The short-run impact of COVID-19 Pandemic and Stay-At-Home (SHO) policies on air pollution in USA.

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Major Paper presented to the
Department of Economics of the University of Ottawa
in partial fulfillment of the requirements of the M.A. Degree
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Ottawa, Ontario
April 2021

Abstract

This paper investigates the short-run effects of stay-at-home orders measured by policymakers on air pollution in USA, using daily air pollutants' data from Environmental Protection Agency (EPA) database between 2018-2020 along with CDC's (Centers for Disease Control and Prevention) database for stay-at-home orders' types and timing. Many recent studies worldwide find that the concentration of various air pollutants has decreased because of the pandemic and lockdown; however, few of them have analyzed causality. This paper has used a specific categorization of stay-at-home orders by grouping the orders into two major groups. 1) Strict-SHO, which includes the states with mandatory SHO orders; 2) Less-Strict SHO, which includes the states with non-mandatory SHO and no SHO issued states. The paper finds a causal relationship between a decrease in NO2, PM10 and AQI in states with Strict-SHO relative to states with Less-Strict SHO by 1.73, 2.75 and 1.12, respectively. Moreover, as secondary results, the impact of SHO on air pollution considering states' GDP elaborate that O3 and AQI in states with Strict-SHO and High-GDP have decreased by .00346 and 2.0081 units relative to states with Low-GDP.

Keywords: COVID-19 Pandemic, Air pollution, Stay-at-home Orders, Differences in Differences (DiD.)

1. Introduction

The COVID-19 pandemic, also known as the coronavirus pandemic, is an ongoing pandemic of coronavirus disease 2019 (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). It was first identified in December 2019 in Wuhan, China. The World Health Organization declared the outbreak a public health emergency of international concern in January 2020 and a pandemic in March 2020 (WHO 2020). The spread of this contagious disease has had exponential growth, requiring both non-pharmaceutical and pharmaceutical aid to overcome.

In response to this pandemic, on the side of non-pharmaceutical aid, several national responses have been implemented by governments worldwide. They have included measures such as lockdowns, quarantines, and stay-at-home [1]orders to prevent the expansion of the virus and flatten the curve of Covid-19 cases ranging from voluntary compliance (e.g., Sweden) to complete lockdowns (e.g., China, Italy, and Spain). Imposing shut down in various social gathering places such as schools, universities, shopping complexes, cinemas, industrial and business activities are examples of restricting people's movement to attain social distancing. Nevertheless, reductions in economic activities and business closures following lockdowns have led to a global economic shock triggering recession across countries (World Bank, 2020).

Also, adopting such responses to the pandemic has had significant impacts on the environment, especially air quality and pollutants' concentration. The social pause could provide a valuable opportunity to study the effects of human activities on air pollution. The COVID-19

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[1] . In terms of terminology, A stay-at-home order (more common in U.S), movement control order (more common in Southeast Asia), or lockdown restrictions (in the United Kingdom) is an order from a government authority that restricts a population's movements as a mass quarantine strategy for suppressing or mitigating an epidemic or pandemic by ordering residents to stay home except for essential tasks or for work in essential businesses. (Wikipedia: Wikipedia contributors. "Stay-at-home order." *Wikipedia, The Free Encyclopedia*. Wikipedia, The Free Encyclopedia, March 14. 2021. Web. March 19. 2021.)

responses, especially stay-at-home orders and lockdowns are believed to make both productive activities and traffic to a low level for over a short period (Tian et al., 2020, Pei et al. 2020). Several studies focus on air pollution changes during lockdowns, using before-after analysis (Nature.com[2]). Such studies would be report-based without a proper counterfactual (He et al. 2020). Some other studies have tried to find a correlation between lockdowns and air pollution changes which will be pointed in the upcoming section. However, as an example, in a paper by Guojun He et al. 2020, they have introduced a methodology providing a work-frame to elaborate the causal effect of lockdown on air pollution in China using difference-in-differences models to compare air quality in cities with and without lockdown policies.

One possible challenge in identifying lockdown effects (stay-at-home orders) on air pollution or other outcomes could be the lockdown's meaning. Because of varying prevalence speed, the terms and requirements of the lockdown could differ. Thus, in the beginning, the order should be adequately defined. In our case study, US, each state and territory began to enact its own laws and policies to slow down the spread of Covid-19. The US President and the federal government have limited powers, and only state governors have the authority to impose state-wide lockdowns (Wetter & Gostin, 2020). Thus, these laws varied widely in the timing and detail of orders issued related to stay-at-home requirements (Figure 1 shows variation in policy makers' implemented orders in April 2020).

Amanda Moreland et al. (2020) in the paper called "Timing of state and territorial COVID-19 stay-at-home orders and changes in population movement in the United States" have done interesting categorization. Given the data on state and territorial stay-at-home orders from various

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[2] Holcombe, M. & O'Key, S. Satellite images show less pollution over the US as coronavirus shuts down public places. CNN (23 March 2020); https://go.nature.com/2VzglPH. 2020 Airborne nitrogen dioxide plummets over China. NASA Earth Observatory (2 March 2020); https://go.nature.com/2Vxj3oQ. 2020 Air pollution goes down as Europe takes hard measures to combat coronavirus. European Environmental Agency (25 March 2020); https://go.nature.com/38ho2PH .

sources, they coded SHO in seven groups and five mutually exclusive categories based on the legal language in each state or territorial order. I will use the same publicly available data, in this paper. The more detailed information regarding stay-at-home orders and their timing could be found in Figure2.

With this background in mind, I will use data from the United States Environmental Protection Agency (EPA) and CDC's (Centers for Disease Control and Prevention) National Environmental Public Health Tracking websites, along with the Differences in Differences (DiD) technique, to measure effects of stay-at-home (SHO) orders on air pollution to see whether SHO causes a reduction in air pollution in states with Strict-SHO relative to states with Less-Strict SHO. This paper will contribute to the growing literature on the short-run effects of particular policies on air pollution. Moreover, by identifying an important causal relationship, this paper will provide insight to the policymakers trying to implement measures to decrease air pollution in a short-run period. However, there is no doubt that such policies requiring business closers which will have a considerable cost on the economy.

