.9	5.1	5.8	4.6	−24	−33	−15	−25
			Amb.	3.3	3.5	5.2	4.3	−6	−39	−23	−24

¹ Reg. = region; Amb. = urban ambient station; Tra. = urban traffic/roadside station; Grey area: cities with lockdown policy; CN—China; LA—Los Angeles; ² cities that have implemented other NPIs (not full lockdown policy), and Bold font indicates negative numbers.

For cities with non-lockdown NPIs, reductions in ambient PM_{2.5} were also observed. These cities include Hong Kong (−17%), Tokyo (−28%), Abu Dhabi (−56%), and Zurich (−9%). In Japan, the declaration of a state of emergency with school closure and restricted international travel was adopted, while Abu Dhabi and Zurich implemented multiple mini-lockdowns with staging (3 days to 1 week). All non-food stores, restaurants, bars, and gyms were closed. In Tokyo, the original congestion level of 60–70% in February and March 2020 was down to 30–40%, after implementing the policy in April. The traffic volumes of driving, walking, and taking transit reduced by −25%, −36%, and −41%, respectively [35]. In Zurich, a reduction in personal trips within the city was also observed [36,37]. Although these policies were less restrictive than a full lockdown, they still reduced the willingness of people to go out for activities. With the volunteer programs for staying at home or WFH offered by various industries to protect their employees, the traffic volume and emissions were brought down in these cities. Within a city, more PM_{2.5} reduction was generally observed at traffic stations than at ambient stations, regardless of the type of NPIs. This result is expected as the reduction in traffic emissions caused by those policies should be more visible at traffic stations, due to their proximity to the emission source. In London, the percentage of changes in PM_{2.5} were −24% and −12% for traffic and ambient stations during the full lockdown, respectively. The difference in percentage change between them was close to double. A similar phenomenon was observed for a place with non-lockdown NPIs, such as Hong Kong. The reduction in PM_{2.5} at traffic stations (−22%) was also larger than the reduction at ambient stations (−17%), though the difference was less remarkable than that observed in cities with the full lockdown. School shutdown, WFH, and social distancing have caused some observed reductions in both daily traffic volume (−14% to −22%) and rush-hour congestion level (−15 to −20%) [27,28,38]. For some cities, an increase in pollution levels was observed. In Jakarta, the ambient PM_{2.5} has increased by +16%. With the reported monthly average concentration (50.4 µg m⁻³) in 2020, between the minimum and maximum concentrations of 32.2 µg m⁻³ and 51.8 µg m⁻³ observed in 2017–2019, there is some possibility that the increase in PM_{2.5} concentration may be caused by the variation of meteorological conditions, instead of being induced by changes made during the pandemic. On the other hand, for Pristina, an increasing trend of PM_{2.5} was clearly observed between 2020 and 2017–2019. One possible reason may be the

implementation of city quarantine (no going in and out of the city), which elevates citizens' anxiety on resource scarcity (e.g., food, gasoline, etc.) and results in more trips for resource hunting within the city. The induced traffic congestion has elevated traffic emissions and triggered an increase in $PM_{2.5}$. The situation is similar to the pre-hurricane or -typhoon conditions, where people go out for food and consumables. Such actions would worsen air quality in the affected cities.

Overall, no clear signal of continental or regional dependence on “the percentage of $PM_{2.5}$ reduction” among the cities. The percentage reduction was calculated based on the difference between the reported concentrations in 2020 and concentrations in 2017–2019, under the BAU condition; therefore, the influence of location dependence has been diminished when evaluating using percentage of $PM_{2.5}$ reduction. On the other hand, in terms of the absolute value of $PM_{2.5}$ reduction, the heavily polluted cities seemed to receive more reduction in $PM_{2.5}$ than the other two groups. As these polluted cities were concentrated in East and South Asia, there was a clear regional pattern. For the heavily polluted cities, the reduction from the COVID-related NPIs ranged from $-16.9 \mu g m^{-3}$ to $-41.1 \mu g m^{-3}$. In contrast, for the medium polluted and relatively clean cities, the reductions were from $-1.6 \mu g m^{-3}$ to $-13.7 \mu g m^{-3}$ and $-1.1 \mu g m^{-3}$ to $1.3 \mu g m^{-3}$, respectively. The observed trend was mainly caused by the difference in the baseline concentrations under the BAU condition, where high concentrations were observed in Asia cities, due to the rapid economic development with limited pollution controls, as well as low concentrations in Europe and North America, due to the success of continuous efforts of implementing air pollution controls in their cities.

