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Road traffic and air pollution: Evidence from a nationwide traffic control during coronavirus disease 2019 outbreak

Chengyong Jia¹, Wending Li¹, Tangchun Wu, Meian He *
Department of Occupational and Environmental Health, Ministry of Education and State Key Laboratory of Environmental Health (Incubating), School of Public Health, Tongji Medical College, Huazhong University of Science and Technology, 13 Hangkong Road, Wuhhan 430030, Hubei, China

HIGHLIGHTS
• Traffic control reduced air pollution (except O₃) during China’s COVID-19 outbreak.
• Vehicle density was found dose-dependently associated with PM₂.₅, PM₁₀, NO₂, and CO.
• The associations can be significantly attenuated by urban greening.
• Finding may assist policymaking in developing countries.

GRAPHICAL ABSTRACT

ABSTRACT
Existing estimations of air pollution from automobile sources are based on either experiments or small-scale governmental interventions. China’s nationwide traffic control during the coronavirus disease 2019 outbreak provided us a unique opportunity to assess the direct dose-effect relationship between vehicle density and air pollution. We found that, during the coronavirus disease 2019 outbreak, the nationwide reduced air pollution (except for O₃) could be largely explained by traffic control measures. During the traffic control period, every doubling of vehicle density was associated with a decrease of 4.2 (2.0, 6.4) μg/m³ in PM₂.₅, 5.5 (2.9, 8.1) μg/m³ in PM₁₀, 1.5 (0.9, 2.0) μg/m³ in NO₂, and 0.04 (0.02, 0.07) mg/m³ in CO comparing cities with different vehicle densities. Similarly, for every 10% increase in the truck proportion, PM₂.₅ decreased by 12.3 (4.1, 20.6) μg/m³, PM₁₀ decreased by 14.3 (4.6, 23.9) μg/m³, and CO decreased by 0.14 (0.05, 0.23) mg/m³. Moreover, the associations between vehicle density and reduction in PM₂.₅, PM₁₀, and CO during the traffic control period were stronger and showed near-complete linearity in cities with low green coverage rate (All P < 0.05 for interaction). According to our estimation, PM₂.₅ emissions from every doubling of vehicle density can lead to over 8000 excess deaths per year, 66% of which were caused by cardiopulmonary diseases. This natural experiment study is the first to observe the dose-effect relationship between on-road traffic and traffic-generated air pollution, as well as the mitigating effect of urban greening. Findings provide key evidence to the assessment and control of traffic-generated air pollution and its public health impact.

Abbreviations: TC, traffic control; AQI, air quality index; PM₂.₅, particulate matter with aerodynamic diameters less than or equal to 2.5 μm; PM₁₀, particulate matter with aerodynamic diameters less than or equal to 10 μm; SO₂, sulfur dioxide; NO₂, nitrogen dioxide; O₃, ozone; CO, carbon monoxide; CVD, cardiovascular disease; HHD, hypertensive heart disease; CHD, coronary heart disease; COPD, chronic obstructive pulmonary disease.

* Corresponding author.
E-mail address: hemeian@hotmail.com (M. He).
¹ These authors contributed equally to the article.

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1. Introduction

China has witnessed an exponential growth in automobile amount, from 5.5 million in 1990 to 254 million in 2019 (National Bureau of Statistic of China, 2020), raising serious concerns about urban road network (Wu et al., 2017), air quality, and the consequent impact on public health (Jiang et al., 2017). Existing methods for quantifying road vehicle contribution to air pollution are mainly conducted under experimental conditions (Wang et al., 2011), e.g., at fixed speed or for selected vehicle types (Weiss et al., 2011), to eliminate interference from other pollution sources. Although several studies have demonstrated that air quality could be improved by reducing on-road traffic through administrative measures (Cai and Xie, 2011; Friedman et al., 2001; Li et al., 2017), a dose-effect relationship between the number of vehicles and air pollution is still lacking. Moreover, diesel engines and trucks produce more air pollutants (particularly particulate matter, PM and nitrogen dioxide, NO2) in experimental settings (Dallmann et al., 2012; Li et al., 2020; Song et al., 2018); however, their relative contribution (as compared to passenger vehicles) to ambient air pollution in the real world is more important in policymaking, but research in this regard remains scarce and controversial (Liu et al., 2017; Shen et al., 2014).