This paper will also provide secondary results by comparing the effects of SHO on states considering their contribution to GDP. For categorizing and sorting states considering their GDP, I will use a dataset from The US Bureau of Economic Analysis (BEA) for GDP by the state of the United States in 2019. I will categorize states into two groups 1) High-GDP 2) Low-GDP. Finally, the DiD framework with triple differences will be conducted to compare the impacts of SHO on air pollution in states with High-GDP to those with Low-GDP.

Section 2 provides a literature review and explains the recent studies done by researchers in related fields. Section 3 provides a description of the data. Section 4 concentrates on the methodology. Section 5 explains the results, and finally, section 6 will conclude.

2. Literature review

This section reviews some analyses of changes in air pollution during the Covid-19 pandemic and its lockdowns that have been carried out recently worldwide. On the one hand, these papers are important because they inform readers about changes in air quality during the pandemic. On the other hand, some will provide an analytical framework in which the correlation of these changes with various controls is investigated.

Starting with USA, Jesse D. Berman et al. (2020) have done analysis considering pollution during the COVID-19 period (March 13–April 21) and the pre-COVID-19 period (January 8th-March 12th) where 2020 represents 'current data' and 2017–2019 represents 'historical' data. They have shown pieces of evidence that measured air pollution has declined across the US during the pandemic, expressly NO2 declined 25.5% during the COVID-19 pandemic compared to historical years. Moreover, they have found that urban counties compared to rural counties showed more considerable percent reductions in NO2 (26.0% vs. 16.5%, respectively), with the absolute reduction nearly 5-times greater in urban counties. Decreases in NO2 are likely associated with reduced vehicular traffic from people working remotely and limited domestic travel. As well as this, they have observed an overall decline in PM2.5. They have identified larger reductions in PM2.5 from states instituting early non-essential business closures compared to those that did not close businesses early. Moreover, Bekbulat et al. (2020) calculate a "robust differences" metric (the weekly median concentration for 2020, relative to the temporally corrected historical median, normalized to the interquartile range) to identify the impacts of stay-at-home orders on air pollution. They have elaborated that during stay-at-home orders, ozone, NO2, CO and PM10 were lower than expected levels. In contrast, PM2.5 was higher than expected levels by 1%-30% of their multi-year interquartile range. Jianbang Xiang et al. (2020), in their study, investigate the impacts of the COVID-19 pandemic on traffic-related air pollution in a Northwestern US city. The pollutants which have been analyzed were ultrafine particles, PM2.5, black carbon, NO, NO2, NOx, and CO. The pollutants between pre and post stay-at-home order periods were compared by using multivariate autoregressive (MAR) models. They found significant drops in UFPs, black carbon, PM2.5, NO, NO2, NOx, and CO. Additionally, they have found significant differences in meteorological conditions between the two periods. By controlling for meteorological conditions, the COVID-19 responses were associated with significant decreases in median levels of traffic-related pollutants. Chunrong Jia et al. (2020) have tried to investigate the impact of the "stay-at-home" orders from March 25 to May 4 on ambient air quality in Memphis (USA). They have compared the mean concentrations of fine particulate matter (PM2.5), nitrogen dioxide (NO2), and ozone during the lockdown with concentrations measured during the same periods in 2017–2019 using linear regression models. They concluded that the "stay-at-home" orders had an insignificant impact on reducing Memphis's air pollution.

Conducting analyses in China, Pei et al. (2020) investigates the impact of the COVID-19 lockdown on the atmospheric environment using time series. They imply that NO2 plunged across China while PM2.5 kept steady or even increased due to COVID-19 lockdown. Also, they observed the contribution of meteorological factors to these changes.

Patel et al. (2020) provide evidence by using NASA satellite data. They found that satellite-derived concentrations of nitrogen dioxide (NO2) in eastern and central China from early 2020 were 10–30% lower than comparable periods in 2019. Moreover, in the paper by Bauwens et al. (2020), satellite NO2 data suggested that Western Europe and major Northeastern US cities experienced 20–38% NO2 decreases in 2020 relative to the same period in 2019. However, Iran, a region strongly affected by COVID-19, did not show clear evidence of lower NO2 concentrations. European Environment Agency (2020) found a similarly large drop in air pollution across European cities by using satellite data.

Matthew D. Adams (2020) analyzed air pollution changes in Ontario, Canada, during the COVID-19 state of emergency. Their analysis was focused on a five-week period during the state of emergency with a previous five-week period used as a control. It has been observed that fine particulate matter's concentrations did not change. However, he observed moderate evidence of ozone concentration reductions and strong evidence for reductions of nitrogen dioxide and nitrogen oxides. Pollutants with transportation-dominated source profiles responded the most.

Pratima Kumari and Durga Toshniwal (2020) have investigated changes in PM2.5, PM10, SO2, NO2 and O3 in specific locations such as Beijing, Bengaluru, Delhi, Las Vegas, Lima, London, Madrid, Moscow, Mumbai, Rome, Sao Paulo, and Wuhan during their lockdown period. The variation in trends of the five key air pollutants has been analyzed to investigate a comparison in air quality before and after the lockdown. Their result confirms previous studies showing that PM2.5, PM10 and NO2 reduced significantly during the lockdown. However, SO2 and O3 showed a mixed trend. Moreover, observed results showed that the achieved air quality improvement is temporary.

