Title: **Early evidence that COVID-19 government policies reduce urban air pollution**

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Abstract:
Governments have a solemn responsibility to ensure the health and well-being of the populations they govern. The COVID-19 pandemic reveals just how serious governments take this responsibility and that restricting activity to limit pathogen spread can have other public health repercussions. Comparisons between February 2019 and 2020 air quality measures reveal that six cities that were impacted early by government restrictions in response to COVID-19 show consistent declines in five of six major air pollutants. Given that air pollution causes more than four million premature deaths annually, the declines in air pollution in response to activity changes confirm that governments have the capability to improve air quality through policy change.

Main Text:
One of the most pernicious and inevitable consequences of urbanization and industrialization is the release of air pollutants. The World Health Organization (WHO) estimates that about 90% of urban residents experience air pollution that exceeds WHO guidelines and that air pollution is responsible for more than four million premature deaths annually (World Health Organization 2018). Air quality is adversely affected by the aerosol release of a number of chemical compounds from agriculture, manufacturing, combustion engines and garbage incineration, and is usually assessed by measuring the atmospheric concentrations of six key pollutants: fine particulate matter ($PM_{2.5}$), course particulate matter (PM_{10}), ground-level ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and the greenhouse gas, carbon monoxide (CO). Particulate matter is a carcinogen (Raaschou-Nielsen *et al.* 2013) and increases the risk of heart attack (Cesaroni *et al.* 2014). Because of the reactive nature of O_3, it can damage lung tissue (Khaniabadi *et al.* 2017) and prolonged exposure has been linked to increased risk of heart attack (Fann *et al.* 2012). Prolonged exposure to NO_2 and SO_2 can damage lung tissue and be a factor in the emergence of asthma and lung cancer (Greenberg *et al.* 2016; Khaniabadi *et al.* 2017). Reducing inputs of these pollutants into urban areas requires a combination of technological advancement and behavior change that can be stimulated by governmental regulations and incentives.

Alterations of human, transport and industrial activity are usually the result of long-term economic and behavioral change and difficult to legislate under normal situations. However, the recent emergence of the global COVID-19 pandemic has had clear epidemiological impacts with, as of March 25, 2020, almost half a million confirmed infections and close to 20,000 deaths (World Health Organization 2020). This pandemic has resulted in emergency measures attempting to reduce transmission rates that limit activity, movement and commerce in jurisdictions around the world. While these emergency measures are critically important to limit the spread and impact of the coronavirus, they also provide a glimpse into how governmental calls for behavioral change can alter air pollution levels in cities. Here I examine January and February 2020 air pollution levels in Wuhan to what would be expected under normal circumstances. I further compare the change in February air pollution levels over the past two years in six cities that instituted emergency measures by the end of February (early impacted cities) to 11 cities that did not declare states of emergency until March (later impacted cities) using freely available air monitoring data (World Air Quality Index Project 2020).

Wuhan, China was the epicenter for the December 2019 emergence and the first person-to-person spread of the novel coronavirus. In response, authorities initiated a series drastic measures limiting human movement and activity in Wuhan and large parts of Hubei province by the end of January. Three air pollutants: $PM_{2.5}$, PM_{10} and NO_2 all showed substantial January and February declines in Air Quality Index (AQI) (U.S. Environmental Protection Agency 2014) values over 2019 levels for those months and what would be expected from long-term trends (Fig. 1). These long-term declining air pollution trends do reveal that China's recent pollution reduction and mitigation efforts are steadily paying off, but the government-enforced restrictions further reduced pollution levels. The expected air pollution values predicted by temporal trends (red dashed lines in Fig. 1) are all substantially higher than the observed levels, with observed values being between 13.85% lower than expected for January $PM_{2.5}$ and 33.93% lower for January NO_2. Further, the reductions in the pollutants shown in Fig. 1 increased the number of days where pollutant concentrations were categorized as 'good' ($0 \leq AQI \leq 50$) or 'moderate' ($51 \leq AQI \leq 100$) according to the AQI. The three other pollutants: SO_2, O_3 and CO, all showed idiosyncratic or non-significant changes, mostly because their levels have already reduced significantly over time or appear quite variable (Fig. 2).