To contain the rapid spread of coronavirus disease 2019 (COVID-19) in early 2020, China implemented swift and effective non-pharmaceutical public health interventions across the country, which helped control the spread of COVID-19 (Lai et al., 2020; Pan et al., 2020), and unexpectedly, improved the air quality (He et al., 2020). A recent study compared the effect of different air pollution restriction policies among 55 cities in China and found air quality was improved after restriction on private vehicles (Chen et al., 2021). However, this study also indicated that the improvement in air quality was not entirely ascribed to the restriction on private vehicles. Another research used data from 22 provinces to calculate changes in air pollutant levels before and after the first announcement of cordons sanitaire in Wuhan (23 January 2020) and modeled the changes in air pollution with the share of secondary industries and the vehicle population at the provincial level. They concluded that if industrial activity and vehicle emission decreased during the COVID-19 containment, these could be the major factors contributing to the improved air quality (Wang et al., 2020b). However, the study assumed a single COVID-19 control time-point for all provinces, which might be discreet as cities rarely implement the same level of measures on the same day (we found that, from 23 January to 9 February 2020, different cities announced different levels of traffic control measures).

This study collected detailed information on the time and type of traffic control for 361 cities in China and defined the city-specific traffic control period accordingly. We first investigated whether traffic control was the primary cause of reduced air pollution during the COVID-19 outbreak, and further examined the relationships between vehicle density, vehicle type and changes in air pollutants, and estimated the attributable excess deaths accordingly. We also explored whether urban greening could alleviate traffic-generated air pollution.

2. Material and methods

2.1. Traffic control type

We collected announcements related to traffic control from local government websites and various news media for each city (Supplementary data). Based on the magnitude of the most stringent traffic control measure announced, we classified cities into three categories: absolute, limited, and no traffic control. Absolute traffic control measures include: restricting residents from leaving the local community more than once per day, prohibiting any unauthorized automobiles from driving on the road, or entirely locking down communities under local wartime regulations. Limited traffic control measures include: canceling public transportations, suspending taxi or other commercial vehicles, restricting the running time of on-road vehicles, or locking down the highway entrances. No traffic-control measure refers to allowing the vehicles to run without restriction except perhaps routine temperature check. We included all 361 cities (including those with no traffic control; n = 10) in the primary analyses because people may spontaneously avoid unnecessary travel even without governmental restrictions.

2.2. Definition of Pre- and Post-traffic control period

Because traffic control measures for each city may change over time (e.g., from a non-restricting warning to total lockdown), it is pivotal to clearly and accurately define the Pre- and the Post-traffic control period. In this study, the Pre-TC (traffic control) period is defined as the three days (72 h) immediately preceding the day when the first public health response is launched the next day that might affect traffic. The Post-TC period is defined as the three days (72 h) immediately after the day when the most stringent/last measure of traffic control took effect in the previous day (illustrated in Fig. A1). The definition is based on the assumption that the Pre-TC period reflects normal traffic conditions. In contrast, the Post-TC period reflects conditions in which traffic volumes are reduced to minimal levels.

2.3. Air quality monitoring and meteorological data

We collected hourly data on the air quality index (AQI) and six criteria pollutants (PM2.5, PM10, SO2, NO2, O3, and CO) routinely monitored by 1605 air quality monitoring stations covering all prefectural-level cities (Ministry of Ecology and Environment of China, 2020b). Hourly data on meteorological conditions (including temperature, dew point, wind speed, visibility, wind direction, and precipitation) were downloaded from the National Oceanic and Atmospheric Administration website (National Oceanic and Atmospheric Administration, 2020). Then, they were matched to air quality data from the nearest monitoring stations. After imputation and exclusion of missing data (see Supplementary methods for details), 929,004 records (hourly data for Pre- and Post-traffic control period) from 361 cities were included in the analyses.