As well as Pratima Kumari and Durga Toshniwal (2020), there we some other location specified analysis. Zambrano-Monserrate and Ruano (2020) used a parametric approach to elaborate that PM2.5 and NO2 concentration decreased while O3 concentration increased in their study locations (Quito and Ecuador). Collivignarelli et al. (2020) have investigated the impact of the partial and total lockdown on air quality. They concluded that almost all pollutants such as PM10, PM2.5, BC, CO Benzene and NOx except SO2 show a significant reduction in Milan (Italy). Baldasano (2020) elaborated that NO2 concentrations in Barcelona and Madrid (Spain) were reduced by 47% and 62%, respectively. Similarly, Pacheco et al. (2020) have shown NO2 concentration was reduced by up to 23% in Ecuador. Selvam et al. (2020) has shown that in Gujarat (India), NO2 was reduced by 30–84%, while O3 increased by 16–58%. Overall, AQI improved by 58% as compared to 2019.

Guojun He et al. (2020) have introduced a methodology providing a work-frame to elaborate the causal effect of lockdown on air pollution in China. They have used Difference-in-Differences models to compare air quality in cities with and without lockdown policies. Their result suggests that city lockdowns led to a significant improvement in air quality. In short-run (within weeks), the AQI in the locked-down cities decreased by 19.84 points (PM2.5 down by 14.07 μg) relative to the control group. Also, they have shown that the lockdown effects are larger in colder, richer and more industrialized cities.

Overall, regarding changes in air pollution, previous studies have examined the impacts of the COVID-19 responses on ambient PM2.5 and/or some other gaseous pollutants in China ((Bauwens et al. (2020); Chen et al. (2020); Shi and Brasseur (2020); Xu et al. (2020)), India ((Sharma et al. (2020)), Italy ((Collivignarelli et al. (2020)), Brazil ((Nakada and Urban (2020)), and NO2 in Western Europe and major Northeastern US cities ((Bauwens et al. (2020)). Additionally, a study has estimated the impacts on PM2.5 and O3 across the US, as well as NO2 in three US cities, including Seattle ((Bekbulat et al. (2020)). Another recent study tried to exclude meteorological impacts on air pollution change during the COVID outbreak by using the WRF model ((Zhao et al. (2020)). However, the impacts of meteorological factors may not be completely and accurately excluded due to the inherent limitations of the WRF model ((Zhao et al. (2020)).

3. Data

3.1 Air pollution, United States Environmental Protection Agency (EPA.)

The Environmental Protection Agency (EPA) is an independent executive agency of the United States federal government tasked with environmental protection matters. EPA's website provides access to outdoor air quality data collected from state, local and tribal monitoring agencies across the United States. Ambient (outdoor) concentrations of pollutants are measured at more than 4000 monitoring stations owned and operated mainly by state environmental agencies. The agencies send hourly or daily measurements of pollutant concentrations to EPA's database called AQS (Air Quality System). On the website, specific files contain data summarized on an annual basis (annual summary files), some contain data summarized on a daily basis (daily summary), and some contain raw data (sample data as reported). All but the annual summary have data files grouped by parameter criteria gases, particulates and meteorological. Thus, Daily Summary Data have been downloaded for each year for each variable, including O3, SO2, CO, NO2, PM2.5, Pm10, Temperature, wind speed. All the daily data on this website are being reported by the end of the calendar quarter.

Each of the parameters from this website has its unique measurement unit, noted in Table 1. For all the pollutants, the primary sources of emissions are noted.[3] Table 2 shows the mean, standard deviation, min and max of the variables for March 25 – May 31, 2018,2019 and 2020. It is worth to be mentioned that for all the pollutants, "mean" in 2020 is smaller than 2019 and 2018 in the given period. To report statistics for temperature and wind, we have referred to PM2.5's datasets as they include most of the observations.

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[3] These information have been gathered from California Air Resources Board (CARB) https://ww2.arb.ca.gov and United States Environmental Protection Agency (EPA) https://www.epa.gov and https://www.tecamgroup.com/major-air-pollutants-and-sources

3.2 Stay at Home Orders

The stay-at-home policies' data at the state level is derived from Amanda Moreland et al. (2020) and CDC's (Centers for Disease Control and Prevention) National Environmental Public Health website's database. This dataset can be used to determine when individuals in states, territories, and counties were subject to executive orders, administrative orders, resolutions, and proclamations for COVID-19 that require or recommend people stay in their homes. It is worth to be mentioned that any executive orders, administrative orders, resolutions, and proclamations ("orders") not available through publicly accessible websites are not included in this dataset. It has been mentioned in the paper that State, territorial, and county orders and proclamations for individuals to stay at home were obtained from state, territorial, and county government websites. This data includes seven groups and five mutually exclusive categories "1) mandatory for all persons; 2) mandatory only for persons in certain areas of the jurisdiction; 3) mandatory only for persons at increased risk in the jurisdiction; 4) mandatory only for persons at increased risk in certain areas of the jurisdiction; or 5) advisory or recommendation (i.e., nonmandatory). Jurisdictions that did not issue an order were coded as having no state- or territory-issued order. The coding of the mentioned categorization is based on the legal language[4] in each state or territorial order.

Given the categorization above, our identification strategy will be grouping the- mandatory for all persons; mandatory only for persons in certain areas of the jurisdiction; mandatory only for

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[4] Moreland et al. : "An order was coded mandatory if it contained language requiring persons to stay home (e.g., persons "shall," "must," or "are directed to") or advisory or recommendation if it contained permissive language suggesting persons stay home (e.g., persons "should," "are encouraged to," or "are urged to") Orders were coded mandatory only for persons in certain areas of the jurisdiction if the order expressly required persons in certain areas (e.g., counties) to stay home but did not require persons in other areas to stay home. Orders were coded mandatory only for persons at increased risk in the jurisdiction if they expressly required persons who meet certain high-risk criteria (e.g., aged >65 years or those with chronic medical conditions) to stay home while permitting others to leave their homes."

persons at increased risk in the jurisdiction; mandatory only for persons at increased risk in certain areas- orders in a group called **Strict-SHO** along with grouping advisory and nonmandatory orders in **Less-Strict SHO**. The reason behind the generation of such dummy variables for SHO would be the assumption of the restrictive and deterrent impact of Strict-SHO compared with Less-Strict SHO.