Once the pathogen was detected in other jurisdictions, and confirmations of community spread emerged in February 2020, emergency measures, like those in Hubei province, were instituted to limit human movement and interaction. The cities subjected to February restrictions include, in addition to Wuhan, Hong Kong, Kyoto, Milan, Seoul and Shanghai, and the AQI values from these cities were compared to other cities that did not see impacts of the novel coronavirus or have emergency restrictions in place until well into March. Log-response ratios between the air concentrations of pollutants observed in February 2020 to those from February 2019 reveal that all air pollutants except O_3 show a decline in the 2020 values for the early impacted cities (Fig. 3). For later impacted cities, there is no overall trend in changes in the concentrations of pollutants between 2020 and 2019 and the individual cities in this group showed less consistency in the differences between years (Fig. 3).

These results indicate consistent air pollution reduction in cities impacted early by the spread of the novel coronavirus. However, the analyses presented here require further investigation as governments increasingly restrict activity world-wide, and some are discussing the possibility of prematurely lifting restrictions in order to spur economic growth. Further, the data analyzed here present point estimates of air quality but air pollution impacts are not homogeneous through urban landscapes and is influenced by spatial variation in industrial activities and transportation (Adams & Kanaroglou 2016). Thus, as higher resolution spatial air pollution data become available, it would be valuable to see how reduced activity affects air quality in different parts of cities.

This analysis of early data indicates that governmental policies that directly reduce human activity, commercial demand and transportation can effectively and quickly reduce urban air pollution. While the COVID-19 pandemic represents a serious risk for health and wellbeing of populations globally, especially those living in high density urban areas, the impacts of air pollution are equally consequential. If governments are willing to expend trillions of dollars in direct funding and indirect economic costs to combat this disease, then why do these same governments permit or even subsidize activities that emit air pollution? Perhaps mandating changes to economic or transportation activity or investing in clean technology would better protect human health from the effects of air pollution.

Materials and Methods

Six cities that were impacted by COVID-19 by the end of February 2020 were selected for analysis of air pollution levels and compared to 11 cities that were impacted by the virus and resulting government actions in March 2020 (Table 1). The date of impact lacks precision because rapidly changing individual and governmental perception and behavior, but I identified early impacted cities as those that clearly had evidence of community transmission in February and with governmental responses to reduce human movement and activity (e.g., 'social-distancing'). I examined local and global media reports and summaries of events found on the Wikipedia 'Timeline of the 2019-2020 coronavirus pandemic' webpage (https://en.wikipedia.org/wiki/Timeline_of_the_2019%E2%80%9320_coronavirus_pandemic), which was updated daily during the expanding crisis.

For each city, I downloaded Air Quality Index (AQI) data *(8)* on six major and commonly reported air pollutants: from the World Air Quality Index Project (https://waqi.info/), which compiles air quality data available from different publicly available weather station and monitoring programs. The pollutants include: fine particulate matter ($PM_{2.5}$), course particulate matter (PM_{10}), ground-level ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), and carbon monoxide (CO). The AQI scales the 'dose' or pollutant concentrations by their known human health effects and places values on a scale from 0 to 500, and divides values into six categories: 'good' air quality (0 – 50), 'moderate'(51-100), 'unhealthy for sensitive groups' (101-150), 'unhealthy' (151-200), 'very unhealthy' (201-300), and 'hazardous' (301-500). The values for individual cities come from municipal, regional or national authorities that have jurisdiction over air monitoring and the specific sources are listed in Table 1.

Available data ranged in the time span available and the completeness of the coverage, but most cities used here have data starting from 2014 and all from 2018. I examined Wuhan air pollution trends over the past six years and assess whether there are long-term linear trends in AQI values because of China's concerted effort to reduce pollution. I then compare January 2019 AQI values to January 2020 values, and to that predicted by the long-term trend. I do the same with February 2019 and 2020 values and assess differences using one-way ANOVAs.