2.4. Vehicle density and proportion of trucks

Data on counts and subtypes of vehicles were collected from the local Statistical Yearbook and were estimated according to standard procedures (Supplementary methods). The number of vehicles was defined as the sum of passenger vehicles (including large, medium, small, and minicars) and trucks (including heavy, medium, light, and mini trucks), which accounted for more than 99% of on-road automobiles in China (National Bureau of Statistic of China, 2020). Since air pollution from traffic sources was inversely associated with land area (Marshall et al., 2005), we divided the number of vehicles by city area to obtain vehicle density (number of vehicles per square kilometer). Because the vehicle counts of the subtypes are highly correlated with each other, it is impossible to distinguish the independent contribution of a particular vehicle subtype from other subtypes. Therefore, in the primary analyses, we included the proportion of trucks and vehicle density as predictors to reflect a relative change in automobile composition. Vehicle density was log2-transformed to satisfy normality.

2.5. Industrial density

The industrial output data were obtained from the local Statistical Yearbook in 2018 and were imputed according to standard procedures (Supplementary methods). Similarly, we calculated industrial density by dividing industrial output value by city area. Because the high correlation between industrial density and vehicle density leads to collinearity in the modeling, we used the residuals of industrial density in the
analysis of vehicle density to adjust for pollution from industrial sources.

2.6. Green coverage rate

Data on the urban built-up area and its green coverage area were obtained from China Urban Construction Statistical Yearbook 2018, released by the Ministry of Housing and Urban-Rural Development of the People’s Republic of China (MOHURD) (2020). The green coverage rate was calculated as green coverage area of the built-up area divided by the urban built-up area.

2.7. Statistical analysis

City-specific three-day mean concentrations, change differences, and change percentages of each pollutant were calculated for the Pre- and the Post-TC period or their difference (Post − Pre-TC period) and were summarized as mean (95% CI). We also estimated the adjusted mean levels of each pollutant for the Pre- and the Post-TC period using the following equation:

$$Y_i = [\text{traffic control}]_{it} \times \beta + (1 + [\text{traffic control}]_{it}) \times \alpha + \text{ind}_i + \text{type}_i + e_{it}$$

(1)

where

- $i$ denotes city,
- $t$ denotes the time (hour) of the Pre- or Post-TC period,
- $Y_i$ denotes the level of air pollutant in city $i$ at time $t$,
- $[\text{traffic control}]_{it}$ denotes whether the traffic control measure was in place in a city $i$ at time $t$, and $0$ if $t$ was in the Pre-TC period and $1$ if in the Post-TC period,
- $\text{X}_i$ denotes the meteorological factors (hourly temperature, dew point, wind speed, visibility, wind direction, 3-hour average precipitation, and the mean values of these factors during the preceding 24 h before the observation hour to control for the lagged effect).
- $\text{ind}_i$ denotes the industrial density of city $i$.
- $\text{type}_i$ denotes the traffic control type for city $i$.

To explore the association between vehicle density, truck proportion, and changes of each pollutant, we used the following equation:

$$Y_i = v_{di} + t_{pi} + X_i \times \alpha + \text{ind}\_res_i + \text{type}_i + e_{ih}$$

(2)

where

- $i$ denotes city,
- $Y_i$ denotes the change of pollutant level (Post-TC period − Pre-TC period) in city $i$,
- $v_{di}$ denotes log2-transformed vehicle density in city $i$,
- $t_{pi}$ denotes truck proportion in city $i$,
- $X_i$ denotes 3-day mean values of meteorological factors in a city $i$ (temperature, dew point, wind speed, visibility, wind direction, and precipitation during the Pre- and Post-TC periods; and wind speed, visibility, wind direction, and precipitation two days preceding the Pre- and Post-TC periods to control for the lagged effect).
- $\text{ind}\_res_i$ denotes the residual of industrial density in city $i$.
- $\text{type}_i$ denotes the traffic control type for city $i$.