As shown in figures 1 and 2, there is considerable variation in the implementation of stay-at-home policies. At the daily level, the first state to implement lockdown was California on March 19, 2020. Subsequently, 18 states followed suit during the next weeks. However, at the monthly level, most states implemented stay-at-home policies within March and April, however eight states –Iowa, Oklahoma, Utah, American Samoa, Arkansas, Connecticut, Nebraska, North Dakota, and Wyoming. – did not implement state-wide mandatory stay-at-home policies during April 2020. Given this information, I will be doing my analysis for March 25 to May 31 as a maximum period that includes both **Strict SHO** and **Less-Strict SHO** issued states. Another reason for choosing this period is the expiration of Stay-at-home orders in most of the states by June.

3.3 Gross domestic product (GDP)

Is the total monetary value of all goods and services produced by an economy within a certain time period. GDP is used by economists to determine the economic health of an area, as well as to determine the size of the economy. GDP can be determined for countries, states and provinces, and metropolitan areas. Gross Domestic Product (GDP) of the United States in 2019, by state (in billion current US dollars) is downloaded from US Bureau of Economic Analysis (BEA). The states will be categorized into two groups 1) High-GDP 2) Low-GDP. First, the average GDP by the state will be calculated. Then the states with GDP higher than average will be called High-GDP states. In contrast, those states with GDP lower than average will be called Low-

GDP states. The gross domestic product (GDP) of California was about 3.14 trillion US dollars in 2019, meaning that it contributed the most out of any state to the country's GDP in that year. In contrast, Vermont had the lowest GDP in the United States, with 34.78 billion US dollars. The average GDP by state is 417.70 billion US dollars. The table below shows the mean, standard deviation, min and max of the GDP by the state in 2019.

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
GDP-by-state-2019	*51*	*417.79*	*541.085*	*34.78*	*3,137.47*

Combination of datasets; as we have a couple of datasets in this paper for various variables for three different years, Microsoft Access has been used to combine datasets given the daily data. After combining the dataset, some observations have been omitted since they have had some missing data for main variables.

4. Methodology

Identification Strategy: DID. Framework

Difference-in-Differences is a quasi-experimental design to estimate the effect of a specific intervention or treatment by comparing the changes in outcomes over time between "treatment" and "control" groups. As noted earlier, some states implemented Strict-SHO policies while others did not. States implementing the policy are classified as the treatment group, while states which did not implement Strict-SHO policies are classified as control group. This paper uses a DiD Strategy to assess the short-run impact of Strict-SHO on air pollution by comparing states that implemented these policies (treatment group) with those that implemented Less-Strict SHO (control group). Our general DiD model is:

$$y_{it} \equiv \beta_0 + \beta_1 time_t + \beta_2 SHO_i + \beta_3 time_t * SHO_i + \mu x_{it} + \varphi_t + \lambda_i + \varepsilon_{it} \qquad eq(1)$$

Table I The difference-in-difference table and Strict-SHO effect.

	Time=0(25 March-31May 2019)	Time=1(25 March-31May 2019)	Difference
(i)Treatment=1	$\beta_0 + \beta_2$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_1 + \beta_3$
(i) Control=0	β_0	$\beta_0 + \beta_1$	β_1
Difference	$\boldsymbol{\beta_2}$	$\boldsymbol{\beta_2 + \beta_3}$	$\boldsymbol{\beta_3}$

where y_{it} is the outcome variable – concentration of Co, SO2, No2, PM2.5, PM10 and AQI – for state i on date t. Regarding $time_t$ ($t = 1\ if$ the date is between 25 $March - 31May$ 2020 $and\ t = 0\ if$ the date is between 25 $March - 31May$ 2019). Regarding SHO_i { i=1 if the state has issued Strict-SHO (treatment group) And i=0 if the state has Less-strict SHO (control group)}. Therefore, " $time_t * SHO_i$ " is the interaction term between treated group and time. Negative and significant β_3, the coefficient of interest in our equation, will be interpreted as a positive policy effect of the treated group; this shows that policy positively impacts the relevant outcome. x_{it} is a vector of meteorological variables including wind speed, wind direction and temperature. The weather has a significant impact on air pollution. In fact, windy weather causes pollution to be dispersed whilst still weather allows pollution to experience higher levels. The wind direction also affects air pollution. If the wind is blowing towards an urban area from an industrial area, then pollution levels are likely to be higher in the town or city than if the air is blowing from another direction. Temperatures affects the movement of air pollution (convection). For example, in hot days the warmer and lighter air at the surface rises, and in the cooler days, heavier air in the upper troposphere sinks. Thus, the ground level air pollution could be higher in lower temperatures. φ_t, will elaborate time-invariant fixed effect.λ_i, will elaborate county invariant fixed effect. The county fixed effects, which are a set of county-specific dummy variables, can control for time-invariant confounders specific to each county. For example, the geographical conditions and economic structure can be controlled by introducing the county fixed effects. The time fixed effects are a set of dummy variables that account for date related shocks that are common to all counties in a given date such as holidays.ε_{it} is the random error term. The standard errors are clustered at the state level and will be explained below.

Standard errors and cluster. Given one of the main assumptions in OLS, the diagonal variance-covariance matrix for the error term and assumption of homoskedasticity, there is a probability of rejection of this assumption in practice by having a block diagonal matrix; This means correlation of error term within the state level. Since our treatment is assigned at the state level, we have a source of variation that comes from differences across states level at which most of the state-at-home policies were implemented. Given that clustered standard errors are often helpful when treatment is assigned at the level of a cluster (here state-level) and they are widely used in a variety of applied econometric settings, including difference-in-differences (our model). Implementing a straightforward way by using the "cluster" command in STATA and choosing entire states as clusters we would have a correct way to construct standard errors here.

The underlying assumption for the DiD estimator is that treated, and control groups would have parallel trends in air quality in the absence of the treatment.

Falsification test regarding primary Identification Strategy

In the falsification test, equation (1) will be used.