I primarily focus on February 2019 and 2020 data to compare pre- and post-COVID-19 air pollution levels across early and late impacted cities (Table 1). I use each city as a replicate and calculate the log-response ratio between February 2019 and 2020 values, and estimate the mean effect for the two groups of cities for each pollutant. Significant reductions are evidenced by the mean log-response ratio values and their 95% C.I. values being lower than 0.

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Table 1. The eleven cities used in this analysis, the month that emergency measures were enacted and two- to six-year AQI averages of the pollutants measured.

City	Country	Emergency declared	PM2.5	PM10	O3	NO2	SO2	CO
Bangkok[1]	Thailand	March	88.64	39.56	20.77	15.45	3.12	9.47
Delhi[2]	India	March	167.6	149.49	27.5	28.85	7.16	14.04
Hong Kong[3]	Chinese Special Administrative Region	Feb	80.22	35.39	30.11	39.17	5.33	6.61
Jakarta[4]	Indonesia	March	109.9	54				
Johannesburg[5]	South Africa	March	82.3	47.65	19.08		2.17	
Kyoto[6]	Japan	Feb	62.31	23.21	38.68	28.51	4.55	4.91
London[7]	United Kingdom	March	64.81	26.63	24.71	41.6	4.16	5.4
Los Angeles[8]	USA	March	55.94	32.77	29.03	13.08	1.07	5.58
Mexico City[9]	Mexico	March	89.8	43.29	40.72	21.66	8.86	9.17
Milano[10]	Italy	Feb	79.99	32.2	30.27	32.55	2.24	6.3
Sao Paulo[11]	Brazil	March	54.7	29.39	27.59	16.49	1.2	4.13
Sarajevo[12]	Bosnia and Herzegovina	March	96.56	44.24	21.6	17.05	12.33	3.06
Seoul[13]	South Korea	Feb	85.4	45.69	26.87	34.83	7.02	6.39
Shanghai[14]	China	Jan	109.1	49.26	44.18	20.77	5.67	6.49
Tel Aviv[15]	Israel	March	83.45	44.09	34.13	29.69	1.99	7.07
Toronto[16]	Canada	March	38.59		29.05	16.18	1.52	2.31
Wuhan[17]	China	Jan	148	78.63	54.52	30.93	11.6	13.4

[1] Division of Air Quality Data, Air Quality and Noise Management Bureau, Pollution Control Department, Thailand (http://aqmthai.com).
[2] Delhi Pollution Control Committee (http://www.dpccairdata.com).
[3] Hong Kong Environmental Protection Department (http://www.epd.gov.hk).
[4] BMKG | Badan Meteorologi, Klimatologi dan Geofisika (http://www.bmkg.go.id).
[5] South African Air Quality Information System - SAAQIS (http://saaqis.environment.gov.za).
[6] Japan Atmospheric Environmental Regional Observation System (http://soramame.taiki.go.jp/).
[7] UK-AIR, air quality information resource - Defra, UK (http://uk-air.defra.gov.uk).
[8] South Coast Air Quality Management District (AQMD) (http://www.aqmd.gov/).
[9] INECC - Instituto Nacional de Ecología y Cambio Climático (http://sinaica.inecc.gob.mx).
[10] Agenzia Regionale per la Protezione dell'Ambiente della Lombardia (http://ita.arpalombardia.it).
[11] CETESB - Companhia Ambiental do Estado de São Paulo (http://cetesb.sp.gov.br).
[12] Department of Public Health of the Sarajevo Canton (http://mpz.ks.gov.ba/).
[13] Air Korea Environment Corporation (http://www.airkorea.or.kr).
[14] Shanghai Environment Monitoring Center (http://sthj.sh.gov.cn).
[15] Israel Ministry of Environmental Protection (http://www.svivaaqm.net).
[16] Air Quality Ontario - the Ontario Ministry of the Environment and Climate Change (http://www.airqualityontario.com/).
[17] Wuhan Environmental Protection Bureau (http://www.whepb.gov.cn/).

