




How do the stay-at-home (SAH) orders affect air quality? Evidence from the northeastern USA

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Abstract

This paper examines whether the SAH orders, implemented in the USA from mid-March to late May 2020, improved air quality in the northeastern states. The estimates are based on panel data from the Environmental Protection Agency and an identification strategy that exploits the exogenous variation in the timing of the SAH orders. We find that the SAH orders reduced the concentrations of the air pollutants nitrogen dioxide (NO₂) and carbon monoxide (CO), whose dominant source is motor vehicle emissions, by approximately 24% and 13%, respectively. The effects were larger for areas of high population density and areas near major roads. We also find that the reductions got smaller, and air pollution gradually approached normal levels, after the orders were lifted. This suggests that the air quality improvements were temporary.

Keywords COVID-19 · SAH orders · Air pollution · Panel data

JEL Classification C13 · C23 · Q53

1 Introduction

In response to COVID-19, many U.S. states issued SAH orders mandating the closure of nonessential businesses and requiring residents to remain indoors except for essential activities between mid-March and late May 2020.¹ Despite their controversial and adverse socioeconomic impacts (Baek et al. 2021; Baron et al. 2020; Bullinger et al.

¹ Eight U.S. states never issued statewide SAH orders during the pandemic: Arkansas, Iowa, Nebraska, North Dakota, Oklahoma, South Dakota, Utah and Wyoming. However, these states imposed various restrictions on businesses and activities, which also helped to contain the virus.

I would like to thank the editor Joakim Westerlund, an associate editor and two anonymous referees for their helpful comments. All errors are my own.

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2021; Forsythe et al. 2020; Leslie and Wilson 2020; Silverio-Murillo et al. 2021), the SAH orders were found to be effective in reducing social interactions and in slowing the spread of the virus (Chernozhukov et al. 2021; Medline et al. 2020).

This paper aims to evaluate an unintended consequence of the SAH orders—improvement in air quality. With businesses closed and people working from home, there was a sharp drop in road traffic and, therefore, motor vehicle emissions. We estimate the impacts of the SAH orders on two criteria air pollutants in the northeastern USA—nitrogen dioxide (NO₂) and carbon monoxide (CO). Motor vehicles are the dominant source of these emissions, responsible for over 50% of CO and 34% of NO₂ emissions in the USA (Currie and Walker 2011). We focus on six northeastern US states: Connecticut (CT), Massachusetts (MA), New Jersey (NJ), New York (NY), Pennsylvania (PA) and Rhode Island (RI). We use panel data from the Environmental Protection Agency (EPA) to estimate the changes in the concentrations of NO₂ and CO during the SAH orders. The panel data consist of daily concentrations of these two air pollutants and cover the period from January 1, 2015, to December 31, 2020. Baltagi (2008) and Hsiao (2014) have documented that panel data can help reduce estimation bias by controlling for unobserved heterogeneity.

We find significant reductions in the concentrations of NO₂ and CO during the SAH orders: NO₂ decreased by about 24% and CO by about 13%. Next, we consider the heterogeneity of the estimated effects with regard to population density and to the proximity of the monitor to major roads. We find that the reductions were larger for areas of high population density and for areas near major roads. Finally, we use an event study to examine how these impacts varied over time in each state. For most states, we see a general trend of reductions beginning 1–3 weeks before the orders took effect. This trend began to reverse 6–8 weeks after the orders were lifted, suggesting that the air quality improvements were temporary.

This paper is closely related to the growing literature on the impacts of COVID-19 responses on air quality. While most of the recent studies have found that the SAH orders led to significant improvements in air quality, the effects varied across locations. For example, Berman and Ebisu (2020) find that NO₂ decreased by 25.5% in the USA. Dang and Trinh (2021) estimate that global concentrations of PM_{2.5} and NO₂ decreased by 4–5%. Zhang et al. (2021) show that PM_{2.5} declined in rural areas of New York state but remained unchanged in urban areas. On the other hand, Jia et al. (2020) find no significant reductions in air pollution in the Memphis metropolitan area. Our paper is also related to the literature on the relationship between air pollution and COVID-19 outcomes. Some recent studies have found that air pollution is associated with a more rapid spread of COVID-19 and a higher mortality rate (Kasioumi and Stengos 2022; Kim and Bell 2021; Travaglio et al. 2021; Wu et al. 2020). The findings from these studies, together with those of our study, suggest an indirect channel through which the SAH orders slowed the spread of virus and saved lives.

This paper makes three contributions to the literature. First, our results provide a more comprehensive picture of the impacts of the SAH orders by focusing on the Northeast, which was among the areas hardest hit in early 2020. Similar to most of the previous studies, ours finds that air quality improved during the SAH orders. It is important to note that because we use monitor-level data, our findings can better speak to the areas in the vicinity of the monitors than to the areas far from the moni-

tors. Second, while much of the previous work uses air pollution data from the early pandemic period, our study includes data through the end of 2020. This allows us to examine how the air quality changed weeks after the SAH orders were lifted and whether the air quality improvements were temporary. Third, we extend our analysis and document the heterogeneous effects of the SAH orders with regard to population density and to the proximity of the air pollution monitors to major roads. Because of data limitation, we are not able to disentangle the effects of all the possible factors and mechanisms contributing to air quality improvements. However, by focusing on the major pollutants from motor vehicles and examining the heterogeneous effects of population density and proximity to major roads, we can provide suggestive evidence on how changes in human mobility affect air quality.

