ARTICLE IN PRESS

Atmospheric Environment xxx (xxxx) xxx

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: http://www.elsevier.com/locate/atmosenv

COVID-19 mitigation measures and nitrogen dioxide – A quasi-experimental study of air quality in Munich, Germany

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HIGHLIGHTS

- The effect of COVID-19 mitigation measures on NO_2 in Munich was unclear.
- We applied two robust quasi-experimental approaches.
- All hypotheses, as well as main and additional analyses were defined a priori.
- As hypothesized, we observed largest reductiotns in NO_2 at traffic sites.

ARTICLE INFO

Keywords:
Accountability
Quasi-experimental study
Nitrogen dioxide
Air quality
COVID-19

ABSTRACT

Background: In response to the COVID-19 pandemic, the Bavarian State government announced several COVID-19 mitigation measures beginning on March 16, 2020, which likely led to a reduction in traffic and a subsequent improvement in air quality. In this study, we evaluated the short-term effect of COVID-19 mitigation measures on NO_2 concentrations in Munich, Germany.

Methods: We applied two quasi-experimental approaches, a controlled interrupted time-series (c-ITS) approach and a synthetic control (SC) approach. Each approach compared changes occurring in 2020 to changes occurring in 2014–2019, and accounted for weather-related and other potential confounders. We hypothesized that the largest reductions in NO_2 concentrations would be observed at traffic sites, with smaller reductions at urban background sites, and even small reductions, if any, at background sites. All hypotheses, as well as the main and additional analyses were defined a priori. We also conducted post-hoc analyses to ensure that observed effects were not due to factors other than the intervention.

Results: Main analyses largely supported our hypotheses. Specifically, at the two traffic sites, using the c-ITS approach we observed reductions of 9.34 $\mu g/m^3$ (95% confidence interval: −23.58; 4.90) and 10.02 $\mu g/m^3$ (−19.25; −0.79). Using the SC approach we observed reductions of 15.65 $\mu g/m^3$ (−27.58; −4.09) and 15.1 $\mu g/m^3$ (−24.82; −9.83) at these same sites. We observed effects ranging from smaller in magnitude to no effect at urban background and background sites. Additional analyses showed that the effect was largest in the first two weeks following introduction of measures, and that a 3-day lagged intervention time also showed a larger effect. Post-hoc analyses suggested that at least some of the observed effects may have been attributable to changes in air quality occurring before the intervention, as well as unusually high concentrations in January 2020.

Conclusion: We applied two quasi-experimental approaches in assessing the impact of the COVID-19 mitigation measures on NO_2 concentrations in Munich. Taking the 2020 pre-intervention average concentrations as a reference, we observed reductions in NO_2 concentrations of approximately 15–25% and 24–36% at traffic sites, suggesting that reducing traffic may be an effective measure to reduce NO_2 concentrations in heavily trafficked areas by margins which could translate to public health benefits.

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https://doi.org/10.1016/j.atmosenv.2020.118089
Received 27 June 2020; Received in revised form 17 November 2020; Accepted 19 November 2020
Available online 22 November 2020
1352-2310/

Please cite this article as: Jacob Burns, *Atmospheric Environment*, https://doi.org/10.1016/j.atmosenv.2020.118089

1. Background

In December 2019 the first cases of the novel coronavirus, SARS-CoV-2, were observed in Wuhan, China. Over the next days and weeks the virus, and the associated respiratory disease referred to as COVID-19, spread further into China and by mid-January cases were documented in Thailand, Japan and South Korea (WHO, 2020a). By March 11, 2020, when the World Health Organization declared COVID-19 a global pandemic, cases had been observed in over 100 countries and territories across the globe (WHO, 2020b).

To slow the spread of this viral respiratory infection, the effects of which range from limited or no symptoms to death, national and sub-national governments have implemented numerous mitigation measures (Health System Response MONITOR, 2020). These mitigation measures differ between countries, but include, for example, social distancing recommendations and requirements, school closures, border closures, non-essential business closures and required wearing of masks.

Such external shocks can be conceptualized as natural experiments to explore the short-term effect that decreased automobile traffic or industrial activity has on ambient pollutant concentrations. A recent systematic review (BURNS et al., 2019, BURNS et al., 2020) identified a range of such studies, for example, evaluating the effect on air quality or health of the closure of a main highway for construction in California, US (HONG et al., 2015), the US Democratic National Convention in Boston (LEVY et al., 2006), the suspension of the public transportation system due to a strike in Ottawa, Canada (DING et al., 2014), the suspension of trucking operations due to a nationwide strike in India (Latha et al., 2004), political demonstrations in Nepal (Fransen et al., 2013) and Hong Kong (Brimblecombe and Ning, 2015), and the closure of a copper smelter due to a strike in the Southwest US (POPE et al., 2007).

Limited evidence already suggests that COVID-19 mitigation measures may have led to reductions in air pollution. For example satellite imagery has shown that concentrations of nitrogen dioxide (NO_2), a pollutant largely stemming from automobile traffic, have decreased in China (ESA, 2020c), India (ESA, 2020a) and across several European cities (ESA, 2020b). Monitor-based measurements have also implied decreased NO_2 concentrations in some European cities (EEA, 2020). Researchers on each of these projects, however, have been quick to emphasize the influential role that weather and other factors, such as celebration of the Chinese New Year, have on NO_2 concentrations, and that fully adjusting for the effects of such measures using standard epidemiological approaches is challenging.

Embedded in the national COVID-19 response, the Bavarian State government announced several COVID-19 mitigation measures beginning on March 16, 2020 (Bayerische STAATSREGIERUNG, 2020). As several of these measures could plausibly lead to reduced automobile traffic, it provided a unique opportunity to assess the effects of these measure on air quality, and to do so using rigorous quasi-experimental.

2. Objective

In this study, we applied two quasi-experimental approaches, a controlled interrupted time-series (c-ITS) approach and a synthetic control (SC) approach, to evaluate the short-term effect of COVID-19 mitigation measures on NO_2 concentrations in Munich, Germany.