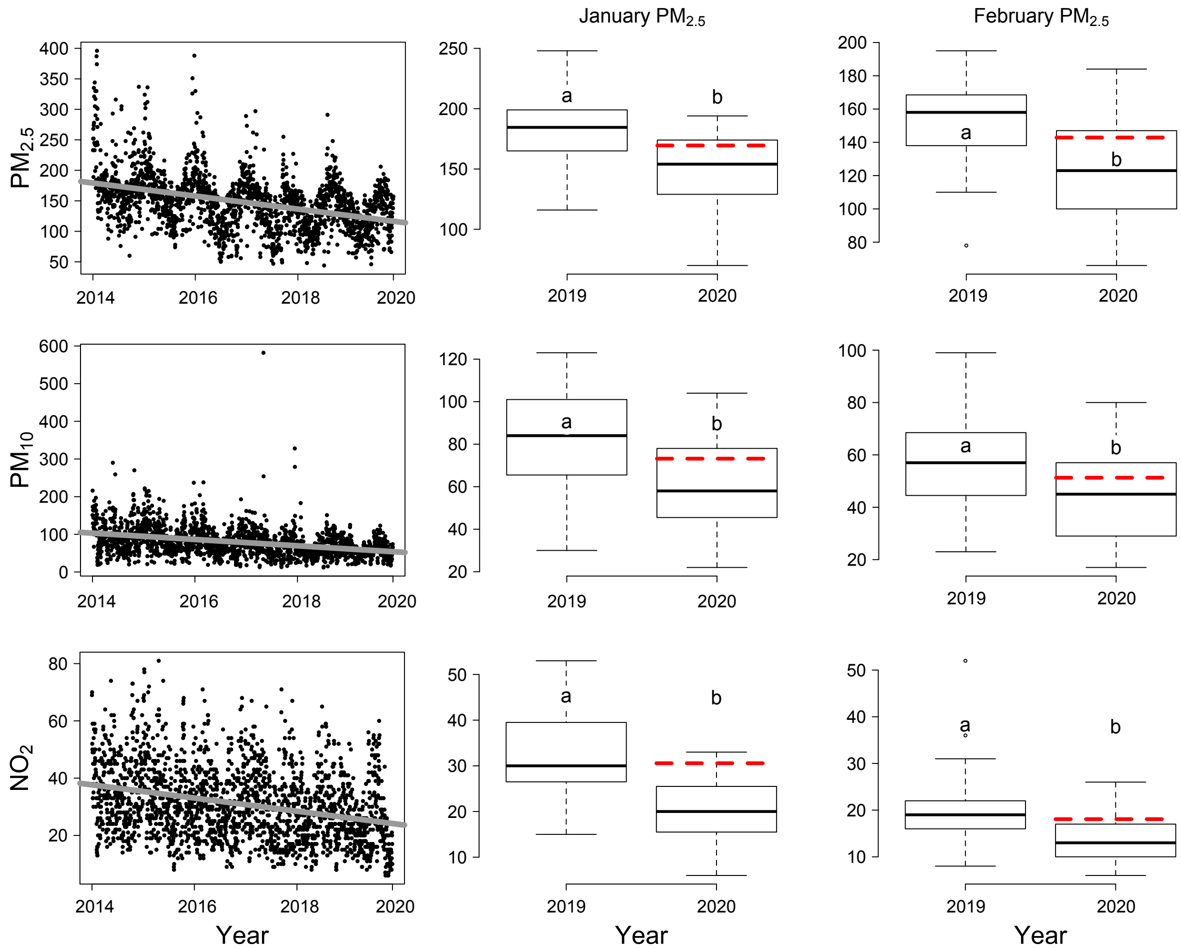

Fig. 1. Temporal patterns of Air Quality Index (AQI) $PM_{2.5}$, PM_{10} and NO_2 values in Wuhan, China. Both January and February, 2020 values show significant declines compared to 2019 levels and to that predicted from long-term trends (red dashed line).