The remainder of the paper is organized as follows: Section 2 describes the data and provides an overview of the timeline of the statewide SAH orders. Section 3 describes our empirical approach. Section 4 presents the estimation results. Section 5 concludes.

2 Data

2.1 Timeline of SAH orders

We obtain the dates of each state's COVID-19 policy responses from *The New York Times* and local government websites.² The timeline is summarized in Table 1. Most states declared a state of emergency in early March, and all of the states in our sample had announced an SAH order by the end of March, with the effective date in the same or the following week. Each state's reopening followed a multi-phase, data-driven plan, and the restrictions on businesses and economic activities were relaxed gradually.³ The "Date Lifted" column in Table 1 lists the earliest reopening dates for counties that met the key metrics in each state.⁴

2.2 Air pollution data

We collect data on the daily concentrations of the criteria air pollutants NO₂ and CO from the EPA's Air Quality System (AQS), which contains ambient air pollution data measured by a network of air quality monitoring stations across the USA.⁵ We focus on six northeastern states: Connecticut, Massachusetts, New Jersey, New York, Pennsylvania and Rhode Island. The Northeast is the most economically developed and densely populated region of the four U.S. Census regions. During the early pandemic

² Here are the links with information regarding the timeline of the SAH orders and the reopening plans: (1) <https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html>, (2) <https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html>.

³ None of the states in our sample re-issued SAH orders after they were lifted. Instead, states had various restrictions in place. Some states also issued "stay-at-home" advisories. For example, Massachusetts issued a 10pm-5am "stay-at-home" advisory from Nov. 6, 2020, to Jan 25, 2021.

⁴ Some counties in Massachusetts and New York reopened at a later date, and all the counties in our sample had reopened by the end of June 2020.

⁵ This data is available at <https://www.epa.gov/outdoor-air-quality-data/download-daily-data>.

Table 1 Timings of COVID-19-related statewide policy responses

States	State emergency Declaration date	School closure	Stay-at-home (SAH) order			Reopening	
			Date announced	Effective date	Date lifted	Phase-II date	Phase-III date
Connecticut	March 10	March 16	March 20	March 23	May 20	June 17	October 8
Massachusetts	March 10	March 17	March 23	March 24	May 18	June 8	July 6
New Jersey	March 9	March 18	March 20	March 21	June 9	June 15	N/A
New York	March 7	March 15	March 20	March 22	May 15	May 29	June 12
Pennsylvania	March 6	March 13	March 23	April 1	May 8	N/A	N/A
Rhode Island	March 9	March 16	March 28	March 28	May 8	June 1	June 30

period (March–April 2020), 40% of northeastern counties (representing 84% of the region's population) were identified as COVID-19 hotspots (Oster et al. 2020).

Our dataset covers the period from January 1, 2015, to December 31, 2020. The observation is at the monitor level. We only consider monitors that were active for at least two years during our sample period and that had data readings for 2020. This leads to 51 NO₂ monitors in 39 counties and 33 CO monitors in 23 counties. Panel A of Table 2 presents the summary statistics of the data on air pollutants. Daily NO₂ denotes the maximum one-hour average concentration and is measured in parts per billion (ppb). Daily CO denotes the maximum eight-hour average concentration and is measured in parts per million (ppm).⁶

Figure 1 plots the monthly average concentrations of the two air pollutants from 2015 to 2020. They are computed as the average daily concentrations in one month across the six northeastern states. We can see that air pollution has distinct seasonal and monthly variations. The concentrations of NO₂ and CO are higher during colder seasons and lower in warmer seasons. Table 3 displays the average air pollution levels in March, April, and May during the years 2015–2019 (without SAH orders) and the year 2020 (with SAH orders). Columns (1) and (2) present the average concentrations of the air pollutants in each month during the pre-pandemic period (2015–2019) and during the pandemic (2020), respectively. Both the time-series plot in Fig. 1 and a simple mean comparison in Table 3 suggest that the air pollution levels in March, April, and May of 2020 were lower than the levels in those same months averaged over 2015–2019. Note that the analysis here only suggests a correlation, not a causation. Without further study, it is not clear whether the reductions in air pollution were due to the SAH orders or to other factors because air pollution typically is affected by various factors that could vary from year to year and location to location. This motivates our panel data approach in Sect. 3.

Notes: The orange icons in Panel A denote the NO₂ monitors, and the purple icons in Panel B denote the CO monitors.