3. Methods

3.1. Intervention and context

On March 13, 2020 the Bavarian state government announced that, aiming to mitigate the spread of COVID-19, schools across Bavaria would be closed from 16 March until at least April 19, 2020. This initial announcement was followed by several further mitigation measures over the next week. The measures implemented in Bavaria included:

March 2020 – closure of schools and daycare facilities

March 17, 2020 – closure of public facilities, ban on gatherings and events, closure of retail stores, restrictions on the restaurant industry;

March 18, 2020 – closure of institutes of higher education, ban on visits to hospitals and care facilities;

March 21, 2020 – ban on dine-in services for restaurant industry, partial lockdown (Bayerische Staatsregierung, 2020).

As a part of these various measures, individuals were encouraged, and then required, where possible, to remain home. Evidence suggests that Bavarian residents largely adhered to these measures. An analysis of the effective reproduction number of the virus, i.e. the expected number of cases generated by an infected individual, showed that the number fell from approximately 3.5 to 1.0 between 16 March and 3 April in Bavaria. In Munich, the effective reproduction number fell from approximately 3.0 to 0.5 over the same time period (Khailaie et al., 2020). Given that these measures initially encouraged and later on required people to stay at home, it is likely that these measures led to a decrease in people's movements. Indeed, mobility data released by Apple and Google show a clear reduction in traffic during this time (APPLE (2020); GOOGLE (2020)). Traffic critical to essential supply chains, as well as some local traffic related to grocery shopping or outdoor recreational activity, likely did not decrease or decreased to a lesser extent, so any change was likely driven by a reduction in driving by those commuting to work and/or driving their children to school. We assume that this reduction in traffic likely also subsequently led to reduced concentrations of automobile-related pollutants like NO_2.

3.2. Study design overview

The study uses an approach that compares the trend in NO_2 concentrations in 2020, i.e. the intervention year, with the trend in several years in which no mitigation measures for COVID-19 control were implemented, i.e. the control years. The use of historical controls is advantageous in this study, because, given that virtually all European cities implemented mitigation measures in March of 2020, no appropriate geographical control was available. The study period for the intervention year includes Monday, January 6, 2020 (2nd calendar week) – Sunday, April 12, 2020 (15th calendar week). March 16, 2020, the date on which the first major COVID-19 measure was implemented divides this period into pre- and post-intervention periods. The study period for the control years includes this same time period (Monday of the 2nd calendar week – Sunday of the 15th calendar week) in 2014–2019, with the Monday of the 12th calendar week splitting each year into pre- and post-intervention periods.

Both the c-ITS and SC approaches allow for the comparison of serial changes to an intervention unit receiving the intervention with changes to one or multiple control units not receiving the intervention (CRAIG et al., 2017). Thus each approach utilizes serial data from intervention and control units to create a 'counterfactual', i.e. what would have happened had the intervention not been implemented. This allowed us to ensure that any effect observed in 2020 is neither due to the current trend in NO_2 concentrations nor due to yearly seasonal fluctuations.

The main difference between the two approaches, however, relates to how data from control units are utilized. The c-ITS study utilizes data from all control units in full. Specifically, we compared the change in NO_2 concentrations between the pre- and post-intervention periods in 2020, the intervention year, to changes in concentrations between the pre- and post-intervention periods in 2014–2019, the control years (LOPEZ BERNAL et al., 2018). The SC study can be utilized when there are multiple controls to draw from, but no clear rationale for choosing which is the most appropriate. Specifically, we compared the change in NO_2 concentrations between the pre- and post-intervention periods in 2020 to changes between the pre- and post-intervention periods in a weighted average of 2014–2019. This data-driven weighted average is calculated to provide the most similar comparison, with respect to the pre-intervention outcome trend and a pre-defined set of covariates (Bouttell et al., 2018).

3.3. Data

3.3.1. Outcome

The Bavarian Environmental Administration (Bayerisches Landesamt für Umwelt) is charged with the monitoring of air quality in Bavaria, and data for the 50 monitoring stations are freely available (LfU BAYERN, 2020). We obtained NO_2 data for the five stations located in Munich, which included two classified as urban traffic monitors – Landshuter Allee (LAN) and Stachus (STA), one as urban background – Lothstrasse (LOT), and two as background – Allach (ALL) and Johaneskirchen (JOH). Hourly data were provided, which we converted to daily averages.

3.3.2. Covariates

We obtained data for other factors that are associated with NO_2 concentrations, including several weather-related variables – daily averages of temperature, rain fall, air pressure, humidity, and wind speed (Peel, 2010). These data were freely available from the German Weather Service (Deutscher Wetterdienst) (DWD, 2020). We also used publicly available information indicating when school holidays were in place – these included the Christmas, winter and Easter holidays. Within these time periods, relevant days were defined as either holiday high travel days (i.e. specific holidays or holiday weekends – Friday and Saturday, on which people tend to travel more) or holiday low travel days (i.e. during the week when people tend to travel less – Sunday through Thursday).

3.4. Statistical analyses

We registered a study protocol on May 3, 2020 through OSF (https://osf.io/7vkfc); all hypotheses and methods for main and additional analyses were defined a priori in the protocol. We designed and piloted these analyses using data from 2014 to 2019. The data for the intervention year, 2020, were downloaded and analyzed only after registration of the protocol.

3.4.1. Main analysis

As part of the main analyses we applied a c-ITS and SC approach. For both of these approaches, it is important to define the impact model, i.e. how the intervention would impact the outcome if it were effective – this subsequently shapes decisions made in defining the analysis parameters (Lopez BERNAL et al., 2016). With regard to the timing of the effect, we assumed that the COVID-19 mitigation measures began influencing NO_2 concentrations immediately after implementation of the first of the measures on March 16, 2020, thus we defined this day as the first day of the post-intervention time period. Given that the mitigation measures could have led to an immediate drop in NO_2 concentrations and that we are interested in the effect of the measures over the entire post-intervention period, we assumed and tested for a level change. This level change represents an immediate change, which is sustained across the post-intervention period.

As described above in section 3.3, we obtained data from five air quality monitoring stations. Our a priori hypothesis was that the observed effect would be greatest at the two traffic monitors LAN and STA, a smaller effect at the urban background monitor LOT, and the smallest effect, if any, at the two background monitors ALL and JOH.