We used restricted cubic spline to model the association of vehicle density and proportion of trucks with the changes of pollutant level (Post-TC period − Pre-TC period), with adjustment for truck proportion or log2-transformed vehicle density (mutually adjusted), and the same group of covariates as in Eq. (2). Knots were set at the 5th, 50th, and 95th. To further explore whether urban greening could reduce traffic-originated air pollution, we stratified and compared the splines by green coverage rate (low versus high according to the median).

Based on previous exposure-response relationships established in 272 Chinese cities (Chen et al., 2017, 2018; Chen et al., 2019b; Liu et al., 2018; Wang et al., 2018), we estimated the annual excess deaths attributable to the estimated PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and CO emissions for every doubling in vehicle density and every 10% increase in truck proportion. The excess deaths ($ED$) is calculated by:

$$ED = N \times (e^{\beta c} - 1)$$

(3)

where

- $N$ denotes the number of deaths from all or specific causes (including cardiovascular disease (CVD), coronary heart disease, hypertensive heart disease, stroke, respiratory disease, and chronic obstructive pulmonary disease, derived from the China Health Statistics Yearbook 2019 in China (Beijing Union Medical University Press, 2019),
- $\beta$ refers to the effect coefficient of the exposure-response relationship.
- $c$ refers to the increase in pollutant (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and CO) ascribed to every doubling in the vehicle density or every 10% increase in truck proportion.

All statistical analyses were conducted using R software, version 3.6.3 (R Foundation for Statistical Computing, Vienna, Austria).

3. Results

3.1. Traffic control and air pollution

To contain the spread of the COVID-19, the measures that led to nationwide traffic control has substantially reduced air pollution (Fig. 1A, A.2). NO$_2$ showed the greatest decrease of 40.5%, followed by PM$_{10}$ (−30.9%), PM$_{2.5}$ (−27.7%), AQI (−25.5%), CO (−19.2%), and SO$_2$ (−13.1%), whereas O$_3$ slightly increased (14.5%) (Table A.2). Furthermore, cities with more stringent traffic control measures had greater reductions in AQI, PM$_{2.5}$, PM$_{10}$, NO$_2$, and CO levels (Fig. 1A and Table A.1). After adjustment for meteorological factors and traffic control type, the average reduction during the traffic control period was 18.1 (95% CI 14.1, 22.1) for AQI, 15.2 (11.7, 18.8) μg/m$^3$ for PM$_{2.5}$, 22.1 (17.9, 26.2) μg/m$^3$ for PM$_{10}$, 2.6 (2.0, 3.1) μg/m$^3$ for SO$_2$, 9.9 (9.1, 10.8) μg/m$^3$ for NO$_2$, and 0.18 (0.14, 0.21) mg/m$^3$ for CO, whereas O$_3$ increased by 4.2 (2.7, 5.7) μg/m$^3$ (Table 1). When further adjusted for industrial density, the estimated mean levels of pollutants for the Pre- and Post-TC periods decreased. However, the differences remained materially unchanged (Table 1), suggesting that emissions from industrial sources may have contributed to air pollution but maintained at a stable level during the traffic control implementation.