Figure 2 presents the distributions of the NO₂ and CO monitors. We observe that the monitors are not evenly distributed. About 67% of CO monitors are located in counties that also have NO₂ monitors. The number of monitors in a given core-based statistical area is determined by a variety of factors, such as local population and through-traffic. Typically, the literature treats the siting of monitors as exogenous and the resulting sample data as representative. Grainger and Schreiber (2019) find that new monitors tend to be placed in relatively less polluted areas and that race may play a role in local siting decisions. We believe this is not a major concern in our analysis because all of the monitors in our sample were sited at least two years before the COVID-19 pandemic. Therefore, it is reasonable to assume that the SAH orders were not correlated with the location of the monitors.

⁶ The EPA's air quality standards have been built around these measures. For example, the EPA nitrogen dioxide standard (effective since April 6, 2018) is a one-hour average of 100 parts per billion (ppb). This standard reflects what the EPA believes is the maximum allowable nitrogen dioxide concentration that protects public health.

Table 2 Summary statistics of data variables

	Obs	Countries	Mean	Std	5th Petile	Median	95th Petile
<i>Panel A: air pollutants</i>							
NO ₂	97,845	39	19,907	12,620	3	18.2	42.7
CO	63,375	23	0.386	0.242	0.1	0.3	0.8
<i>Panel B: population density (people per square mile)</i>							
Cities with NO ₂ Monitors	51	39	7,662.631	7,284.255	784.22	5,470.77	20,907.4
Cities with CO monitors	33	23	10,966.6	12,499.49	784.22	7,178.8	32,903.6
<i>Panel C: distance to Roadway (in miles)</i>							
NO ₂ Monitors	51	39	0.269	0.429	0.007	0.113	1.54
CO monitors	33	23	0.235	0.588	0.009	0.047	2.26

The statistics in panel A are based on daily data spanning from 2015 to 2020 for the six northeastern U.S. states. NO₂ is measured in parts per billion (ppb); CO is measured in parts per million (ppm)

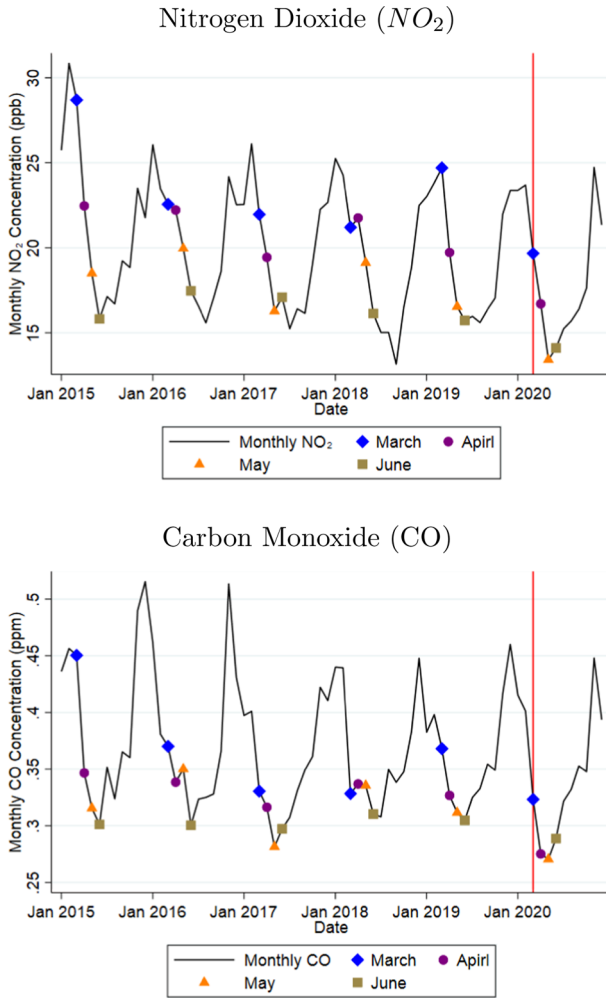


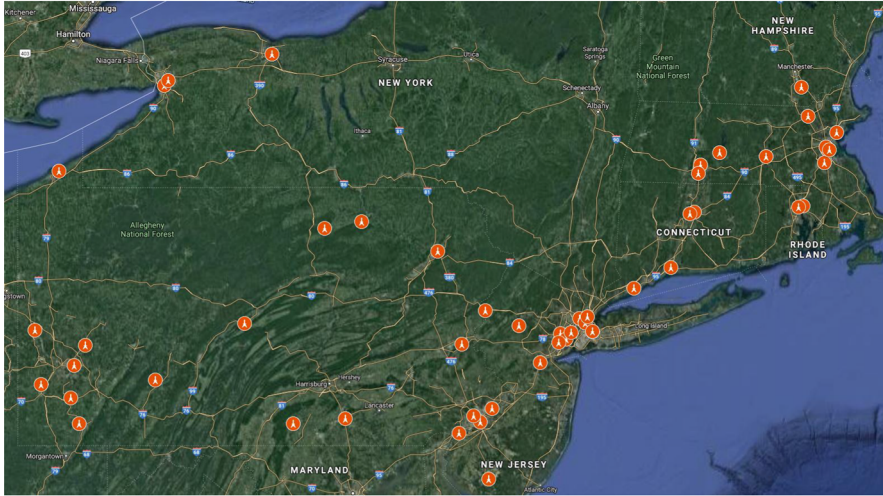
Fig. 1 Monthly average air pollutant concentrations, 2015–2020