For the c-ITS approach, we fitted a linear model using the general least squares method. The model took the following form:

$$NO_2 = \beta_0 + \beta_1 Day + \beta_2 Year + \beta_3 Post + \beta_4 Int + \beta_5 Post{*}Int + \beta_{6-13} Covs$$

where, NO_2 represents the outcome, NO_2 concentrations in $\mu g/m^3$ at a given monitor; *Day* is a continuous variable from 1 to 98, from the first to the last day of the study period in each year, thus capturing the underlying trend in the outcome over the study period; *Year* is a categorical variable taking the value of the year between 2014 and 2020; *Post* is a dummy variable taking the value of 0 in the pre-intervention period and 1 in the post-intervention period in each year (March 16, 2020, or Monday of the 12th calendar week in all years was treated as the first day of the post-intervention period), thus capturing the change in the outcome in the post-intervention period relative to the pre-intervention period; *Int* is a dummy variable taking the value for the control years 2014–2019 and 1 in the intervention year 2020; *Post*Int* is an interaction term which captures the change in *Post* in 2020 compared to in 2014–2019; *Covs* includes the potentially important covariates, including temperature, rain fall, air pressure, humidity, wind speed, holiday high and low travel days and day of the week. β_5, the change in NO_2 concentrations between the pre- and post-intervention periods in 2020 relative to the change in 2014–2019, represents the level change described above in section 3.3, and is thus the effect estimate of interest. Given the serially correlated nature of the data, we used auto-correlation and partial auto-correlation plots to determine an appropriate correlation structure for each model. For the site ALL, substantial data were missing for the year 2014 (23%); because of this, 2014 was excluded from the c-ITS analysis for ALL only.

The SC approach was structured similarly. However, instead of comparing changes in 2020 to changes in 2014–2019, the method allows for the construction of a synthetic control, ensuring that the intervention year and synthetic control year were similar with regard to the pre-intervention outcome trend and potentially important covariates. Specifically, this synthetic control was constructed using input data from the pre-intervention NO_2 concentrations, as well as the covariates listed above, from 2014 to 2019. Based on a linear interactive fixed effects model, we calculated the effect of interest. This effect is the average difference between the observed time series, i.e. the post-intervention outcome trend observed in 2020, and the synthetic control time series, i.e. the post-intervention counterfactual series. This approach allows for a treatment effect to be calculated for each post-intervention time point, allowing an investigation of how the intervention effect changes over time, as well as for the entire post-intervention time period, allowing an investigation of the average effect of the intervention, or the average treatment effect (ATT).

3.4.2. Additional analyses specified a priori

We conducted a series of sensitivity analyses to evaluate the extent to which our results were robust to changes to our assumptions, and to further explore how the intervention effect developed and changed over time.

The mitigation measures were dependent on individuals changing their behavior, and this behavior may have been adapted over time. We suspected that the effect in the two weeks immediately following the intervention may have been larger than the effect in the subsequent two weeks. We investigated this using both the c-ITS and SC approaches. For the c-ITS approach, we modelled two intervention effects separately, one specifically for the first two-week period, and the other for the second two-week period. For the SC approach, we shortened the post-intervention time period to two weeks.

It is also plausible that individuals did not immediately change their behavior on March 16, 2020, but instead slowly adapted as further mitigation measures were announced. To investigate this possibility, we mimicked the main analyses, treating March 19, 2020 as the first day of the post-intervention period, under the assumption that behaviors changed measurably after a lag of three days.

3.4.3. Post hoc analyses

After conducting the a priori specified main and additional analyses, we further conducted three sets of analyses to ensure that observed changes were not due to factors other than the mitigation measures. To ensure that concentration changes occurring prior to the intervention were not driving observed changes, we conducted all analyses with a series of backdated intervention start points 2, 4 and 6 weeks prior to March 16, 2020. Each of these 'placebo analyses' assessed whether changes occurred within two weeks of the respective intervention point, although no intervention actually occurred. Next, to assess whether high concentrations in January 2020 may have biased the pre-intervention trend and thus the calculated effects, we conducted all analyses with a shortened pre-intervention period lasting 6 weeks. Finally, to ensure that the noisy nature of daily air quality data, characterized by serial correlation as well as random noise, was not driving observed concentration changes, we repeated all analyses with smoothed NO_2 data. To do so, we analyzed only the trend component of the decomposed data.

All data processing and analyses were conducted using R version 3.6.3. The c-ITS approach was conducted using the Fit Linear Model Using Generalized Least Squares (nlme) (WEISBERG and FOX, 2015) and the SC approach was conducted using the Generalized Synthetic Control Method (gsynth) package (Xu, 2017).

4. Results

4.1. NO_2 concentrations in munich

Concentrations of NO_2 improved in Munich over the period 2014–2020, as illustrated by Fig. 1. For all five monitoring sites, concentrations in 2020 were lower than during any of the previous years, with the greatest differences observed for the year 2014. Taking March as an example, concentrations in 2020 were lower than in 2014 by 47% at LAN, 55% at STA, 43% at Loth, 45% at ALL and 51% at JOH. It is also evident that concentrations at traffic sites (LAN and STA) were, as expected, higher than at urban background (LOT) and background sites (ALL and JOH).

4.2. Effect of COVID-19 mitigation measures on NO_2 concentrations

Regarding the effect of the COVID-19 mitigation measures on NO_2 concentrations across the post-intervention period, our main analyses are summarized in Fig. 2 (panel A) and Table 1.

At traffic sites, where we hypothesized the largest reduction in NO_2 concentrations, reductions of 9.34 μg/m^3 (95% confidence interval: −23.58; 4.90) and 10.02 μg/m^3 (−19.25; −0.79) were observed at LAN and STA, respectively, using the c-ITS approach, and 15.65 μg/m^3 (−27.58; −4.09) and 15.1 μg/m^3 (−24.82; −9.83) using the SC approach. At LOT, the urban background site, where we hypothesized a smaller reduction, small decreases of 1.94 μg/m^3 (−11.90; 8.03) and 8.84 μg/m^3 (−20.04; −2.51) were observed using the c-ITS and SC approach, respectively. At background sites, where we hypothesized a small effect if any, a small reduction of 1.37 μg/m^3 (−12.77; 10.02) was observed at ALL, while a slight increase of 0.75 μg/m^3 (−8.79; 10.29) was observed at JOH using the c-ITS approach; using the SC approach slight decreases were observed at both sites, −3.08 μg/m^3 (−12.59; 5.39) at ALL and −4.69 μg/m^3 (−11.65; 1.86) at JOH. Confidence intervals for all estimates should be noted; for the c-ITS approach, a significant effect was observed only at STA, while for the SC approach significant effects were observed at LAN, STA and LOT. For all other estimates, confidence intervals included 0, indicating some uncertainty regarding the direction of these effects.