3.2. Vehicle density, truck proportion, and air pollution

Vehicle density of most vehicle subtypes showed consistent associations with a reduction in PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and CO during the traffic control period (Table A.2). Heavy trucks showed the strongest association (−4.8 (95% CI −7.2, −2.5) for AQI, −4.3 (−6.3, −2.2) μg/m$^3$ for PM$_{2.5}$, −5.8 (−8.2, −3.4) μg/m$^3$ for PM$_{10}$, −0.7 (−1.1, −0.3) μg/m$^3$ for SO$_2$, −1.4 (−1.9, −0.9) μg/m$^3$ for NO$_2$, 1.5 (0.6, 2.4) μg/m$^3$ for O$_3$, and −0.04 (−0.06, −0.02) mg/m$^3$ for CO). Due to the multicollinearity between vehicle subtypes, we assessed the association of total vehicle density and truck proportion with pollutant change. Every doubling in vehicle density was associated with a 4.5 (95% CI 1.9, 7.0) decrease in AQI, a 4.2 (2.0, 6.4) μg/m$^3$ decrease in PM$_{2.5}$, a 5.5 (2.9, 8.1) μg/m$^3$ decrease in PM$_{10}$, a 1.5 (0.9, 2.0) μg/m$^3$ decrease in NO$_2$, a 0.04 (0.02, 0.07) mg/m$^3$ decrease in CO, but a 1.8 (0.8, 2.8) μg/m$^3$ increase in O$_3$ during the traffic control period (Table 2). However, higher truck proportion was only significantly associated with a reduction in AQI, PM$_{2.5}$, PM$_{10}$ and CO during the traffic control period (for every 10% increase in truck proportion, changes were −10.5 (95% CI −20.0, −1.1) μg/m$^3$, −12.3 (−20.6, −4.1) μg/m$^3$, −14.3 (−23.9, −4.6) μg/m$^3$, and −0.14 (−0.23, −0.05) mg/m$^3$, respectively).
Fig. 1. Change percentages of air quality index (A) and criteria air pollutants by traffic control type (B).
The restricted cubic spline showed similar results with a clear linear relationship between vehicle density and reduction in NO2 and CO, and increase in O3; however, when the vehicle density exceeded 50/km², the linear association slightly attenuated for PM2.5 and PM10, and even reversed for SO2 (Figs. 2 and A.4). In contrast, linear associations between truck proportion and reduction in PM2.5, PM10, and CO were only observed at high levels (>12%; Fig. A.3). There was no significant association between truck proportion and reduction in NO2 (Table 2 and Fig. A.3).

### 3.3. Urban greening and air pollution from automobiles

Cities with high urban green coverage rate had less air pollution reduction due to traffic control compared with cities with low green coverage rate (Fig. 3). The stratified analysis revealed remarkable linear associations between vehicle density and AQI, PM2.5, PM10, NO2, and CO among cities with low urban greening levels; however, in cities with high urban greening levels, vehicle density was only associated with NO2. The associations between vehicle density and reduction in PM2.5, PM10, and CO were significantly weaker in cities with high urban green coverage rate (P < 0.05 for interaction; Fig. 3). Nevertheless, no interaction effect was found for SO2 and O3 (P > 0.05 for interaction; Figs. 3 and A.6). Besides, cities with high urban greening were more likely to be in eastern China (Fig. A.7).

### 3.4. Automobile-generated air pollution and attributable deaths

According to our estimates, every doubling in vehicle density was associated with a 4.2 μg/m³ increase in PM2.5, an 5.5 μg/m³ increase in PM10, a 0.6 μg/m³ increase in SO2, and a 1.5 μg/m³ increase in NO2 (Table 2), which are equivalent to 8.43 (95% PI 5.75, 10.73), 11.54 (6.52, 16.57), 3.23 (2.30, 4.21), and 12.32 (9.58, 15.06) thousand total deaths, 4.38 (2.92, 5.84), 5.31 (2.76, 7.86), 1.62 (1.13, 2.11), and 5.21 (4.05, 6.95) thousand CVD deaths, and 1.22 (0.72, 1.77), 1.44 (0.39, 2.54), 0.33 (0.14, 0.51), and 1.81 (1.36, 2.26) thousand respiratory deaths in China each year; every 10% increase in truck proportion was associated with a 12.3 μg/m³ increase in PM2.5, and a 14.3 μg/m³ increase in PM10, which are equivalent to 24.71 (95% PI 16.84, 31.46) and 30.04 (16.97, 43.13) thousand total deaths, 12.83 (8.55, 17.12) and 13.81 (7.18, 20.46) thousand CVD deaths, 3.59 (2.10, 5.20), and 3.74 (1.01, 6.62) thousand respiratory disease deaths in China each year (Tables 3 and A.3).