Table 3 Mean concentrations of air pollutants (2015–2019 vs. 2020)

Air Pollutant	March		April		May	
	(1)	(2)	(1)	(2)	(1)	(2)
NO_2	24.234	19.668	21.659	16.470	18.813	13.591
CO	0.390	0.337	0.352	0.283	0.341	0.281

NO_2 is measured in parts per billion (ppb); CO is measured in parts per million (ppm)

Panel A: NO_2 Monitoring Stations



Panel B: CO Monitoring Stations

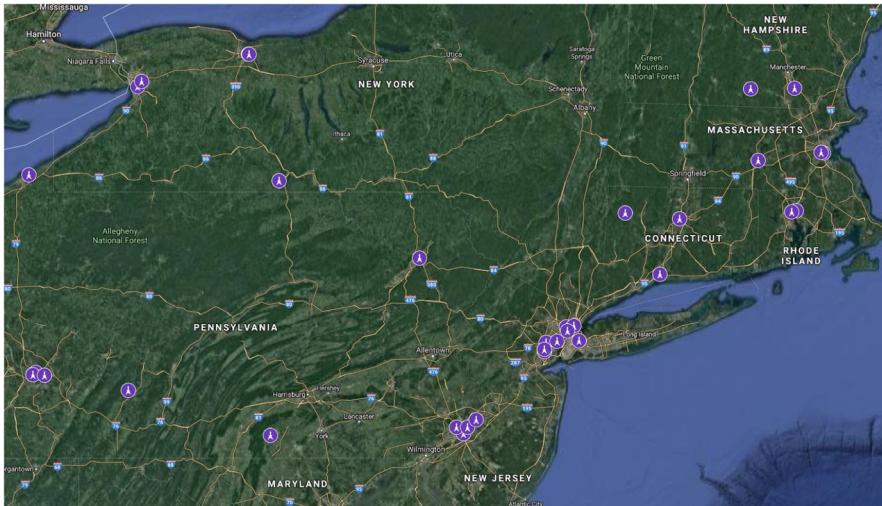


Fig. 2 NO_2 and CO monitoring stations

2.3 City-level population density

We collect data from the U.S. Census Bureau on city-level population density (based on the 2020 Census). Panel B of Table 2 presents the summary statistics of population density.

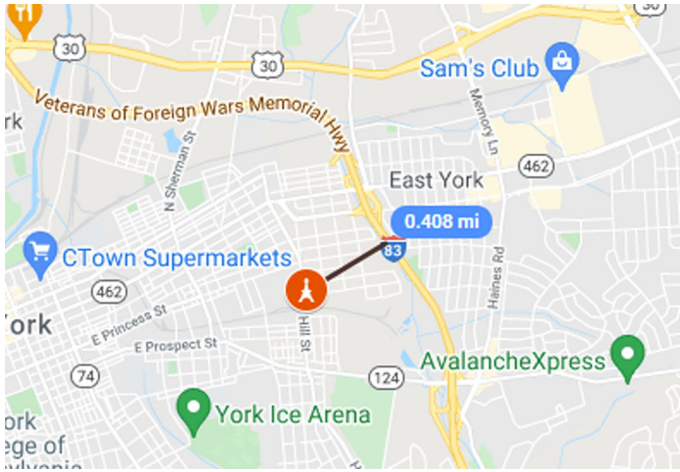


Fig. 3 Illustration of using Google Maps to measure the distance between monitoring station and the nearest major road

2.4 Distance to major roads

We use Google Maps to measure the distance between the monitoring station and the nearest major road.⁷ Panel C of Table 2 presents the summary statistics of distance to major roads. Figure 3 illustrates how we measure the distance using Google Maps.

3 Empirical approach

Our baseline econometric model is the following:

$$\log(y_{icst}) = \alpha_i + \alpha_c + \alpha_{sy} + \mathbf{X}_t + \beta_1 \text{SAH}_{icst} + \beta_2 \text{PreSAH}_{icst} + \beta_3 \text{PostSAH}_{icst} + \epsilon_{icst}, \tag{1}$$

where β_1 is the parameter of interest; y_{icst} is the daily concentration of the air pollutant NO_2 or CO at monitor i , county c , state s and time t ; α_i , α_c and α_{sy} are the monitor, county and state-by-year fixed effects, respectively; \mathbf{X}_t is a collection of time-varying controls that captures any time-varying shocks to air pollution common across counties—these include month fixed effects, week fixed effects, day-of-week fixed effects and indicators for holidays;⁸ SAH_{icst} is an indicator equal to one if the county c where monitor i is located was under a SAH order at time t ; PreSAH_{icst} is an indicator equal to one if the county where monitor i is located at time t was in

⁷ Here, major roads include arterial roads that are typically busy roadways, interstate highways, U.S. highways, state highways and county highways. Google Maps displays several different kinds of roads, including neighborhood streets and major roads. Streets are displayed in white; major roads are in yellow.