Fig. 3 illustrates, based on the SC approach, how the effect of the mitigation measures changed over time. Across all sites, a reduction in NO_2 concentrations shortly after the implementation of the measures can be seen. It is also evident across sites that concentrations began

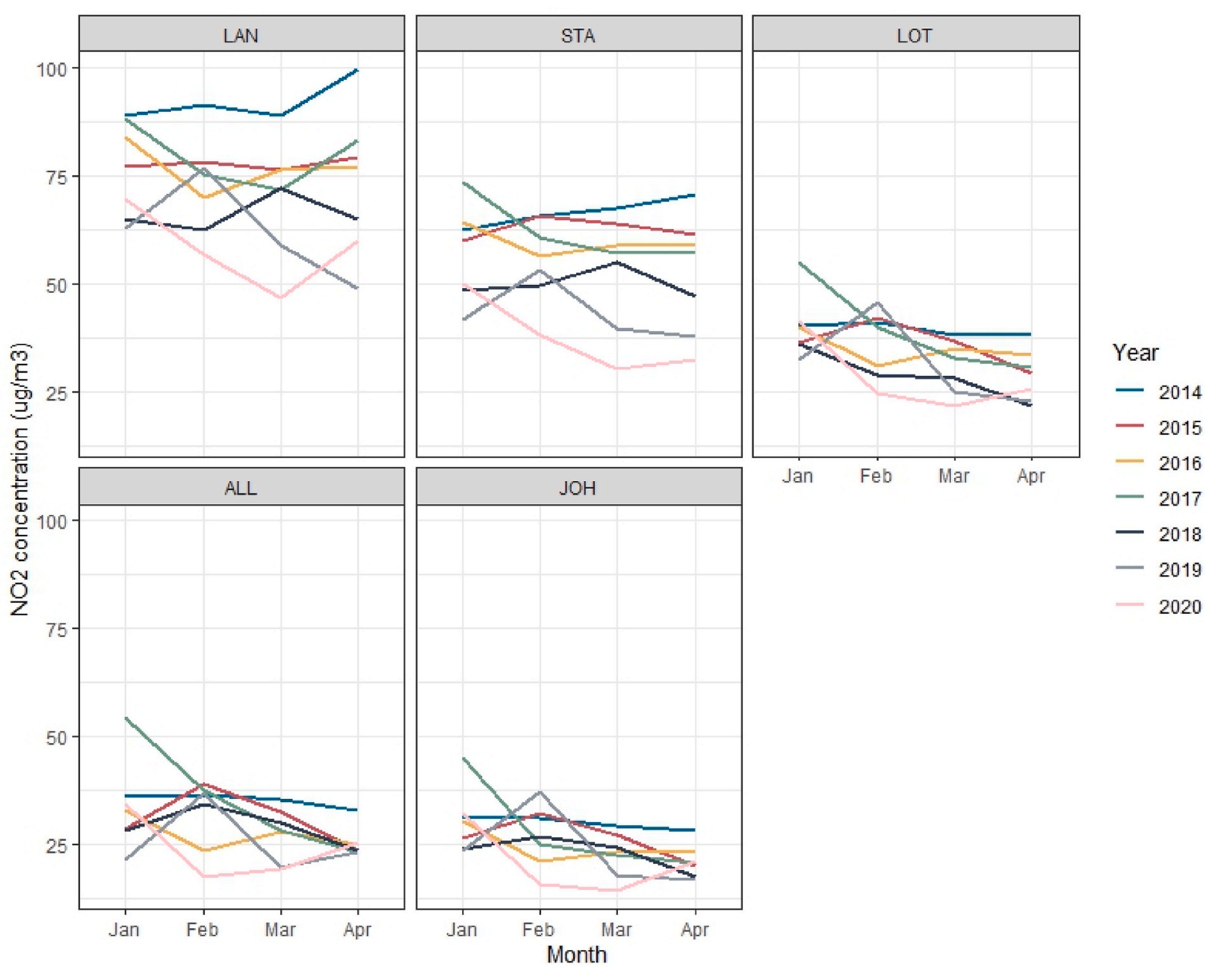

Fig. 1. NO_2 concentrations from January–April in 2014–2020 at LAN, STA, LOT, ALL and JOH.