Case Studies on the Relationship of Traffic Reduction and $PM_{2.5}$ Concentration

To better understand the relationship between traffic reduction and change in $PM_{2.5}$ during the COVID pandemic, $PM_{2.5}$ observations and TomTom traffic data in 2019 and 2020 were collected for the detailed analysis [28]. Figure 2 shows the correlations between a change in $PM_{2.5}$ and congestion level for (a) all cities and (b) cities with a full lockdown policy in place. Detailed TomTom data for congestion level is available in Appendix A Figure A1. In general, only a minor signal (R^2 of 0.24) was observed when all stations were considered. Low R^2 (closer to 0) reflects a low correlation between traffic congestion and air quality. As mentioned earlier, some cities even showed an increase in ambient concentration during the period. Figure 2b shows the case for the stations with lockdown (greyed in Table 2). By excluding stations which did not implement the lockdown policy, the estimated correlation has increased by more than 50%. In general, the correlation for traffic stations (R^2 of 0.53) is a bit higher than for ambient stations (R^2 of 0.49). It reflects that $PM_{2.5}$ reduction is strongly tied to the improvement of traffic congestion during the lockdown. As vehicles driving at low speeds (below $15 km h^{-1}$) produce two times more emissions than the vehicles moving at cruising speed ($40\text{--}80 km h^{-1}$), alleviating traffic congestion would reduce $PM_{2.5}$ air pollution in cities [39,40]. It should be noted that, since no traffic volume data was available from the selected cities, the reduction contribution in $PM_{2.5}$ from the change in traffic congestion and volume cannot be separated. Moreover, due to the limited number of cities/stations (i.e., less than 10) being included in each analysis group (i.e., 11 samples for (a) and 5 and 3 for (b)), no statistical significance from regression analysis was performed.

To better illustrate the relationship between traffic congestion level and $PM_{2.5}$, six cities, including New Delhi, Beijing, London, Hong Kong, Zurich, and New York, with detailed data were selected for a closer examination. All selected cities have implemented various forms of COVID-related NPIs. Among them, New Delhi and Beijing are in the group of heavily polluted cities, while London and Hong Kong are medium polluted cities, and New York and Zurich are relatively clean cities. Figure 3 shows the daily 24-h $PM_{2.5}$ concentrations for 2019 (blue dash line) and 2020 (solid orange line), from January to 15 May. To make the comparison more apparent and visible, while showing the seasonal variations, data from January to 31 March 2019 was omitted. Moreover, black lines indicating the

WHO AQG of $25 \mu\text{g m}^{-3}$ were added to illustrate whether the $\text{PM}_{2.5}$ concentration data had exceeded the AQG.