The main difference will be, moving our analysis a year back. This means ($t = 1\ if$ the date is between 25 $March 31 May$ 2019 $and\ t$ equal to 0 if the date is between 25 $March - 31 May$ 2018). All the other variables and their definition will remain the same. Again, " $time_t * SHO_i$ " is the interaction term between treated group and time. Consequently, the falsification test hypothesis would be the insignificant impact of Strict-SHO policies on the relevant outcome by moving our timeline one year back. Thus, insignificant β_3 will be expected. Similarly, the standard errors are clustered at the state level.

Identification strategy for secondary result: Triple differences framework

Treatment assignment rule may sometimes suggest a triple or higher-order differences setup for the estimation. Various states introduced SHO in our interest time period, which is 25 March-31 May. Given the details in the data section regarding GDP categorization, there are two types of states 1) High-GDP 2) Low-GDP. DiD framework with triple differences will be conducted to compare the impacts of SHO on air pollution in states with High-GDP to those with Low-GDP. The main equation will be as follows:

$$y_{itj} \equiv \beta_0 + \beta_1 time_t + \beta_2 SHO_i + \beta_3 time_t * SHO_i + \beta_4 GDP_j + \beta_5 time_t * GDP_j + \beta_6 SHO_i * GDP_j + \beta_7 time_t * SHO_i * GDP_j + \mu x_{itj} + \varphi_{tj} + \lambda_{ij} + \varepsilon_{itj} \qquad \text{eq(2)}$$

where y_{itj} Is the outcome variable – concentration of Co, SO2, No2, PM2.5, PM10, AQI – for state i on date t and GDP category j. Regarding $time_t$ ($t = 1\ if$ the date is between 25 $March - 31 May$ 2020$and\ t = 0\ if$ the date is between 25 $March - 31 May$ 2019). Regarding SHO_i { i=1 if the state has issued Strict-SHO (treatment group) And i=0 if the state has Less-Strict SHO (control group)}. Regarding GDP_j, j=1 if a state has High-GDP and j=0 if a state has Low-GDP. There will be two by two interaction terms between $Time_t, SHO_i and GDP_j$. The interest coefficient (β_7), will be interpreted as a more considerable positive policy effect of the treated group with

High-GDP; this shows that policy positively impacts the relevant outcome. Here also the standard errors are clustered at the state level

5. Results

5.1 Graphical Analysis

Figures 3-8 show the daily average concentration of main pollutants before and after implementation of stay-at-home orders. From Pre/post-treatment figures could be seen that except O3 the average concentration of CO, NO2, Pm2.5, SO2 and PM10 have decreased in the weeks after the first stay-at-home order issued by California on March 19. The reduction in Co, No2 and PM2.5 had been more drastically than SO2 and PM10. In fact, SO2 and PM10 roughly experienced a steady trend.

Given the information in the table 7, the reduction of mentioned pollutants could be related to drops in traffic movement and manufacturing activities. Moreover, the main source of O3 is chemical reactions between oxides of nitrogen (NOx) and is not emitted directly into the air. This is probably the reason behind increase of O3 concentration. (Sillman,S.(1999)- Seinfeld, J. H.(2016))

5.2 Main Results

Using our main regression, table 4 shows the vector of coefficients estimated in equations (1). Each column represents the results for each dependent variable. The standard errors are clustered at the state level (robust standard errors are expressed in the parenthesis). Fixed effects have not been considered in regressions with regard to this table.

As it can be seen, the estimate for the interaction term city_treatment is negative in all columns. However, they are not statistically significant at conventional levels for CO, O3, PM2.5, SO2 and AQI. This means that implementation of Strict-SHO by states did not cause a statistically significant decrease in the concentration of mentioned pollutants relative to states which implemented Less-Strict SHO. Thus, the negative and insignificant results could be related to non-SHO reasons.

Looking at table 4, the estimates for the interaction term city_treatment for NO2 and PM10 are also negative but statistically significant at the 1 percent level for CO and at 5 percent level for PM10. The estimate suggests that the implementation of Strict-SHO policies decreased the average concentration of NO2 by 1.73 units relative to the control group. Similarly, regarding PM10 on average, the concentration of this pollutant in states with Strict-SHO has brought down by 2.75 units in comparison with the control group. For both NO2 and PM10, the falsification test should give us insignificant results to make sure about the existence of the causal effect.

Table 5 also shows the results for equation 1. However, the difference between the results of this table and table 4 is that standard errors are not clustered at the state level. Instead, time-invariant and county invariant fixed effects have been considered.

In this scenario also, the coefficient of interest for CO, O3, PM2.5, SO2 is negative and insignificant. This suggests that even by making some changes in standard errors and main regression, the interpretation would be the insignificant impact of the implementation of Strict-SHO relative to the control group.

In table 5, like table 4, the estimates for the interaction term city_treatment for NO2 and PM10 are negative and significant at 1 and 5 percent level, respectively. It means NO2 and PM10 had been decreased by 1.27 and 2.23 units respectively in states which have issued Strict-SHO in comparison with the states with Less-Strict Stay-at-Home Orders. Looking at table 5, AQI has a decrease by 1.12 units in states which have issued Strict-SHO in comparison with the states with Less-Strict stay-at-home orders.

Falsification test, the identifying assumption for DiD, is that the outcome variable's trend between treated and control observations (conditional on observables) should not be different absent treatment. As mentioned in the methodology section, we will conduct our analysis to check whether the trend is the same in the pre-treatment period (2019-2018 instead of 2020-2019).

From the interpretation of the results shown in tables 4 and 5, NO2 and PM10 and AQI have had a negative and significant coefficient of interest in equation (1) and were interpreted as a positive policy effect of the treated group. Thus, the falsification test is warranted to confirm the causal treatment's impact on these outcomes.