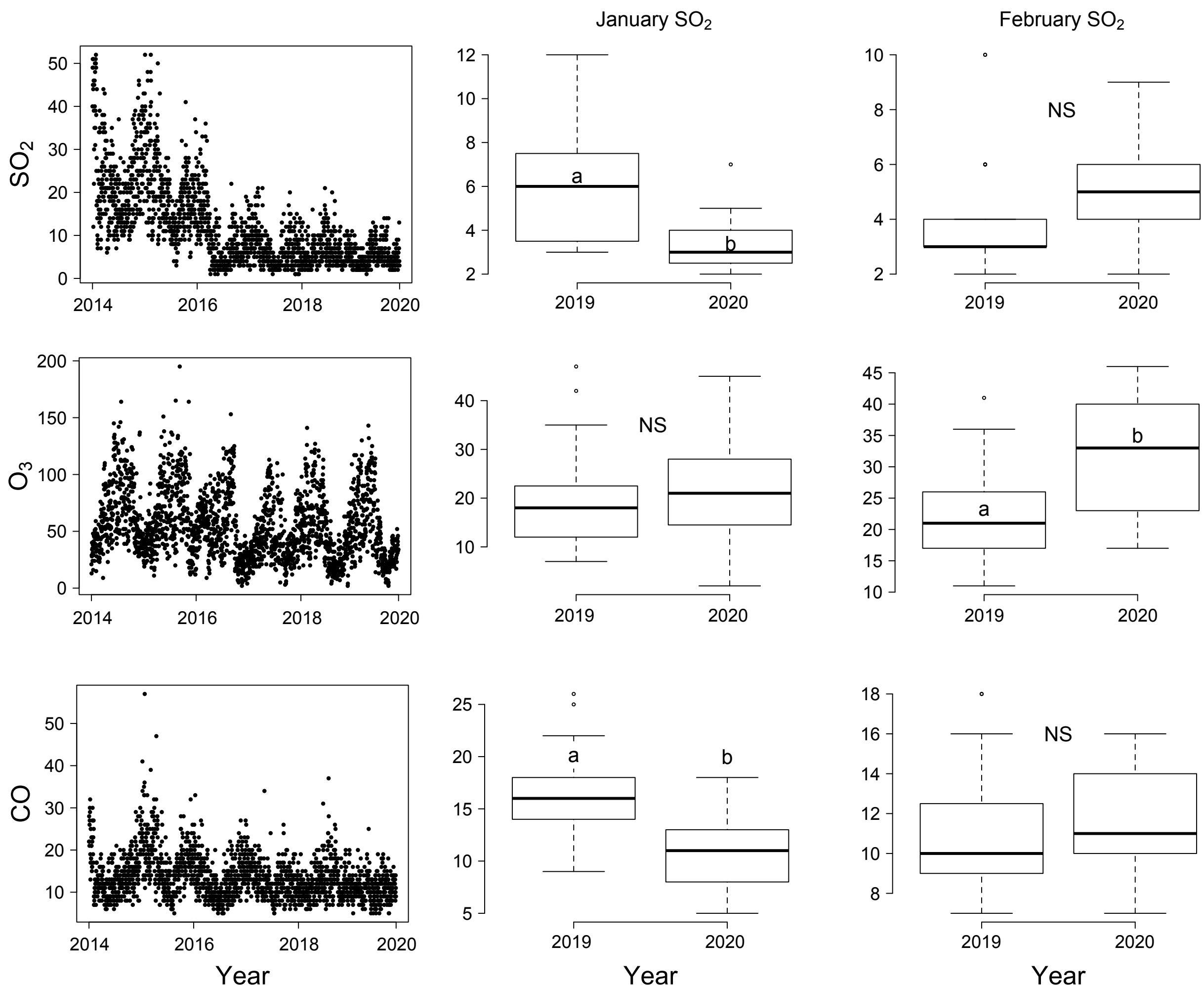

Fig. 2. Temporal patterns of Air Quality Index (AQI) SO_2, O_3 and CO values in Wuhan, China.