⁸ Holiday controls include Martin Luther King Jr. Day, Memorial Day, Independence Day, Columbus Day, Labor Day, Veterans Day, Thanksgiving, Christmas Eve, Christmas, New Year's Eve and New Year's Day.

the preSAH orders period, which is defined as the period from the state of emergency declaration date to the day before the SAH order effective date; PostSAH_{icst} is an indicator equal to one if the county c where monitor i is located at time t was in the postSAH orders period; and ϵ_{icst} is an error term.

The monitor and county fixed effects control the time-invariant monitor-specific and county-specific characteristics, respectively. The state-by-year fixed effects capture the differences across states (e.g., state-level economic environment and policies) that vary from year to year. We include the holiday and day-of-week fixed effects to account for the fact that people may exhibit different travel behavior during holidays and weekends. The month fixed effects account for seasonality in air pollution. The PreSAH indicator accounts for the fact that some people started to work from home and reduced travelling before the SAH orders took effect. The PostSAH indicator accounts for possible lagged effects. For example, some people continued to work from home, and businesses only opened at limited capacity. Therefore, there still may have been less travel and reduced economic activity than during the same period over the years 2015–2019.

Our identification strategy exploits the exogenous variation in the timing of the SAH orders, i.e., $E(\text{SAH}_{icst} \cdot \epsilon_{icst} | \alpha_i, \alpha_c, \alpha_{sy}, \mathbf{X}_t) = 0$. More intuitively, the identifying assumption is that the changes in air pollution across the days of the week during the weeks without SAH orders provide a good counterfactual for the changes that would have been observed on the lockdown days in the absence of the SAH orders. We cluster the standard errors by state-year to address the possible serial and cross-sectional correlation of error terms. This allows for the error term ϵ_{icst} to be correlated across all observations within the same state and year.

4 Estimation results

The main estimation results of Eq. (1) are shown in Table 4. Columns (1) and (2) use the full sample, and column (2) includes a third-order time trend. Although we focus our subsequent discussion on the richer specification corresponding to column (2), the estimates vary little across specifications. As expected, the SAH orders led to significant reductions in the concentrations of the air pollutants NO_2 and CO. As shown in column (2), NO_2 and CO decreased by approximately 24% and 13%, respectively. In addition, there was approximately a 15% reduction in NO_2 and a 10% reduction in CO during the preSAH orders period. We also find that NO_2 was approximately 8% lower during the postSAH orders period. However, we find no significant reductions for CO during the postSAH orders period. Columns (3) and (4) report the results of using the sub-samples 2016–2020 and 2017–2020, respectively.⁹ We use the two sub-samples as a robustness check to see if changing the baseline period affects our estimates. Comparing columns (2)–(4) shows that, overall, the estimation results using different samples are quite similar.

⁹ As the estimates from the baseline model and the one with time trends are similar, to save space, we only report the results of the model with time trends.

Next, we explore the potential heterogeneity of the impacts of the SAH orders with regard to population density. Specifically, we use the same empirical strategy as in Sect. 3, but we separately estimate Eq. (1) for “low population density areas” and “high population density areas”. The “low population density areas” are defined as areas located in cities with population densities below the median, and the “high population density areas” are defined as those with population densities above the median.¹⁰ The results are presented in Table 5. We observe that the estimated reductions in NO₂ are larger for the high population density areas; the reductions in CO are similar for the two areas.

We also evaluate the potential heterogeneity with regard to proximity to major roads. Similar to what we show in Table 5, we split the samples based on the distance between the monitor and the nearest major road with the cutoff at the median, and we estimate Eq. (1) for areas “near major roads” and areas “far from major roads”, respectively.¹¹ The results are shown in Table 6. We observe that there are significant estimated reductions in air pollution for both areas near and far from major roads. In addition, in general, the reductions are larger for the areas near major roads than for those far from major roads. Our findings indicate that with people working from home and driving less, the decrease in road transportation led to reductions in emissions and, therefore, improvement in air quality. This analysis provides suggestive evidence that a drop in motor vehicle use is a possible channel for air quality improvement.

Given that the states had slightly different timelines of SAH orders, we further conduct an event study analysis to examine how the concentrations of the air pollutants changed over time for each state. Specifically, we average the daily data by week and include indicators for the weeks prior to and after the SAH orders. The model is as follows:

$$\log(y_{ict}) = \alpha_i + \alpha_c + \mathbf{X}_t + \sum_{j=-6}^{24} \beta_j \mathbf{1}\{j \text{ weeks since SAH orders}\} + \epsilon_{ict}, \quad (2)$$

where y_{ict} is the weekly concentration of the air pollutant NO₂ or CO at monitor i , county c and week t ; α_i and α_c are the monitor and county fixed effects, respectively; \mathbf{X}_t is a collection of time-varying controls that captures any time-varying shocks to air pollution common across counties—these include year fixed effects and month fixed effects; $\mathbf{1}\{j \text{ weeks since SAH orders}\}$ is an indicator which takes the value one if the SAH orders have been in effect for j weeks, and ϵ_{icst} is an error term. We include six weeks prior to and twenty four weeks after the implementation of the SAH orders.¹² The event study coefficients allow us to examine the dynamics of air pollution during the pandemic.