Table 6 shows our results for the falsification test. Each column represents the results for each dependent variable. The standard errors are clustered at the state level (robust standard errors are expressed in the parenthesis). Except for AQI, fixed effects have not been considered in regressions regarding this table. The estimates for the interaction term city_treatment for NO2 and PM10 are also negative and positive for AQI but statistically insignificant. We have met an important assumption of the insignificant impact of Strict-SHO policies on the relevant outcome by moving our timeline one year back. Thus, these findings confirm the causal impact of Strict-SHO on decreasing the NO2 and PM10 and AQI in the treatment group relative to the control group.

5.3 Secondary Results

Using our secondary regression, table 7 shows the vector of coefficients estimated in equations (2). Each column represents the results for each dependent variable. The standard errors are clustered at the state level (robust standard errors are expressed in the parenthesis). Except for AQI fixed effects have not been considered in regressions with regard to this table.

As it can be seen, the estimate for the interaction term City_Treatment_High_Gdp is negative in all six columns. However, they are not statistically significant at conventional levels for CO, NO2, PM10, PM2.5, SO2. This means that implementation of Strict-SHO by states with High-GDP did not cause a statistically significant decrease in the concentration of mentioned pollutants relative to states which implemented Strict-SHO and have Low-GDP. Thus, the negative and insignificant results could be related to other reasons.

Table 7 includes the primary estimate for the interaction term, City_Treatment_High_Gdp, which is also negative but statistically significant for O3 at the 1 percent level. The estimate suggests that the implementation of Strict-SHO policies by states with High-GDP decreased the average concentration of O3 by .00346 units relative to states with Low-GDP. For O3, the falsification test should give us insignificant results to make sure about the existence of a significant effect. AQI's results suggest that by considering fixed effects in our regression, AQI reduced by 2.0081 units in states with Strict-SHO policies and High-GDP relative to states with Strict-SHO and Low-GDP. For AQI, the falsification test should give us insignificant results.

A falsification test is needed to assure the causal effect absent treatment. As mentioned before, we will conduct our analysis to check whether the trend is the same in the pre-treatment period (2019-2018 instead of 2020-2019).

From the interpretation of the results shown in Table 7, O3 and AQI have had a negative and significant coefficient of interest in equation (2) and were interpreted as a positive policy effect of the treated group with High-GDP. Thus, the falsification test is warranted to confirm the causal treatment's impact on O3 and AQI.

Table 8 shows our results for the falsification test. Each column represents the results for each dependent variable. The standard errors are clustered at the state level (robust standard errors are expressed in the parenthesis). Except for AQI, fixed effects have not been considered in regressions with regard to this table. Looking at table 8, The estimates for the interaction term City_Treatment_High_Gdp for O3 and AQI are statistically insignificant. We have met an important assumption of the insignificant impact of Strict-SHO policies in states with High-GDP on the relevant outcome compared to states with Low-GDP by moving our timeline one year back. Thus, these findings confirm the relationship between the decrease in O3 and AQI and the states with Strict-SHO and High-GDP compared to states with Strict-SHO and Low-GDP.

6. Conclusion

The social pause as a non-pharmaceutical aid to slow down the spread of Covid-19 has impacted the economy, environment, jobs description, etc. This paper focuses on the impacts of such pauses on the environmental side by investigating the short-run impacts of Stay-at-Home Orders on air pollution using EPA and CDC datasets. The stay-at-home orders have been grouped in two 1) Strict-SHO 2) Less-Strict-SHO categories. Considering the variation in the implementation of the stay-at-home orders across states, the Difference-in-Differences (DiD) model has been used to identify the causal relationship between SHO types and air pollution.

The DiD results show that Strict-SHO implementation did lead to a decrease in CO, SO2, PM2.5 and O3, although the point estimates are not statistically significant at conventional levels. However, a causal relationship has been identified between reducing the concentration of NO2, PM10 and AQI in states with Strict-SHO relative to states with Less-Strict SHO by 1.73 and 2.75 and 1.12 units, respectively. As secondary results, this paper tries to identify the impact of Strict-SHO in states considering two different GDP categorizations; 1) High-GDP (states with GDP higher than average) 2) Low-GDP (states with GDP lower than average). The findings suggest that O3 and AQI have decreased by 0.00346 units and 2.0081 units, respectively, in states with Strict-

SHO and High-GDP relative to states with Low-GDP. Also, the falsification test indicated that the result is valid for the DiD approach.

This paper has documented the short-run effects of stay-at-home orders on the concentration of main air pollutants. Although the costs of enforcing these counter-COVID-19 measures are enormous on the economy, they could improve air pollution in the short-run. Besides, given our secondary results, future research could compare the effects of stay-at-home orders on air pollution considering states' population, number of manufacturing firms, traffic volume and construction activities.