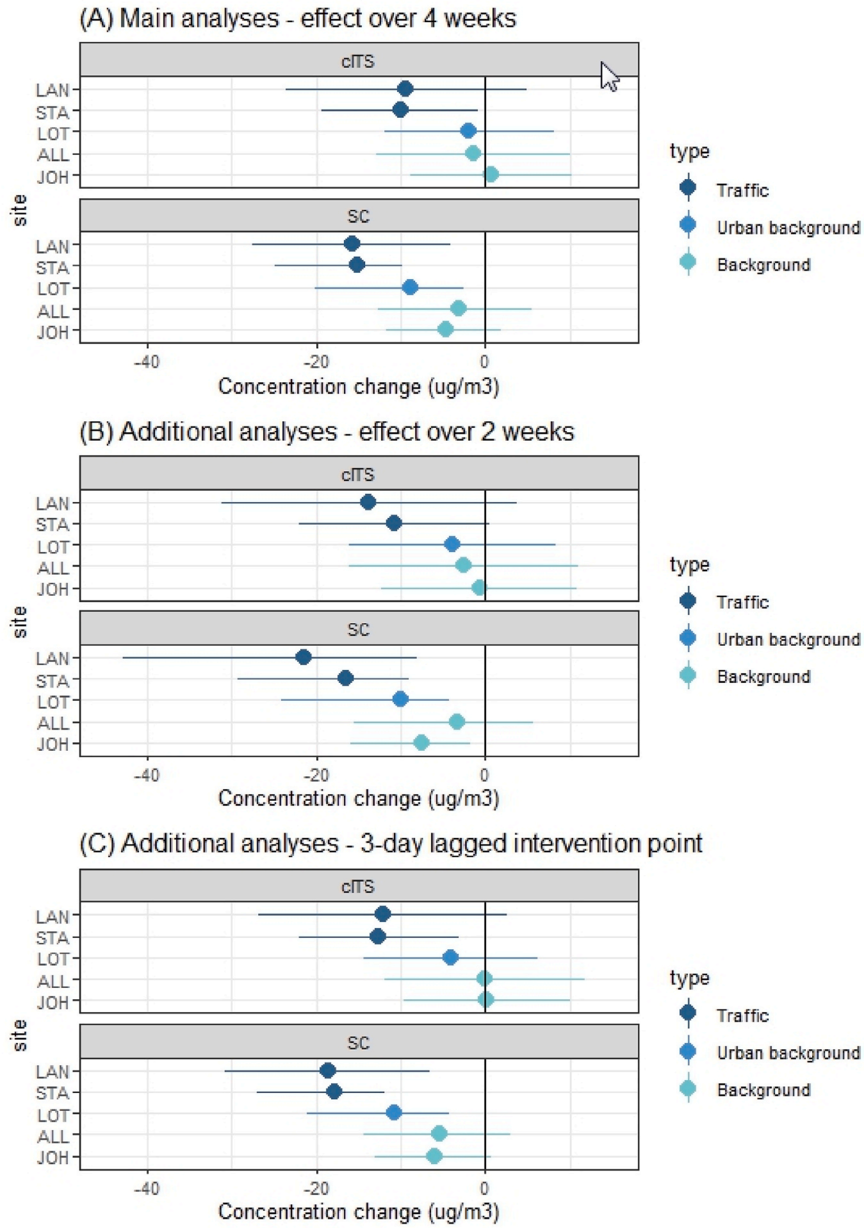

Fig. 2. Effect of the COVID-19 mitigation measures on NO_2 concentrations at the five sites from (A) main analyses, and additional analyses of (B) a two-week post-intervention period and (C) a 3-day lagged intervention point.

creeping upward again after approximately 1.5–2 weeks. Additional analyses below explore how the intervention effect developed and changed over time.

Fig. 3 shows that the SC approach was not able to calculate an optimal counterfactual – for an optimal counterfactual, the pre-intervention ATT would lie very close to 0 at all points along the time series. Additionally, one can see that the average NO_2 concentration approximately 4 weeks prior to the intervention appears to lie below the 0 ATT line, meaning that the observed effects may in part be attributable to changes occurring before the intervention. Post hoc analyses, described below, explore whether these aspects may have biased observed effects.

Additional analyses specified a priori.

Regarding the timing of the effect, we further investigated whether the effect in the first two-week post-intervention period was larger in magnitude than the effect over the entire four weeks. These results are summarized in Fig. 2 (panel B) and Table 1. As hypothesized, across sites effects were slightly larger when considering a two-week post-intervention period rather than a four-week period. Regarding the second two-week post-intervention period, which we assessed using the c-ITS approach, observed effects were smaller at all sites than in the first two-week period. Confidence intervals for all estimates should be noted; for the c-ITS approach, a significant effect was observed only at STA, while for the SC approach significant effects were observed at LAN, STA and LOT. For all other estimates, confidence intervals contained 0, indicating some uncertainty regarding the direction of these effects.

Additionally, we investigated whether the effect differed if the intervention start was delayed for three days from 16 March to March 19, 2020. These results are summarized in Fig. 2 (panel C) and Table 1. As hypothesized, a lagged intervention start resulted in a slightly larger effect at traffic sites. At urban background and background sites similar to slightly larger effects were observed. Confidence intervals for all estimates should be noted; for the c-ITS approach, a significant effect was observed only at STA, while for the SC approach significant effects were

Table 1
Summary of results from main and additional analyses.

	4-week post-intervention (main analyses)		2-week post-intervention period, period 1		2-week post-intervention period, period 2		3-day lagged intervention start	
Site	**Effect**[a] (μg/m^3)	**95% CI**	**Effect** (μg/m^3)	**95% CI**	**Effect** (μg/m^3)	**95% CI**	**Effect** (μg/m^3)	**95% CI**
cITS approach								
LAN (T)	−9.34	−23.58; 4.90	−13.73	−31.24; 3.78	−4.72	−22.95; 13.51	−12.08	−26.73; 2.57
STA (T)	**−10.02**	**−19.25; -0.79**	−10.78	−22.04; 0.48	−9.17	−21.07; 2.72	**−12.61**	**−22.00; -3.21**
LOT (UB)	−1.94	−11.90; 8.03	−3.82	−16.01; 8.37	0.27	−12.59; 13.13	−4.08	−14.32; 6.17
ALL (B)	−1.37	−12.77; 10.02	−2.57	−16.09; 10.95	0.17	−14.44; 14.78	−0.06	−11.84; 11.73
JOH (B)	0.75	−8.79; 10.29	−0.73	−12.21; 10.74	2.52	−9.74; 14.78	0.15	−9.69; 9.99
SC approach								
LAN (T)	**−15.65**	**−27.58; -4.09**	**−21.46**	**−42.82; -8.19**	-[b]	–	**−18.49**	**−30.73; - 6.55**
STA (T)	**−15.1**	**−24.82; -9.83**	**−16.52**	**−29.30; -9.01**	–	–	**−17.82**	**−26.91; -11.92**
LOT (UB)	**−8.84**	**−20.04; -2.51**	**−10.04**	**−24.09; -4.32**	–	–	**−10.82**	**−21.06; -4.37**
ALL (B)	−3.08	−12.59; 5.39	−3.35	−15.53; 5.71	–	–	−5.47	−14.40; 2.93
JOH (B)	−4.69	−11.65; 1.86	−7.46	−15.92; −1.71		–	−6.02	−12.98; 0.67

Bold: denotes statistical significance at an alpha level of 5%.
AbbreviationscITS: controlled ITS; SC: synthetic control; (T): traffic site; (UB): urban background site; (B): background site.
[a] Effects are expressed as the effect over the post-intervention time period, e.g. −9.34 corresponds to a reduction in NO_2 concentration of 9.34 μg/m^3 between the pre- and post-intervention periods in 2020 relative to the control year(s).
[b] The SC approach did not allow for testing the second 2-week post-intervention period, thus no results are reported.