¹⁰ As shown in Panel B of Table 2, the median population density is 5470.77 per square mile for cities with NO₂ monitors and 7178.8 per square mile for cities with CO monitors.

¹¹ As shown in Panel C of Table 2, the median distance between the monitor to the nearest major road is 0.113 miles for the NO₂ monitors and 0.047 miles for the CO monitors.

¹² Most states in our sample declared a state of emergency two weeks before the SAH order effective date, and all counties had reopened within twelve weeks of the SAH order effective week.

In Figs. 4 and 5, we present the event study graphs that show the estimates of the effects of the SAH orders on the air pollutants NO₂ and CO, respectively. The corresponding 95% confidence intervals are shown in gray. In each subfigure, the solid circles represent the estimated effects at different weekly time points. The vertical yellow and purple dashed lines mark the weeks that the statewide SAH order was implemented and lifted, respectively. Although precise magnitudes are difficult to discern from the figures, the results as a whole reveal some clear patterns. Specifically, the estimates show that for most states, there was a general trend of reduction in air pollution 1–3 weeks before the SAH orders took effect, and that trend started to reverse 6–8 weeks after the orders were lifted. The reductions prior to the SAH order effective date might be due to the fact that some people started to work from home and drove less after the declaration of the state of emergency and the closure of schools. The reversed trend suggests that the air quality improvements were temporary.¹³

Finally, we note that the econometric approach in this paper uses the pandemic-caused SAH orders as exogenous policy shocks to identify the causal effects of the SAH orders on air quality. However, if there are some unobserved pre-COVID time-varying state characteristics correlated with the orders, there will be endogeneity and biased results. For example, some states may already have had better measures in place to protect air quality. These same states may also tend to be more protective of workers. Therefore, such states would be more likely to issue stringent SAH orders. In this case, the effects of the SAH orders will be overestimated.¹⁴ In addition to the results presented in this paper, we conduct an event study using Model (2), where we include 16 weeks of indicators prior to the implementation of the SAH orders to examine the dynamics of air pollution prior to the pandemic. However, we do not observe a persistent downward trend in the concentrations of air pollution, which provides suggestive evidence in favor of the exogeneity identification assumption.¹⁵

5 Conclusion

In this paper, we study the effects of SAH orders on air quality in the northeastern USA. We find that during the SAH orders, there were significant reductions in the air pollutants NO₂ and CO. However, the reductions got smaller and the air pollution gradually returned to normal levels after the orders were lifted, indicating that the air quality improvements were temporary. One extension of this paper is to consider the quantile treatment effects of SAH orders.¹⁶ We leave this as a future research topic.

Our paper contributes to the growing literature on assessing COVID-19 pandemic-related policies and their impacts on the environment as well as on human health and well-being. This paper has two policy implications. First, the reductions in air

¹³ It is also noticeable that the effects on CO in Massachusetts lasted the whole postSAH orders period, and there were no significant changes in CO for New Jersey during the SAH orders. We conjecture that the stringency of the orders along with the degree of public compliance with the orders may have also affected the impacts of the SAH orders on air pollution.

¹⁴ We are grateful to an anonymous referee for pointing out the endogeneity issue.

¹⁵ To save space, we have omitted the results. They are available upon request.

¹⁶ I am grateful to an anonymous referee for pointing this out.

Table 4 Estimated effects of SAH orders on air pollution

Regressor	Air pollutant					
	NO ₂		CO			
	All observations (2015–2020) (1)	Sub-sample (2016–2020) (3)	Sub-sample (2017–2020) (4)	All observations (2015–2020) (1)	Sub-sample (2016–2020) (3)	Sub-sample (2017–2020) (4)
SAH orders	-0.213*** (0.037)	-0.235*** (0.038)	-0.252*** (0.038)	-0.236*** (0.040)	-0.121*** (0.041)	-0.143*** (0.045)
PreSAH orders	-0.143*** (0.034)	-0.149*** (0.034)	-0.144*** (0.035)	-0.136*** (0.037)	-0.093*** (0.032)	-0.081*** (0.037)
PostSAH orders	0.011 (0.032)	-0.078* (0.047)	-0.135*** (0.049)	-0.146*** (0.051)	0.016 (0.046)	-0.049 (0.061)
Time trend	-	Yes	Yes	Yes	-	Yes
Observations	97,845	97,845	82,871	67,261	63,375	53,022