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6. Figures

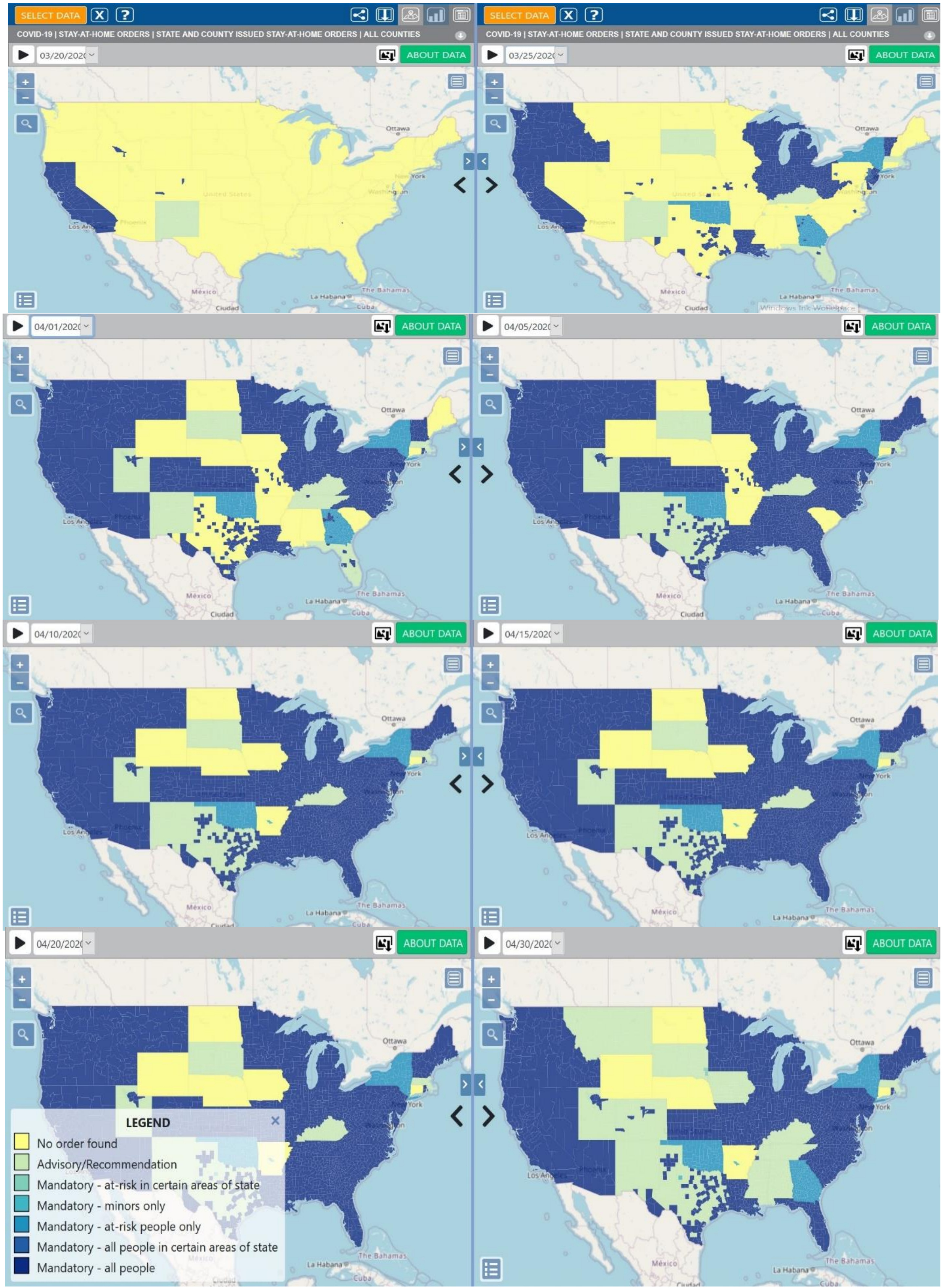


***Figure 1**: Screenshots are for 20,25 March and 1,5,10,15,20, 30 April giving us a graphical view of SHO and its types during March and April. the first state to implement lockdown was California on March 19, 2020. Subsequently, other states followed suit during the next weeks.*

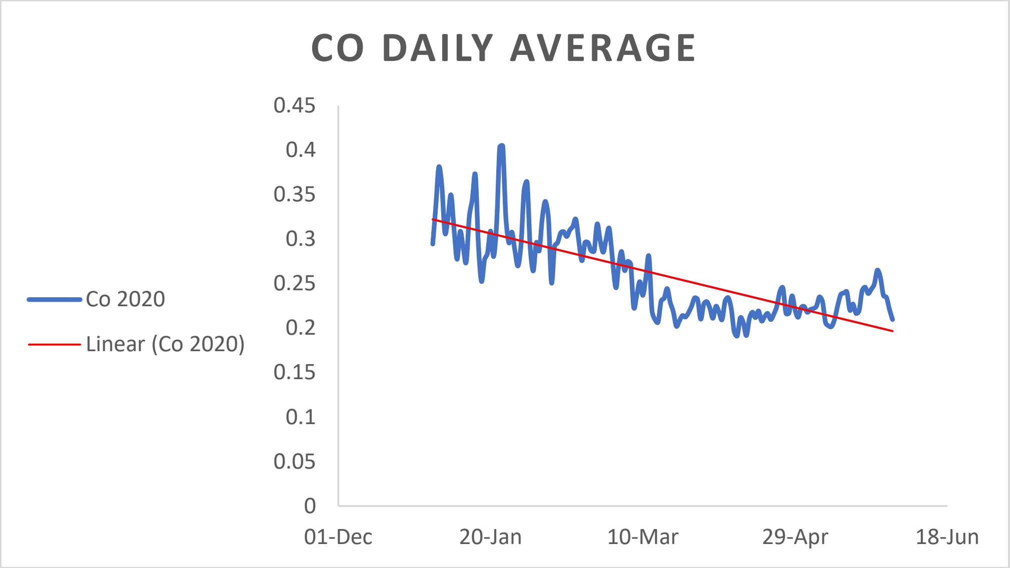
Figure 2. Duration and type of the Stay-at-Home Orders

Figure 2: Screenshot token from the paper by Moreland et al.2020 to elaborate the timing and the type of stay-at-home orders in USA, March 1_ May 31.

Jurisdictions that did not issue any orders requiring or recommending persons to stay home during the observation period were not included in this figure.