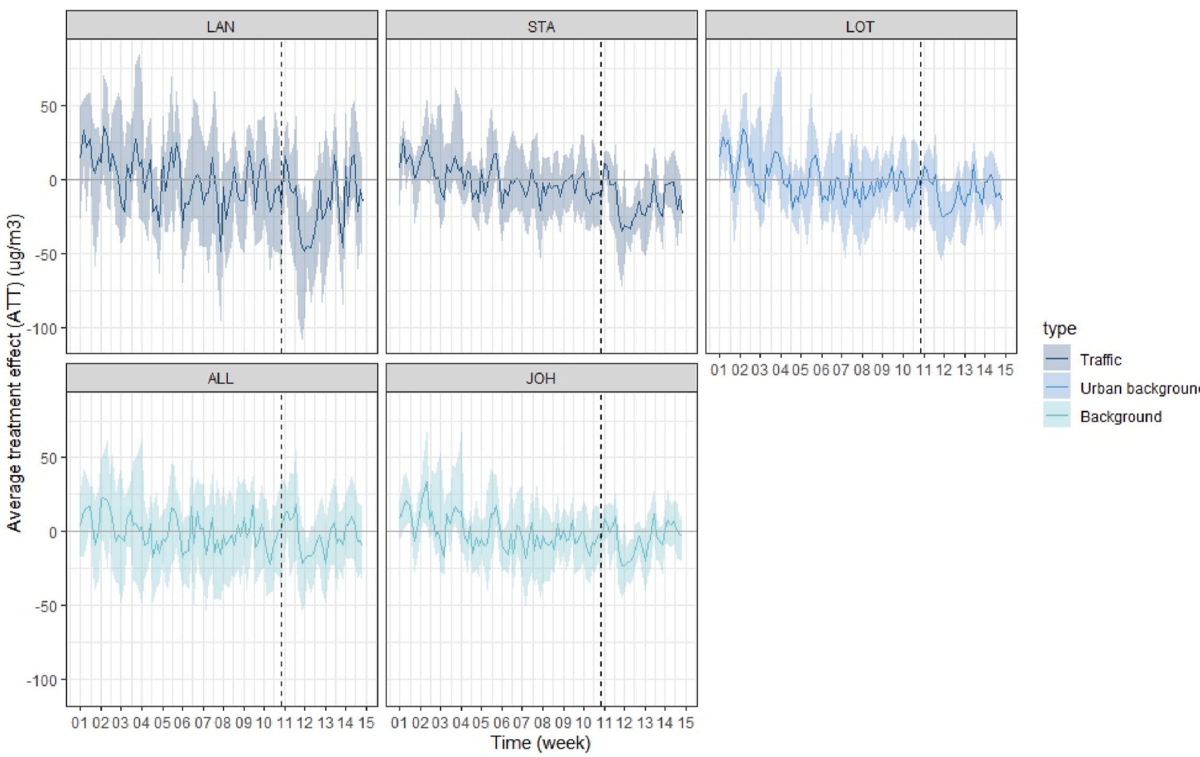

Fig. 3. Difference between the observed NO_2 concentrations in 2020 and those from the SC counterfactual (based on the years 2014–2019) at all investigated sites. The vertical dotted line represents the point at which the intervention was implemented.

observed at LAN, STA and LOT. For all other estimates, confidence intervals contained 0.

Analyses of a backdated intervention points at 3 February, 17 February and March 2, 2020 are summarized in Fig. 4 panels A–C, respectively, and Appendix Table 1 in the supplementary material. Compared to the main analyses, effects at traffic sites are smaller when either 3 February or 2 March is taken as the intervention point. However, for 17 February, observed effects are actually larger than those observed in the main analyses. At urban background and background sites, where we expected a small or no effect due to the COVID-19 measures, larger effects were observed for almost all backdated analyses compared to main analyses. Taken together, this suggests that the effect observed in main analyses may be at least partially attributable to changes in air quality across Munich (i.e. not only in heavily trafficked areas) already occurring prior to March 16, 2020.

Analyses of a shortened pre-intervention period allowed us to assess whether the high concentrations observed in January 2020 influenced the observed effect; these results are summarized in Fig. 5 (panel A) and Appendix Table 2 in the Supplementary material. Smaller effects at traffic sites were observed for the shortened pre-intervention period than for main analyses, potentially suggesting that observed effects are at least partially attributable to high concentrations observed in January 2020. Analyses of smoothed NO_2 data are summarized in Fig. 5 (panel B) and Appendix Table 2 in the Supplementary material. The smoothed data allowed for the calculation of a better counterfactual than the raw data (Appendix Fig. 1). Compared to results from the main analyses, a