The estimation results are based on Eq. (1). The dependent variable is the log of the daily concentration of the air pollutant NO₂ or CO. All the regressions have controlled for day-of-week FEs, holidays, state-by-year FEs, week FEs and county-month FEs. Standard errors in parentheses are clustered by state-year. *** $p < 0.05$; ** $p < 0.01$; * $p < 0.1$

Table 5 Effects by population density

Regressor	Air pollutant			
	NO ₂		CO	
	Low pop. density (Density ≤ 5470.77) (1)	High pop. density (density > 5470.77) (2)	Low pop. density (density ≤ 7178.8) (3)	High pop. density (density > 7178.8) (4)
SAH orders	-0.189*** (0.060)	-0.201*** (0.060)	-0.219*** (0.040)	-0.236*** (0.045)
PreSAH orders	-0.142** (0.059)	0.144* (0.058)	-0.125** (0.038)	-0.133** (0.040)
PostSAH orders	0.093* (0.051)	0.023 (0.070)	-0.045 (0.035)	-0.133** (0.062)
Time trend	-	Yes	-	Yes
Observations	45,097	45,097	52,748	52,748
			32,572	30,803
			-0.116** (0.043)	-0.122** (0.046)
			-0.140** (0.030)	0.073 (0.046)
			0.013 (0.049)	0.010 (0.047)
			-	-
			32,572	30,803

The estimation results are based on Eq. (1). The dependent variable is the log of the daily concentration of the air pollutant NO₂ or CO. All the regressions have controlled for day-of-week FEs, holidays, state-by-year FEs, week FEs and county-month FEs. Standard errors in parentheses are clustered by state-year. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Table 6 Effects by proximity to the major roads

Regressor	Air pollutant			
	NO ₂		CO	
	Near major roads (dist. ≤ 0.113) (1)	Far from major roads (dist. > 0.113) (3)	Near major roads (dist. ≤ 0.047) (1)	Far from major roads (dist. > 0.047) (3)
	(2)	(4)	(2)	(4)
SAH orders	-0.228*** (0.040)	-0.263*** (0.044)	-0.213*** (0.055)	-0.109* (0.056)
PreSAH orders	-0.174** (0.041)	-0.190*** (0.043)	-0.121** (0.051)	-0.129*** (0.038)
PostSAH orders	-0.044 (0.033)	-0.159** (0.057)	0.057 (0.048)	0.008 (0.046)
Time trend	-	Yes	-	Yes
Observations	47,593	47,593	30,800	32,575

The estimation results are based on Eq. (1). The dependent variable is the log of the daily concentration of the air pollutant NO₂ or CO. All the regressions have controlled for day-of-week FEs, holidays, state-by-year FEs, week FEs and county-month FEs. Standard errors in parentheses are clustered by state-year. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