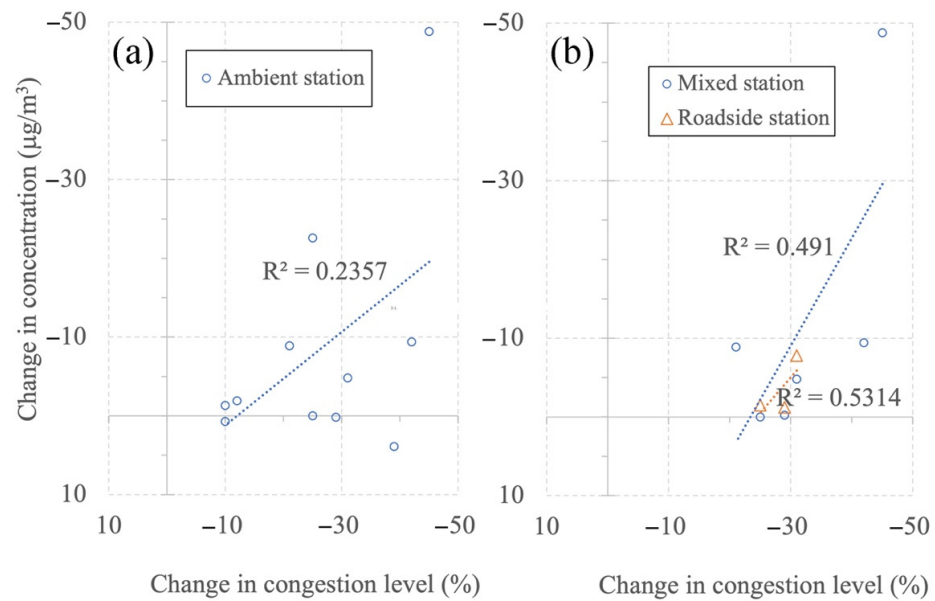


Figure 2. Effect of $\text{PM}_{2.5}$ from the change in congestion level: (a) all ambient stations with or without lockdown and (b) all stations with the full lockdown. The colored dash lines (i.e., blue in (a), blue in (b), and orange in (b)) indicate the linear best fit for ambient (R^2 of 0.2357), mixed (R^2 of 0.491), and roadside (R^2 of 0.5314) stations, respectively.