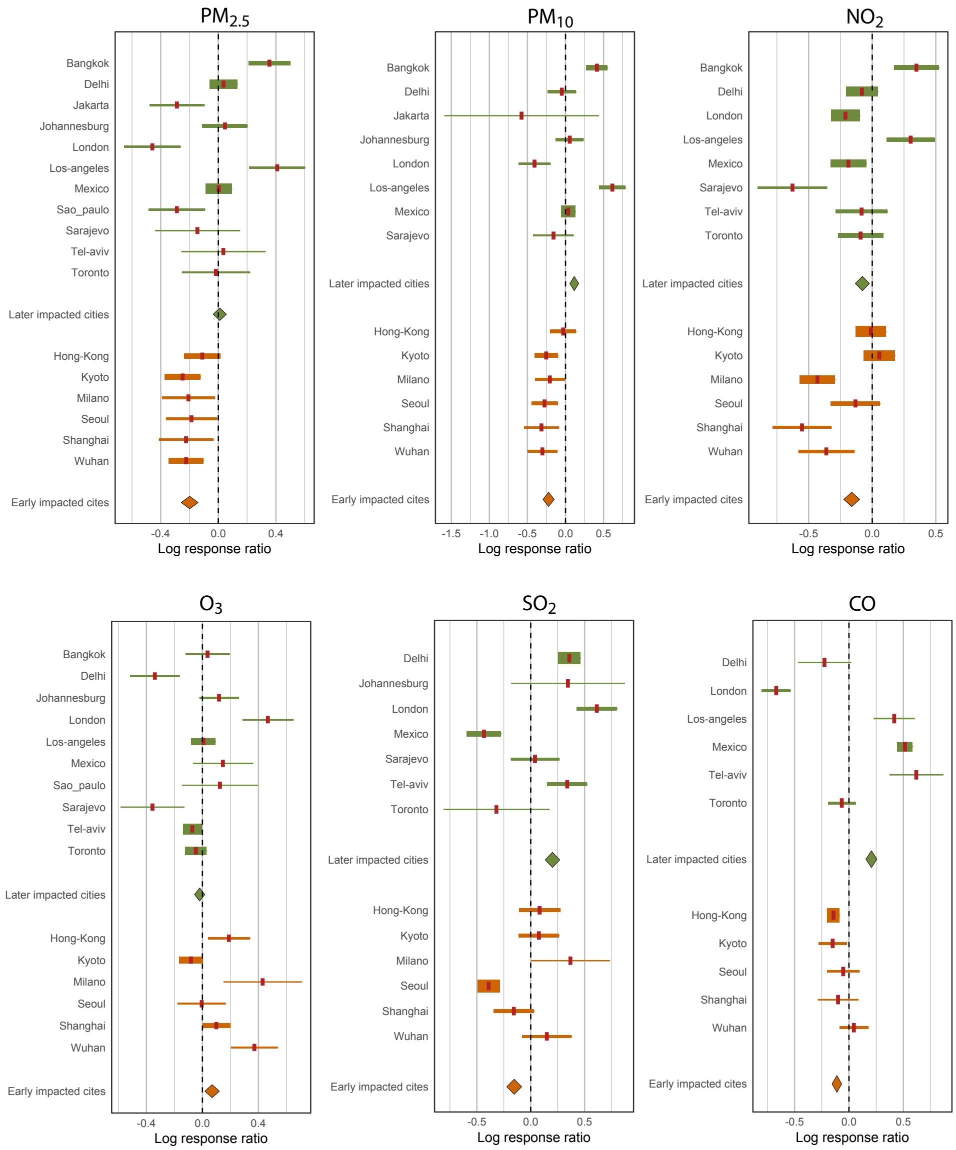

Fig. 3. Log response ratios for Air Quality Index (AQI) $PM_{2.5}$, PM_{10}, NO_2, O_3, SO_2 and CO values between February 2019 and February 2020 values. Negative values indicate a decline in 2020. The green symbols indicate values from an assortment of cities that did not have emergency measures in place until March, 2020 (later impacted cities) and orange symbols are for cities that were impacted by the end of February.