### 4. Discussion

This nationwide natural experiment study showed that during the COVID-19 outbreak in China, governmental measures resulted in reduced air pollution (except for O3) nationwide, which can be largely explained by traffic control measures. We further established dose-effect relationships between vehicle density, the proportion of trucks, and air pollutants, including PM2.5, PM10, NO2, and CO, and estimated attributable deaths accordingly. Besides, urban greening may substantially reduce automobile-generated air pollutants, including PM2.5, PM10, and CO.

During the COVID-19 outbreak in China, the pollutant levels of PM10, PM2.5, NO2, and CO decreased significantly. Consistently, a recent study in China reported that, compared with cities without lockdown, cities with lockdown had a 19.8 and a 14.1 μg/m³ decrease in daily AQI and PM2.5 (He et al., 2020), which were similar to our estimates of 18.1 points and 15.2 μg/m³ respectively. Another evidence from 44 cities in northern China found that travel restrictions during the pandemic reduced the AQI, SO2, PM2.5, PM10, NO2, and CO by 7.8%, 6.76%, 5.93%, 13.66%, 24.67%, and 4.58%, respectively (Bao and Zhang, 2020). Consistent with findings from previous study, O3, as a secondary pollutant of NOx, increased during traffic control period, which is understandable considering the low temperature and reduced NO2 level during the observation period (Sicard et al., 2020).

We found that industrial level did contribute to air pollution during the Pre- and Post-traffic control period but was not associated with air quality changes during the traffic control period. Similarly, a study suggested that changes in pollutant levels during the lockdown might be associated with various traffic control measures such as home quarantine, suspension of public transport, and cancellation of taxi-hailing services (Chen et al., 2021). Another study found that industrial level, if ever changed during the outbreak, might have less impact on the pollutant level changes than the reduction in vehicle emission (Wang et al., 2020b). However, Wang et al. (2020b) found that changes in pollutant levels during the COVID-19 control period could be inversely associated with the number of vehicles, secondary industry share, and annual emissions of industrial nitrogen oxides (NOx) and SO2 at the provincial level (n = 22). Although their study has some limitations (e.g., assuming all provinces initiated COVID-19 control on the same day; the unjustified long pre-COVID-19 control period from 1 Jan to
23 Jan 2020; and lack of control of meteorological factors), their findings of reduced industrial emissions during lockdown were not entirely contradictory to ours. In fact, we assumed that industry output would decline in early January but remain stable from one week before the Lunar New Year (18 Jan 2020), during which most non-essential industries were shut down for the Chinese Spring Festival. However, for indispensable industries (e.g., power plants, iron, and steel industry), they would remain in operation throughout the Spring Festival regardless
of the pandemic (Ministry of Ecology and Environment of China, 2020a). This assumption has been corroborated by a recent finding that the 5-day NOx emissions from four major polluting industries (mining; manufacturing; power, heat, gas and water production and supply; and wholesale and retail industry) reduced to the lowest level on Jan 14, 2020 (before our earliest observation time point) and kept low or slightly increased during our observation periods (He et al., 2021).