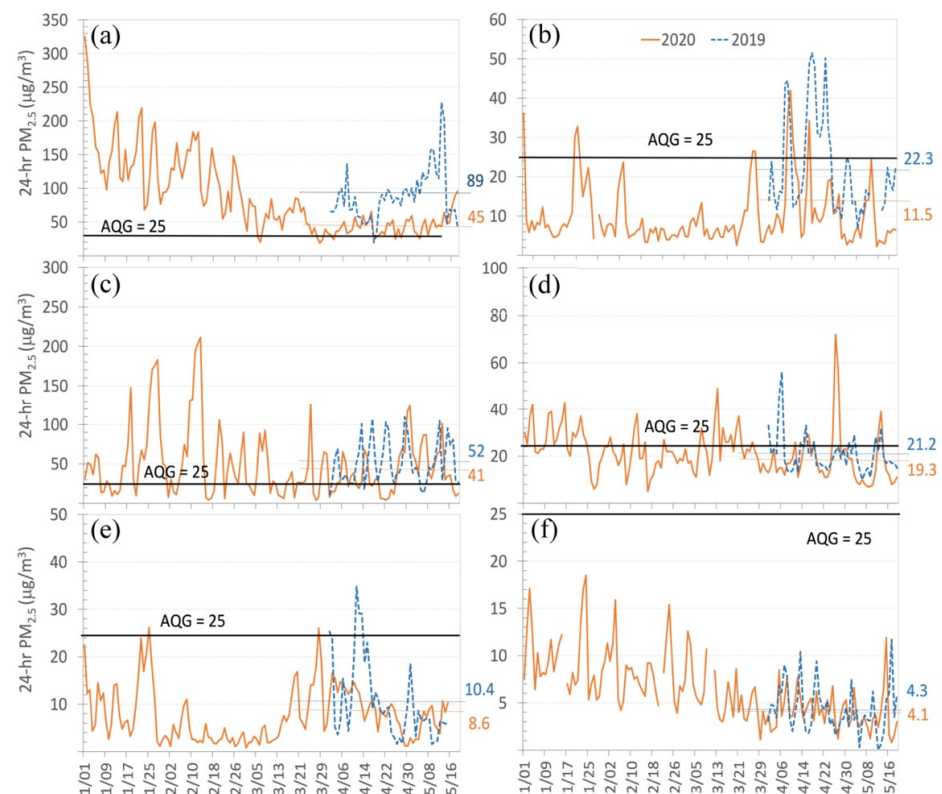


Figure 3. Comparisons of daily 24-h $\text{PM}_{2.5}$ air quality, between 2019 and 2020, during COVID-19, for the selected cities: (a) New Delhi; (b) London; (c) Beijing; (d) Hong Kong; (e) Zurich; (f) New York. The black (solid), blue (dash), and orange (solid) lines represent the AQG standard, $\text{PM}_{2.5}$ concentration from 2019, and $\text{PM}_{2.5}$ concentration from 2020, respectively.

Overall, there were apparent seasonal variations of PM_{2.5} in all stations, except Zurich, in 2020. For New Delhi (a), Beijing (c), and New York (f), PM_{2.5} pollution was more severe in winter than in spring. For London (b) and Hong Kong (d), spring seems to have higher PM_{2.5} than winter. It is commonly known that the winter PM_{2.5} in Hong Kong is usually higher than in spring. However, due to the lockdown policy enforced in late January in China and the lack of facemask supplies during the Chinese New Year (25 January), the emission of PM_{2.5} from both local traffic and the long-range transport of PM_{2.5} and its precursors had been reduced drastically. Hence, it has resulted in low PM_{2.5} in January and February 2020. In general, the average and rush-hour congestion levels have been down by 10% to 45% and 8% to 62%, respectively. For cities without the full lockdown, such as Hong Kong and Zurich, changes of congestion level were about −10% (from 38% to 28%) and −12% (from 37% to 25%), which corresponds to −9% (21.2 to 19.3 $\mu\text{g m}^{-3}$) and −17% (10.4 to 8.6 $\mu\text{g m}^{-3}$) reductions in PM_{2.5}, respectively. In Hong Kong, the policy of WFH, initiated by the government, with the closure of public and private schools reduced the traffic volume by 12%.

Overall, cities with “no lockdown” did not exhibit a substantial reduction in PM_{2.5}. For cities with a full lockdown, such as New Delhi, London, New York, and Beijing, there were −45% (from 50% to 5%), −31% (from 48% to 17%), −29% (from 42% to 13%), and −21% (from 30% to 9%) in congestion level, which corresponds to −49.4%, −48.4%, −4.7%, and −21.2% in PM_{2.5} reductions, respectively. The low reduction (e.g., −4.7%) observed in New York was attributed to a low baseline value (average of 4.3 $\mu\text{g m}^{-3}$ in 2019).

3.2. Potential Health Co-Benefits and PM_{2.5} Reduction

3.2.1. Health Co-Benefits and PM_{2.5} Reduction

Figures 4 and 5 show the summary of PM_{2.5} and corresponding proportion of mortality attributable (MA) from AirQ+, as well as the mortality rate for the six selected cities, respectively. A higher average daily PM_{2.5} level would generally result in a higher MA, when it is beyond the WHO AQG level of 25 $\mu\text{g m}^{-3}$ for the 24-h standard. For the mortality rate, a higher MA with a higher city population would trigger a higher number of premature deaths from air pollution. The MA is defined as the proportion of deaths attributed to the exposure to PM_{2.5}. In Figure 4, high MA values (in %) (blue dots in the figure) are observed mainly in heavily polluted cities, such as New Delhi, Jakarta, Beijing, and Abu Dhabi. Among these cities, New Delhi has the highest MA, ranging from 3% to 12.3% in 2017–2019, with a yearly average of 6.3%. The maximum value of 12.3% is attributed to extended periods exceeding 200 $\mu\text{g m}^{-3}$ on 24-h PM_{2.5}. As PM_{2.5} in 2020 were cut by 49%, due to the lockdown, significant differences in MA values between 2017–2019 (blue dots) and 2020 (orange dot) were observed. The average MA in 2020 was 2%, three times lower than the average in 2017–2019. As shown in Figure 5, the short-term co-benefits of air quality improvement from the lockdown saved 14,718 premature deaths in New Delhi. For Beijing, another heavily polluted city, the average MA ranged between 2% and 8.7%, with an average of 4.1% in 2017–2019, which was two-thirds of the value observed in New Delhi. However, it is noted that Beijing has a much wider range of PM_{2.5} (i.e., 10 to 390 $\mu\text{g m}^{-3}$), partly due to the adverse meteorological conditions in spring (e.g., regional dust storms). As the calculation of MA value considered both the magnitude of 24-h PM_{2.5} and frequency of exceedance, infrequent super high PM_{2.5} (i.e., 390 $\mu\text{g m}^{-3}$) did not trigger a high MA value.