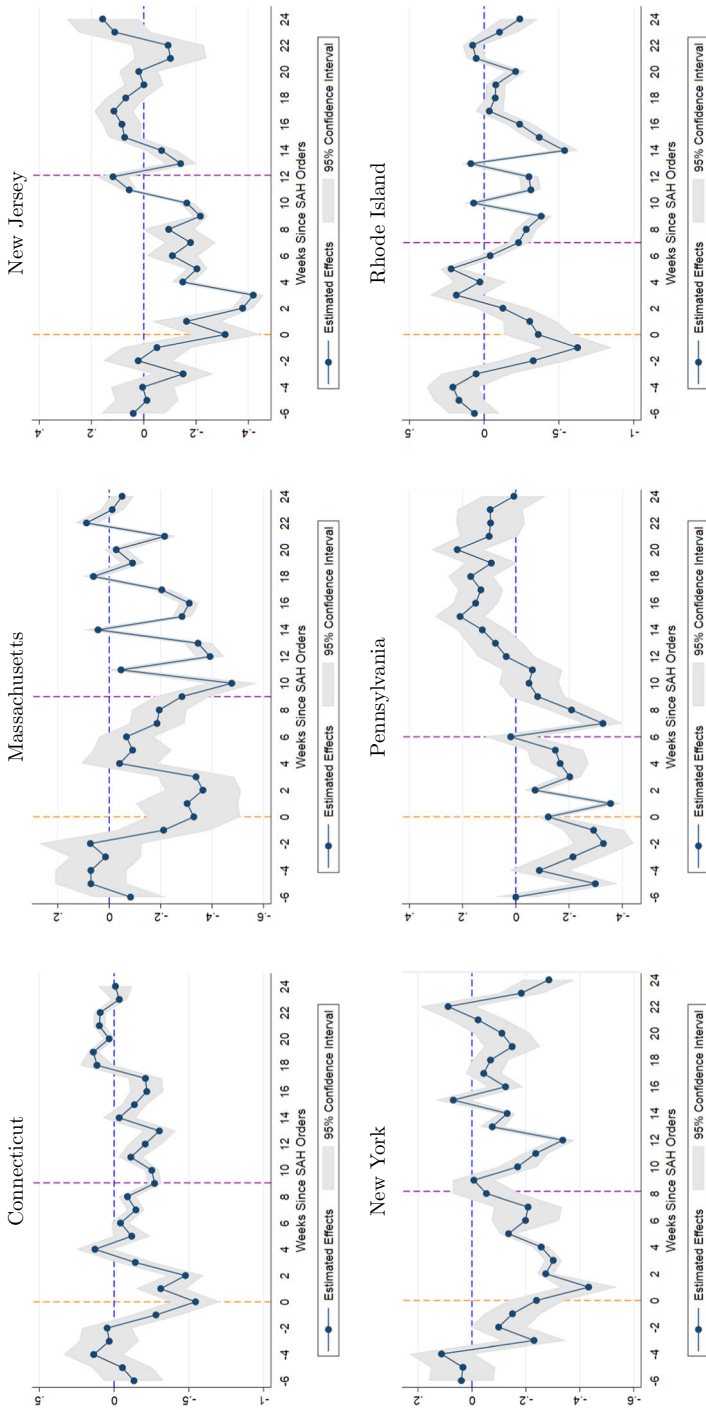


Fig. 4 Effects of SAH orders on air pollutant NO₂ by state

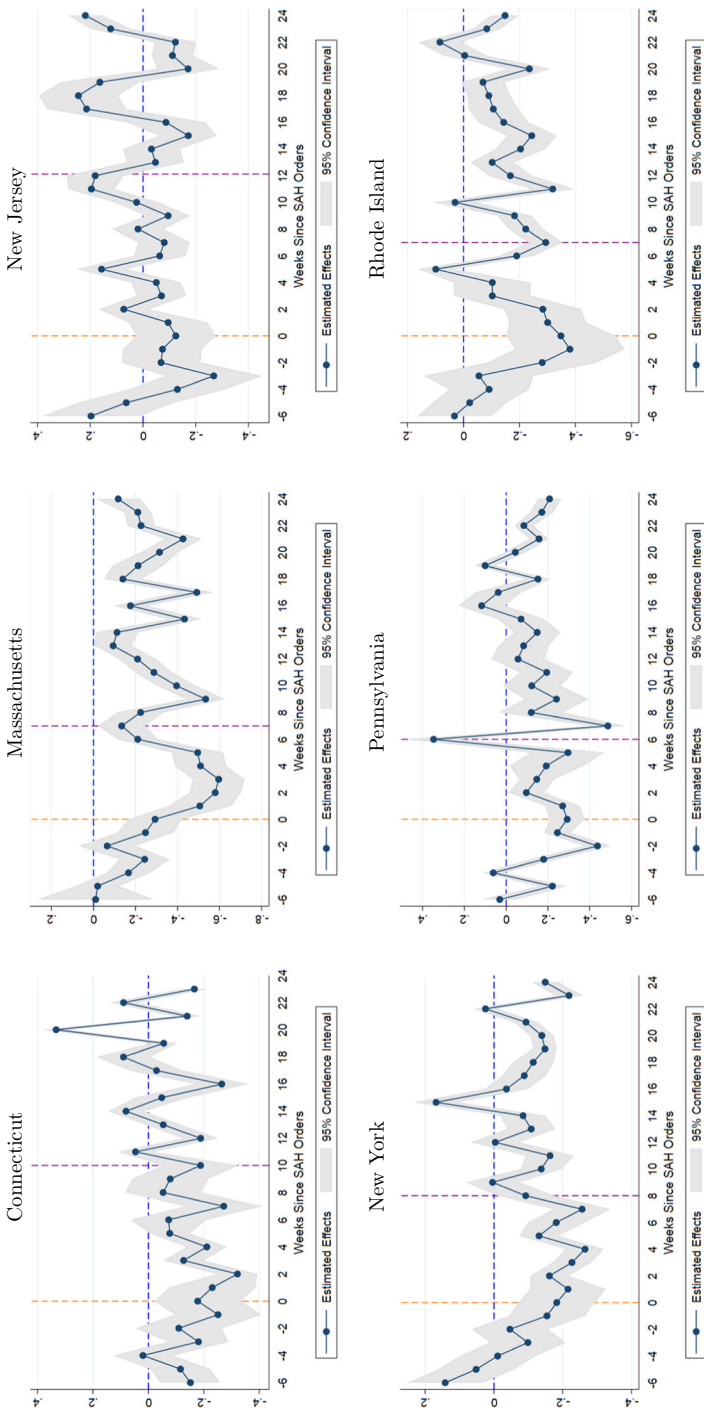


Fig. 5 Effects of SAH orders on air pollutant CO by state

pollution estimated in this study and their associated health benefits found from other studies (e.g., Kasioumi and Stengos (2022) and Kim and Bell (2021)) highlight the need for governments to invest in sustainable transportation and to take actions to protect our environment. Second, as there has been an ongoing debate over the SAH order policies, our findings provide some evidence of their environmental benefits. This can help policymakers weigh the pros and cons of SAH orders and make more balanced decisions in the case of future pandemics.

Declarations

Conflict of interest The author declares that there is no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by the author.

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