Furthermore, reduction in air pollutant level was associated with total vehicle density (including passenger vehicles and trucks), with a
near-complete linear relationship observed for NO2 and CO. At higher vehicle density (>50 vehicles/km²), the associations with PM2.5 or PM10 slightly attenuated. Only one nationwide study (Xie et al., 2019) found a positive association between traffic density (number of vehicles/number of population) and smog pollution based on observational data collected from 283 cities in China from 2003 to 2015, which is consistent with our findings. However, this study indicated that the association was not significant in small cities, which might be due to uncontrolled factors such as truck proportion, meteorological factors, and long-term climate change. Several reasons may explain why we observed an attenuated association with PM at high vehicle density. First, cities with higher vehicle density tend to be more developed, implement new emission standards quickly (especially for PM) (Lang et al., 2016; Wu et al., 2017), have a higher rate of new vehicle purchase, phase out old vehicles faster, implement more stringent emission-control measures (low emission zone, yellow-label vehicle restriction) (Wu et al., 2016), and enforced stricter oil quality standards. On the other hand, the underdeveloped cities with lower vehicle density often have insufficient inspection/maintenance system to guarantee a good state of running vehicles. Nonetheless, linear relations were observed for NO2 and CO, which is consistent with the knowledge that road traffic is the key contributor to the air pollutants NO2 and CO (U.S. Environmental Protection Agency, 2010, 2016). Other real-world evidence is consistent with our findings. For example, researchers in Montreal found that concentrations of NO2 would decrease significantly with increasing logarithmic distance from the trunk road (Gilbert et al., 2003). Another research based on Beijing City found that the mobile sources largely contributed to NO2 and CO emissions in winter (Lin et al., 2011).

Additionally, the proportion of trucks was linearly associated with PM2.5, PM10, and CO, but only at a higher truck proportion (>12%), whereas no significant association was found for NO2. This is consistent with the existing evidence that trucks, typically powered by diesel, contributed predominantly to PM2.5, PM10, and CO emissions. According to the China Mobile Source Environmental Management Annual Report 2020 (Ministry of Ecology and Environment of the People’s Republic of China, 2020), 70.3% of CO from mobile sources was emitted by passenger vehicles, whereas 83.5% of NOx and 90.1% of PM were emitted by trucks. Given that passenger vehicles account for about 90% of total automobiles, each truck emitted more CO than a passenger vehicle. However, contrary to current knowledge, we did not observe a significant linear association between truck proportion and NO2, probably because NO2 only accounts for less than 10% of ambient NOx, and the real association was masked by other atmospheric constituents or chemical processes (U.S. Environmental Protection Agency, 2016; U.S. Environmental Protection Authority, 2016). For example, it is well established that there is a complex interaction among NOx, volatile organic compounds, and O3 (Sillman, 1999). However, it is worth noting that the only conclusion we can draw is that trucks do not contribute disproportionately to NO2 levels; based on the clear linear relationship between vehicle density and NO2, trucks are at least as important in controlling ambient NO2 levels as passenger vehicles. Further studies are needed to validate this finding.

For public health implications, improved air quality has been viewed as a blessing for the environment in this unprecedented disaster for humankind (Muhammad et al., 2020). From the public health perspective, every doubling in vehicle population might increase more than 8000 excess deaths annually via increased PM2.5 alone. More than 60% of the deaths were estimated to be attributable to cardiopulmonary causes. Particulate matter from vehicle engines (especially diesel exhaust) consists mostly of element carbon and organic carbon. However, those from non-exhaust sources often had elevated concentrations of transition metals (brake wear (copper, antimony), tire abrasion (zinc), dust from road surfaces (iron)) (Kelly and Russell, 2015). It has been reported that, compared with ambient PM from other sources, PM emitted by vehicles had higher oxidative activity (Yanosky et al., 2012), which might be driven by metals and element carbon or organic carbon from incomplete combustion (Li et al., 2019). Furthermore, it may lead to higher risks of several diseases (including cancer (Koutros et al., 2020), cardiovascular disease (Guan et al., 2016; Lucking et al., 2011), and pulmonary disease (Peng et al., 2009; Saber et al., 2014)) and mortality (Shang et al., 2013). Therefore, the number of excess deaths due to traffic-generated particulate matter might be underestimated in the present study. Besides, more than 12,000 annual deaths for NO2 (much higher than other pollutants) were estimated to be associated with every doubling in vehicle density, consistent with previous findings that NO2 is a critical air pollutant causing severe health risks (Chen et al., 2018; Lim et al., 2019).