The difference in MA values for Beijing between 2020 and 2017–2019 was about 1.6% (from 4.1% to 2.5%), and the co-benefits of air quality improvement from the lockdown have saved 3946 premature deaths in Beijing. For medium polluted cities, since the 24-h concentration of PM_{2.5} ranged between 10 to 25 $\mu\text{g m}^{-3}$, with occasional incidents exceeding the 24-h WHO AQG, the MA values in 2017–2019 were in the low range, between 0 to 1%. The top three highest MAs from this group were Lima, Hong Kong, and London. Appreciable MA reduction was observed in Lima, while less was found in HK and London. Overall, about 77 and 28 premature deaths were saved in London and Hong Kong, respectively. For

the relatively clean cities, with nearly no 24-h $PM_{2.5}$ concentration exceeding the AQG, the MA values were closed to zero. Hence, almost no health co-benefits were observed in New York and Zurich.

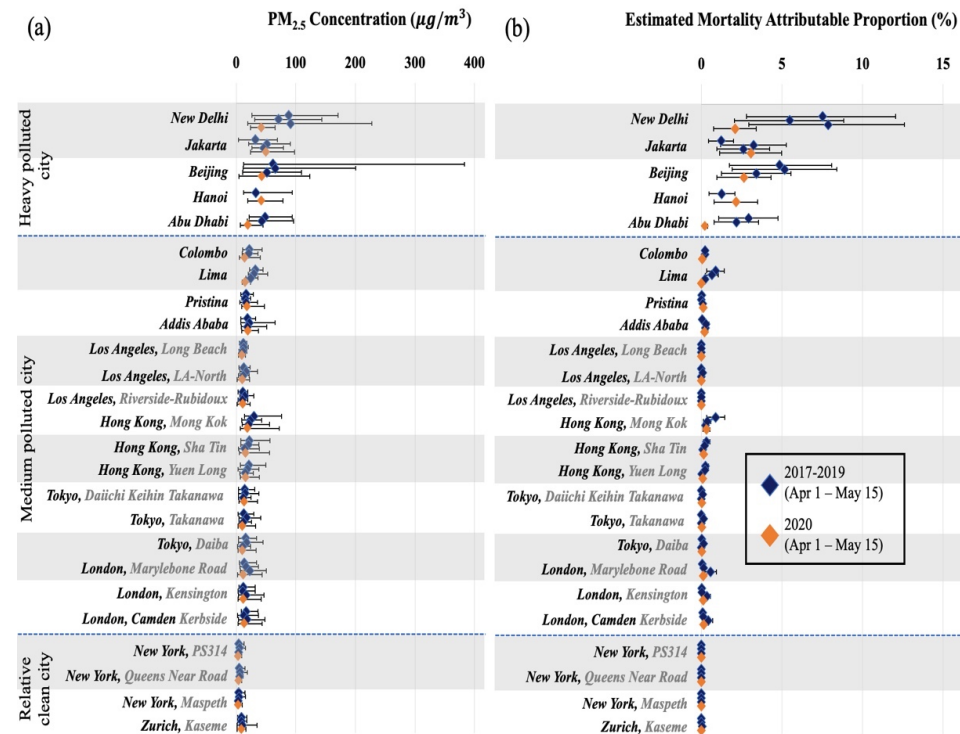


Figure 4. (a) Range of $PM_{2.5}$ concentration from the selected cities and (b) calculated range of estimated mortality attributable proportion from AirQ+.