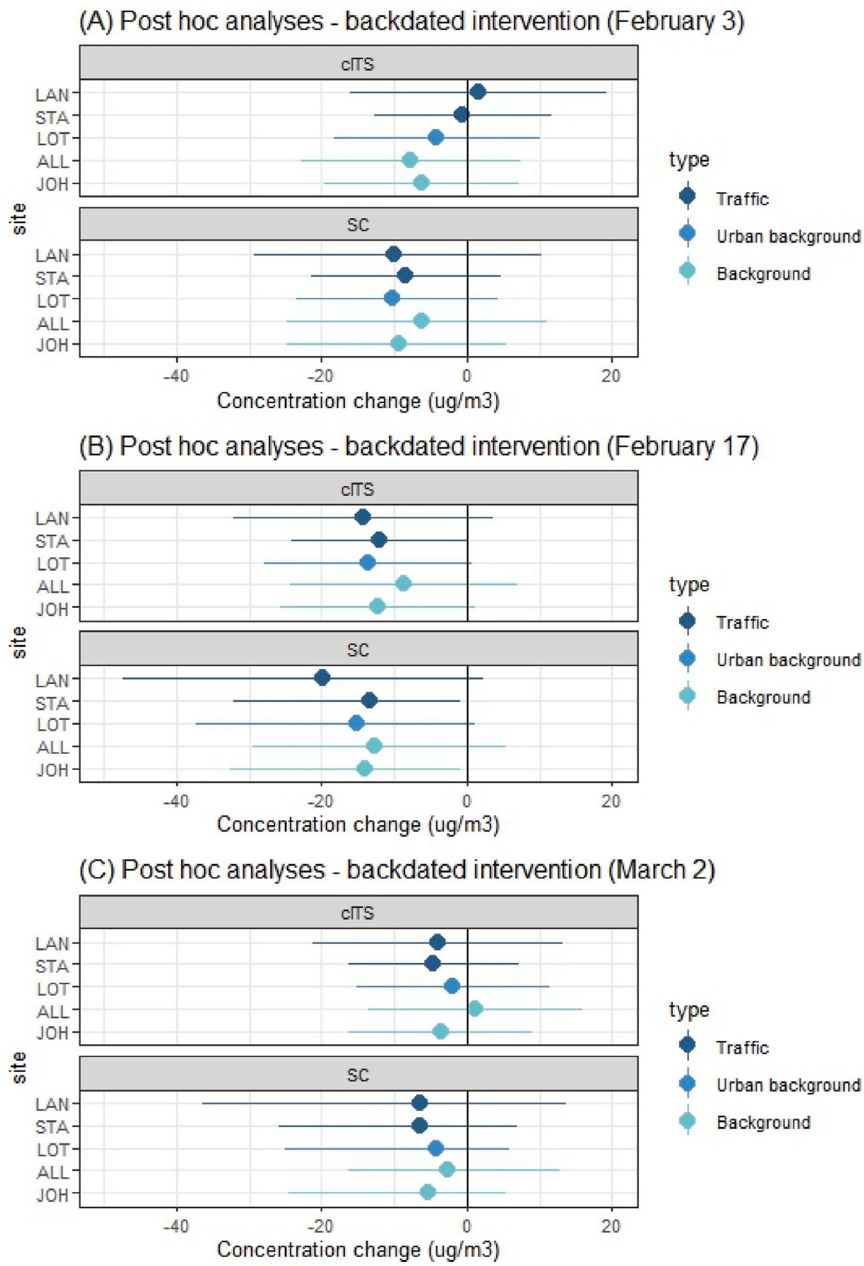

Fig. 4. Effect of the COVID-19 mitigation measures on NO_2 concentrations at the five sites from post hoc analyses assessing backdated intervention points, including (A) February 3, 2020 (B) February 17, 2020 and (C) March 2, 2020.

slightly smaller effect across sites was observed. This suggests that some of the effect observed in main analysis may be attributable to random noise or serial correlation, although at the same time, it is possible that the smoothing of the data smoothed away part of an actual effect.

5. Discussion

In this study, we applied a c-ITS and SC approach to evaluate the short-term effect of COVID-19 mitigation measures on NO_2 in Munich. Main and additional analyses suggest a consistent pattern – after introduction of the mitigation measures decreases in NO_2 concentrations were observed at traffic sites, while little to no change was observed at urban background and background sites. As expected, reductions were largest in magnitude in the two weeks immediately following the introduction; a lagged intervention start suggests that the effect became more pronounced as additional measures were implemented. Post-hoc analyses, however, point to other aspects to which effects may have been partially attributable; these include reductions in NO2 concentrations occurring prior to 16 March, as well as high concentrations observed in January.

Events such as the COVID-19 pandemic with the resulting mitigation measures are natural experiments that provide a unique opportunity to assess how specific policies may influence air quality. This study, for example, provides information on whether policies reducing traffic at heavily-trafficked sites could lead to improved air quality. Reductions in NO_2 of 9.34 μg/m^3 and 15.65 μg/m^3 at LAN and 10.02 μg/m^3 and 15.10 μg/m^3 at STA, corresponding to the c-ITS and SC approach from the main analyses, represent meaningful changes given the current air quality in Munich. Taking, for example, the 2020 pre-intervention average concentrations at LAN and STA of 60.94 μg/m^3 and 41.61 μg/m^3, respectively, these equate to reductions of approximately 15–25% and 24–36%. In Munich and other German cities, where debates around

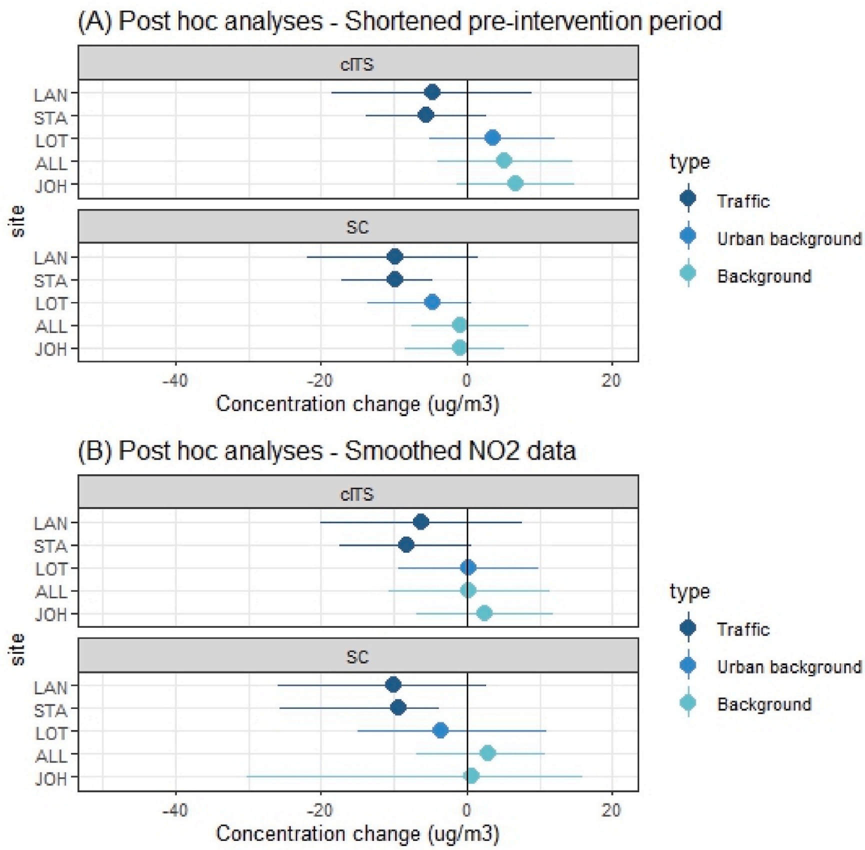

Fig. 5. Effect of the COVID-19 mitigation measures on NO2 concentrations at the five sites from post hoc analyses assessing (A) a shortened pre-intervention period (6 weeks), and (B) analyses of smoothed NO_2 data.

air quality in cities and, in particular, how to further reduce NO2 concentrations are common both in the scientific and political communities, this is an important finding (Bayerische STAATSREGIERUNG, 2019; Leopoldina, 2019).