We also found that higher urban green coverage rate attenuates air pollution from the vehicle, including PM, SO2, and CO. Greening area’s remarkable capability to mitigate NO2 was found in many researches (Chen et al., 2019a; Dadvand et al., 2015). Similarly, urban greening was shown to mitigate gaseous pollutants, including SO2, CO, and NO2 (Selmi et al., 2016; Yang et al., 2008). However, we found the associations between vehicle density and changes in air pollutants during traffic control were not attenuated by urban greening for NO2. A Finland study also found that urban greening has limited ability to remove NO2 and volatile organic compounds (Setala et al., 2013). Nonetheless, more caution is required to interpret our current findings, as cities with higher green coverage rates are mainly located in the more developed eastern part of China. The observed attenuating effect of green coverage in these cities might be partly due to other factors (e.g., more fuel-efficient cars, stricter regulations) (Wu et al., 2017). Therefore, the impact of urban greening on traffic-originated air pollutants, especially on NO2 levels, needs further investigation.

However, this study has several limitations. First, our primary analysis is based on the assumption that changes in air pollution during traffic control are attributable to vehicle elimination. However, it is impossible to completely control for air pollution changes from industrial, commercial, residential, and natural sources. Previous reports have shown that...
emission from living sources (e.g., commercial, residential sources) was unlikely the contributor to reduced air pollutant levels during lockdown (Ministry of Ecology and Environment of China, 2020a; Wang et al., 2020a). He et al. (2021) found that the 5-day NOx emission from four major industries (mining; manufacturing; power, heat, gas and water production and supply; and wholesale and retail industry) reduced to the lowest level on Jan 14, 2020 (before our earliest observation time point) and kept low or slightly increased during our observation periods (Jan 19–Feb 15, 2020). Therefore, at least for NOx, industrial emission cannot explain the observed reduction in our study. Besides, we also defined city-specific traffic control period within the Spring Festival time frame, and included the industrial density as a covariate to control for the impact of pollutants from industrial sectors. Second, we did not collect data on traffic volumes during the observation period, so our estimates may be inaccurate or even biased. Nonetheless, given that it is not practically feasible to collect nationwide traffic volume data during this challenging period, we established a dose-effect relationship using the data most available at hand. Third, because the traffic control period was in late winter and data on green coverage was yearly, the effect of greening on air quality might be limited, particularly in central and north China. However, some findings indicate that the dry deposition of trees was still substantial in winter (Yang et al., 2018). Furthermore, even in the warmer south where evergreens were more common, leaves can emit biogenic volatile organic compounds, which further affect the amount and toxicity of PM2.5 and ozone. Therefore, more caution should be taken when interpreting the effect of urban greening on traffic-generated air pollutants. Fourth, although we adjusted for various meteorological factors, residual confounding remains possible. Finally, in the present study, we explored the association of traffic pollution with excess mortality based on data from traffic control during the COVID-19 pandemic, which may be different from what we might observe in normal time.

5. Conclusions

In this study, traffic control measures aiming at containing the COVID-19 outbreak improved air quality (except for O3) nationwide. Pollutants including PM2.5, PM10, NO2, and CO were linearly associated with vehicle density, whereas urban greening may mitigate these associations. Higher proportion of trucks was associated with increased PM2.5, PM10, and CO, but not NO2. Furthermore, we estimated that, for every doubling of vehicle density, PM2.5 emissions alone might lead to over 8000 excess deaths per year, 66% of which were caused by cardiovascular diseases. In summary, these findings will guide future efforts in evaluating traffic pollution, developing specific pollution control strategies, and estimating potential health risks.

CRediT authorship contribution statement

Chengyong Jia: Conceptualization, Investigation, Methodology, Software, Formal analysis, Writing – original draft, Visualization. Wending Li: Conceptualization, Investigation, Methodology, Software, Formal analysis, Writing – review & editing, Validation. Tangchun Wu: Conceptualization, Supervision. Meian He: Project administration, Supervision, Writing – review & editing, Funding acquisition.

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.scitotenv.2021.146618.

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