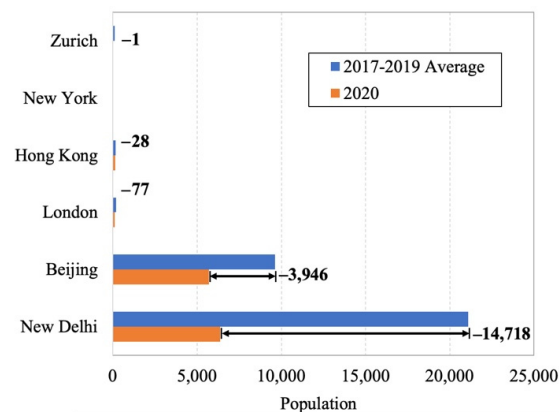


Figure 5. Mortality rate for six selected cities.

Overall, there are appreciable health co-benefits observed in heavily polluted cities, such as New Delhi and Beijing, while mild health co-benefits are found in medium polluted cities. In cities with heavy pollution and a large population, their health co-benefits could be enormous. In this study, baseline concentration is found to be an important benchmark in determining the level of public health co-benefits from the pandemic. As the baseline concentration is highly dependent on the city's location (e.g., Asia or Europe) and economic status, it is expected that some geospatial connection among the cities can be established.

3.2.2. Discussion of Seasonal Variations of Air Quality on Health Co-Benefits

Various studies have demonstrated that COVID-related NPIs have provided some short-term health co-benefits for cities in Europe and China, while there was less discussion

in North America. The reported magnitudes and results of health co-benefits in literature were highly variable and dependent on the selected period and characteristics of the targeted location. The influence of meteorology on the effect of pollutant concentrations is also important. As recalled from the earlier discussion, there was a considerable difference in the short-term health co-benefits among different cities, where New Delhi received the largest co-benefits; no co-benefits were found in New York. In general, a higher monthly $\text{PM}_{2.5}$ concentration suggests a higher overall 24-h concentration and proportion of mortality attributable and, hence, a higher mortality rate. As air quality data commonly follows a log-normal distribution, where the frequency of having a high $\text{PM}_{2.5}$ concentration is relatively small [41,42], the average monthly concentration can be a good proxy to estimate the short-term health co-benefits (in here, mortality).

Next, a simple method for screening the short-term health co-benefits across cities and seasons, using the reported monthly average $\text{PM}_{2.5}$ concentrations, is introduced. To better explain and illustrate the process, Figure 6 shows the summary of monthly $\text{PM}_{2.5}$ from 2019, which also served as the pollution baseline for each city. The colors indicate the US air quality index (AQI) levels for 24-h $\text{PM}_{2.5}$. Green, yellow, orange, red, purple, and brown are referred to as good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, and hazardous conditions, respectively. In the figure, New Delhi had the highest monthly average concentrations of $71.4 \mu\text{g m}^{-3}$ and $76.6 \mu\text{g m}^{-3}$ in April and May 2019, respectively, shown in red, which was much higher than the WHO AQG of $25 \mu\text{g m}^{-3}$. In all 12 months, the average monthly concentrations in New Delhi were higher than the WHO AQG, meaning that, regardless of which month the lockdown occurred, there should be some associated health co-benefits. Strictly speaking, there are more health co-benefits in November, December, and January. Let us look at another example. For London, the previous analysis shows that some health co-benefits were observed during the lockdown, with the monthly $\text{PM}_{2.5}$ concentration of $22.3 \mu\text{g m}^{-3}$ in April (slightly higher than $21.7 \mu\text{g m}^{-3}$ shown in Figure 6). As shown in Figure 3b), all $\text{PM}_{2.5}$ exceedances occurred in April but not in May. Hence, if the lockdown occurred only in May, no co-benefits would be expected. This logic can be applied to all months and cities, in order to quickly determine whether public health co-benefits are present.