Other studies have shown decreases in air pollution linked to COVID-19 measures. Data from satellites have suggested reductions in NO_2 concentrations, ranging from a similar to slightly larger magnitude, in China (30–40%) (ESA, 2020c, MUHAMMAD et al., 2020), India (40–53%) (ESA, 2020a, MAHATO et al., 2020) and in cities across Europe (20–55%) (ESA, 2020b, MUHAMMAD et al., 2020). Data from regulatory monitors across Europe have been somewhat less consistent, although they have also shown decreases ranging from 15% to 50% in cities in Western Europe (EEA 2020). Studies applying similar methods to ours, i.e. quasi-experimental approaches using regulatory monitors and historical controls, also identified reductions in Beijing and Wuhan, China as well as Milan, Italy (Malpede et al., 2020), Rio de Janeiro, Brazil (Dantas et al., 2020), and in Munich (FULLERTON, 2020) ranging between approximately 5 μg/m^3 and 50 μg/m^3. One study, comparing areas of China where lockdowns were implemented to areas where no lockdown was implemented, observed decrease in fine particulate matter of approximately 15% (He et al., 2020). Another study estimated what changes in air quality across Europe could mean for public health, calculating that 11,000 deaths, including approximately 2000 deaths in Germany, may have been avoided due to decreases in air pollution during this time (Myllyvirta and Thieriot, 2020).

Our recent systematic review of ambient air pollution interventions, as well as multiple other reviews have emphasized important limitations of existing studies, including lack of control for underlying outcome trends and lack of control for confounding through appropriate selection of control conditions and assessment of confounding factors (Boogaard et al., 2017, BURNS et al., 2020; HENNEMAN et al., 2017; RICH, 2017). The use of two approaches, each of which represents an internally valid quasi-experimental approach, strengthens the rigour of our study. Both the c-ITS and the SC approaches are appropriate study designs for evaluating changes over time; they utilize the temporal nature of the data to establish a counterfactual (LOPEZ BERNAL et al., 2018; BOUTTELL et al., 2018). Each approach also utilizes data from a control condition, in this study historical controls, to ensure that any observed change in the outcome trend is not due to seasonal patterns. The use of historical controls can add a level of control to studies where no appropriate geographical controls exist; in this study, for example, all urban (as well as rural) areas in Germany and Europe implemented COVID-19 mitigation measures roughly at the same time. Specifically, the c-ITS approach allows comparison of trends in 2020 to the average of trends over the time period of 2014–2019 so that the comparison will not be heavily skewed by any one year that does not fit the true long-term trend. The SC study complements this approach by creating a control condition from 2014 to 2019 that most closely matches the intervention time trend. We further accounted for potentially important confounders in both approaches: the c-ITS model was adjusted for temperature, rainfall, air pressure, humidity, wind speed, day of the week and holidays; the SC approach used these factors in creating an appropriately weighted synthetic control. We defined most hypotheses and analyses a priori and registered a study protocol, before downloading the data for 2020. Only the analyses of a backdated intervention point, a shortened pre-intervention period and smoothed NO_2 data were defined post hoc; these were added to ensure that observed effects were not attributable to other factors.

Nevertheless, there are limitations to this study. We assume that the COVID-19 mitigation measures led to reductions in traffic, which subsequently led to reductions in NO_2 concentrations. Lacking reliable data on traffic, however, we cannot assess to what extent this assumption of effects along the causal chain are appropriate. Mobility data from smartphones made available by GOOGLE, 2020 and APPLE, 2020 suggest that mobility was starkly reduced during these weeks; however the current study would have benefited from the incorporation of long-term, representative routine traffic data. Post hoc analyses suggest that effects observed in main analyses may at least partly stem from factors other than the mitigation measures, including reductions in NO2 concentrations occurring prior to 16 March, high concentrations observed in January and the noisy nature of the data. However, the large decrease immediately after March 16, 2020 is observable across all main and additional analyses, meaning it is unlikely that observed effects are due only to factors other than the mitigation measures. This large decrease is consistent with the reduction in traffic reported in the mobility data described above. While the monitoring sites assessed represent all regulatory sites available for Munich during the study period, it is possible that these are not fully representative of air quality across Munich. Additionally, for the ALL site, the year 2014 was excluded from the c-ITS approach because much of the data from that year were missing. However, we consider it unlikely that this substantially influenced our results. We assessed changes only in NO_2 concentrations, as this allowed us to most closely assess whether changes to air quality were likely due to changes in traffic reductions. Nevertheless, a more comprehensive assessment of the impact of a specific intervention, measure or event would entail the assessment of multiple pollutants. To the best of our knowledge, this is the first use of historical controls within a SC study, and we feel that this is an appropriate use of the available data. Nevertheless, our study highlights challenges associated with calculating an optimal counterfactual using a SC study in the context of air quality data. However, given that the c-ITS approach, which can better account for time-varying confounders, and the analyses of smoothed data yielded similar results, if slightly smaller in magnitude, we think it unlikely that our results are biased by this limitation.

Given that traffic is only one source of NO_2 and other air pollutants, continuing to improve air quality will likely require multiple control measures targeting multiple sources. However, this study suggests that reducing traffic may be an effective measure to reduce NO_2 concentrations in heavily trafficked areas by margins which could translate to public health benefits.

CRediT authorship contribution statement

Jacob Burns: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing - original draft. **Sabine Hoffmann:** Methodology, Validation, Writing - review & editing. **Christoph Kurz:** Methodology, Validation, Visualization, Writing - review & editing. **Michael Laxy:** Methodology, Validation, Writing - review & editing. **Stephanie Polus:** Methodology, Validation, Writing - review & editing. **Eva Rehfuess:** Methodology, Writing - review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing for financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors also submitted the same study in the Indian patent office for consideration.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.atmosenv.2020.118089.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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