Figure 6. Summary of monthly $\text{PM}_{2.5}$ for 15 selected cities.

To make the analysis more conservative, instead of using $25 \mu\text{g m}^{-3}$, a suggestion of using the monthly average of $12 \mu\text{g m}^{-3}$ as the benchmark is proposed. The average monthly $\text{PM}_{2.5}$ of $12 \mu\text{g m}^{-3}$ means that there are still some occasions where the concentration may still exceed $12 \mu\text{g m}^{-3}$ (as shown in Figure 3e) but is less likely to exceed the WHO AQG of $25 \mu\text{g m}^{-3}$. The suggested value aligns well with the AQI index of the healthy class, which has also considered the $\text{PM}_{2.5}$ data distribution, based on the US air quality data. With this approach, we can readily apply monthly $\text{PM}_{2.5}$ data to determine whether health co-benefits exist when a lockdown or other COVID-related NPIs are implemented at a particular place or time. Take the case of Zurich (see Figure 3e), the monthly average concentrations in January and April 2019 were $11.4 \mu\text{g m}^{-3}$ and $12.4 \mu\text{g m}^{-3}$, respectively (See Figure 6), which were below and above $12 \mu\text{g m}^{-3}$. With that, co-benefits are likely to exist in Zurich in April but not in January. Using New York as another example, the monthly $\text{PM}_{2.5}$ in all months in New York are all below $12 \mu\text{g m}^{-3}$ (see Figure 6). Hence, no health co-benefits would be expected from the COVID-related NPIs in New York at all. With this method, public authorities may apply monthly $\text{PM}_{2.5}$ from the IQAir website or their local monitoring networks to see if any short-term co-benefits can be observed in their cities by considering whether some NPIs, associated with COVID-19, may be kept and refined to obtain public health co-benefits. While a recommendation of lockdown simply to obtain health co-benefits is not sensible, measures, such as WFH and staggered work hours, should be more actively pursued in cities where substantial public health co-benefits are expected.

4. Conclusions

In this study, air quality data from 15 selected cities were collected to study the influence of the pandemic on $\text{PM}_{2.5}$ air quality and its relationship to traffic congestion and short-term health co-benefits. The study found a limited continental or regional dependence on the percentage change in $\text{PM}_{2.5}$, between April 2017–2019 and April 2020. A strong dependence was observed on the absolute difference in $\text{PM}_{2.5}$, which was associated with the baseline concentration. In general, heavily polluted cities in Asia received more $\text{PM}_{2.5}$ reduction and health co-benefits under COVID-19 NPIs. In contrast, relatively clean cities in Europe and North America received minor (or even no) health co-benefits. The short-term health co-benefits received in a particular city are strongly tied to its baseline concentration, which varies by location and season. In this analysis, New Delhi and Beijing have received tremendous health co-benefits from the implementation of NPIs. The saving of premature deaths was estimated at over ~3900 and ~14,700 in this period, respectively. One observation was made about New Delhi, where the pollution level (i.e., an average of $45 \mu\text{g m}^{-3}$) during the lockdown was still much higher than the WHO AQG for the 24-h $\text{PM}_{2.5}$ standard (i.e., $25 \mu\text{g m}^{-3}$). It reflects that, even with minimal economic activities, pollution in New Delhi will still be problematic (in winter). Hence, stranger emission control measures, with technological improvements, should be applied in India to drastically reduce primary emission of $\text{PM}_{2.5}$ to safeguard the public's health.

In this study, a simple screening method was also developed to evaluate whether a city would receive the health co-benefits or not under the NPIs implementation. The screening approach utilizes the monthly $\text{PM}_{2.5}$ concentration (i.e., 24-h data) of a city from the IQAir network with the pre-determined cut-off value of $12 \mu\text{g m}^{-3}$ as a benchmark for the evaluation. Although several test cases have been adopted to validate the approach, it should be aware that the statistical distribution of $\text{PM}_{2.5}$ may vary from city to city, due to different meteorological conditions, pollution sources, and reception relationships. Hence, the cut-off value may need to be adjusted. At last, for the relationship between $\text{PM}_{2.5}$ and traffic congestion, there exists a stronger correlation (i.e., ~0.5) between the reduction in congestion level and $\text{PM}_{2.5}$ reduction during COVID-19 for cities with the full lockdown than cities without. Although a significant difference in R^2 is observed between “all data” (i.e., 0.24) and “full lockdown” (i.e., 0.49) cases, no analysis of statistical significance

is conducted, due to limited sample sizes (i.e., <10). Hence, for future studies, more cities/stations should be added to allow a more robust statistical analysis to be conducted.

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Conflicts of Interest: The authors declare no conflict of interest. The views expressed are those of the authors and are not formal positions of their organizations.

Appendix A

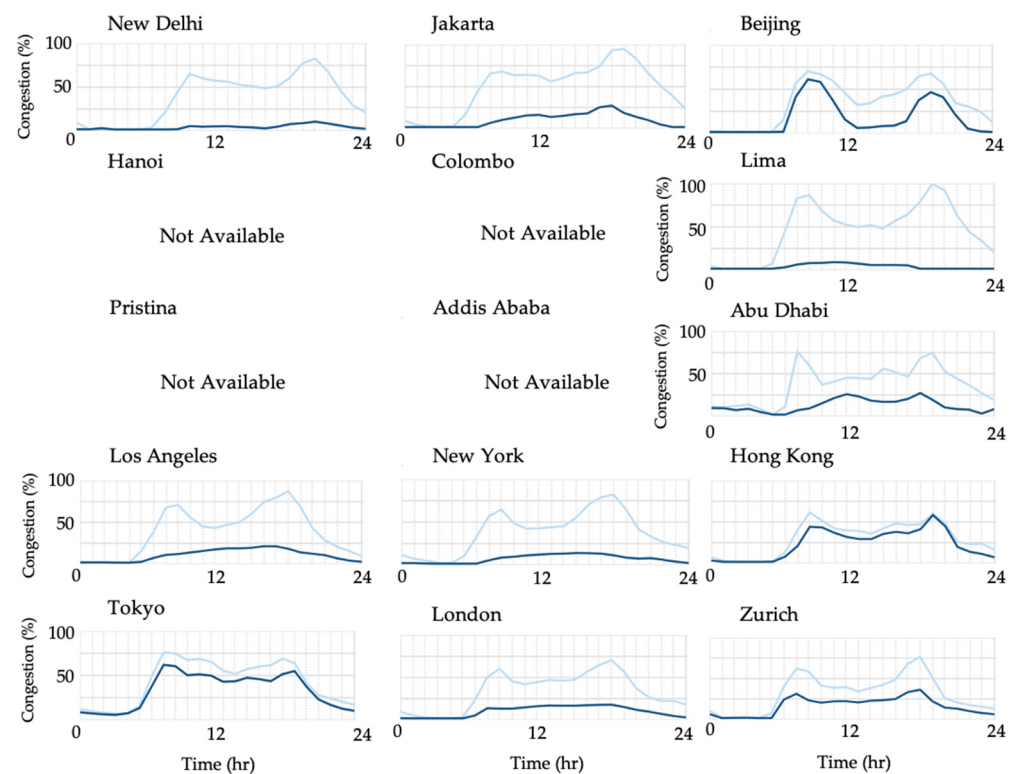


Figure A1. Traffic congestion levels from 15 selected cities.

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