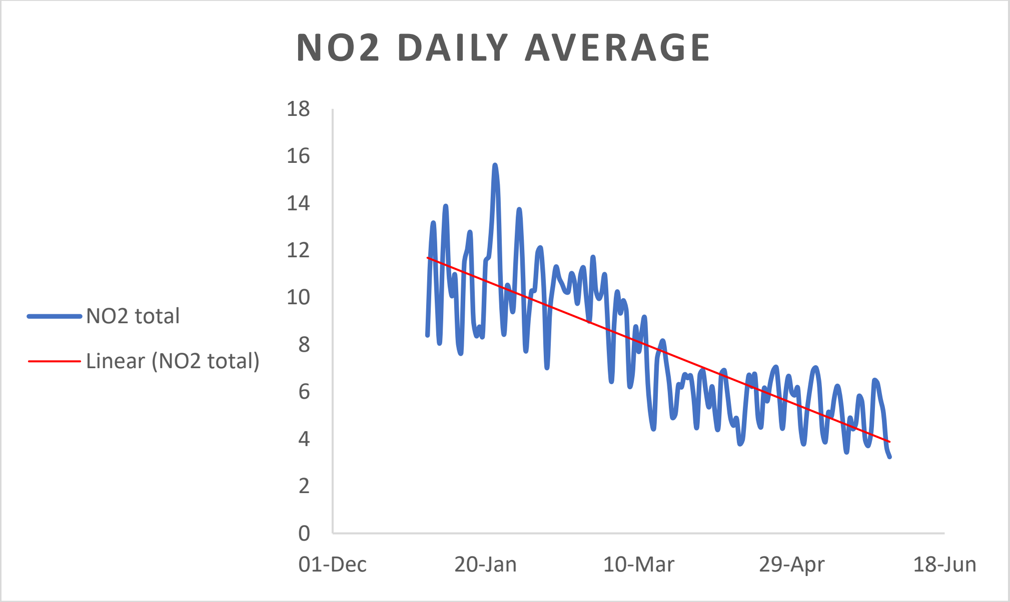
Jurisdictions without any orders were American Samoa, Arkansas, Connecticut, Nebraska, North Dakota, and Wyoming.

Figure 3. Co Pre/post Treatment



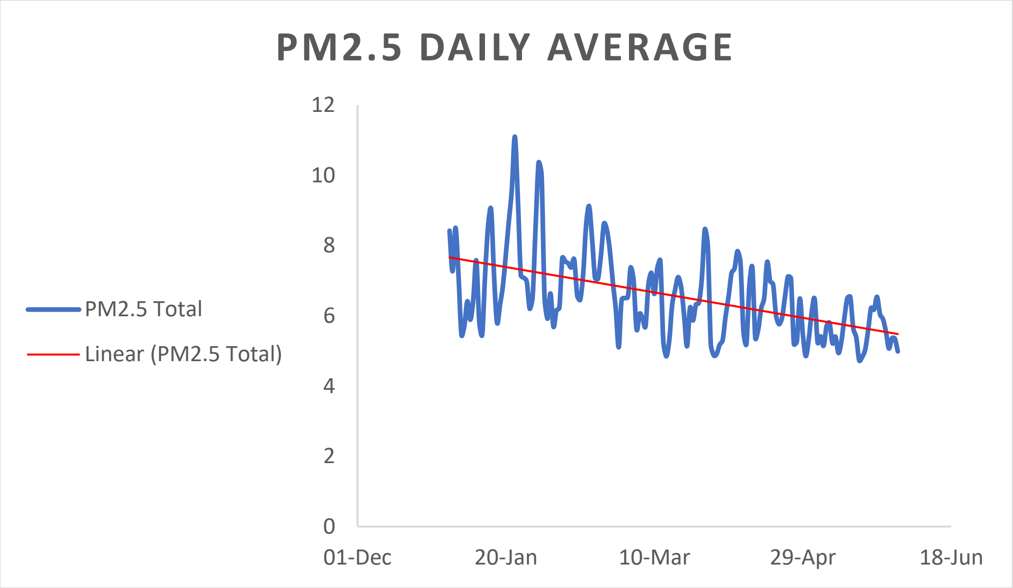
Author's calculation for average daily concentration of CO pre/ post treatment in USA. In January and February which are first two month preceding the lockdown the average daily concentration of Co is much higher than March and April as months in which lockdowns were issued in USA. The red line is a trendline of changes in CO and it is downward sloping.

Figure 4. NO2 Pre/post Treatment



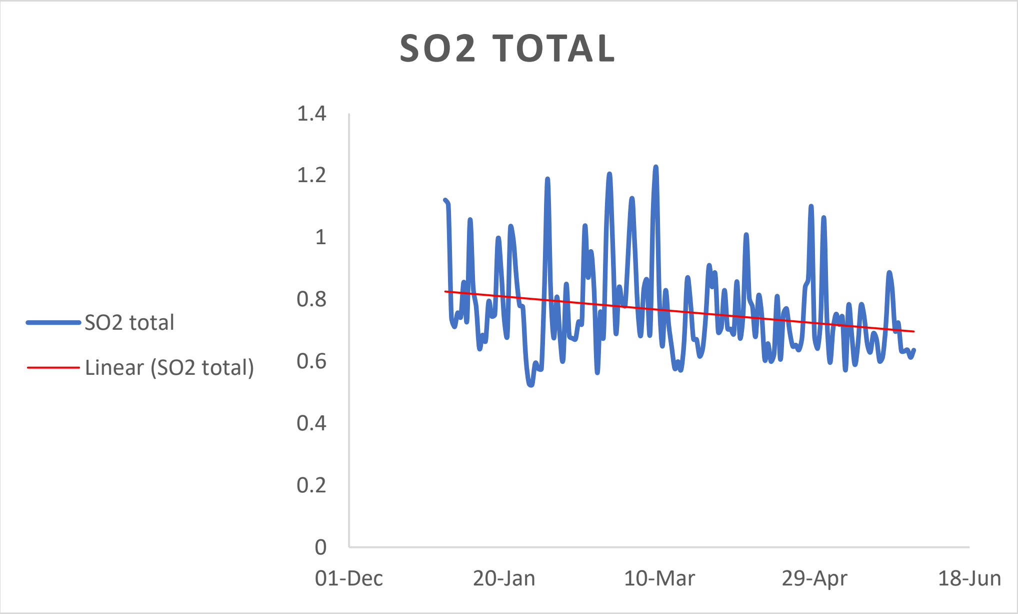
Author's calculation for average daily concentration of NO2 pre/ post treatment in USA. The red trendline is showing the downward daily average trend after announcement of first official covid-19 case in January 21. No2 has experienced huge reduction after first stay-at-home order issued by California in the third week of March.

Figure 5 PM2.5 Pre/post Treatment



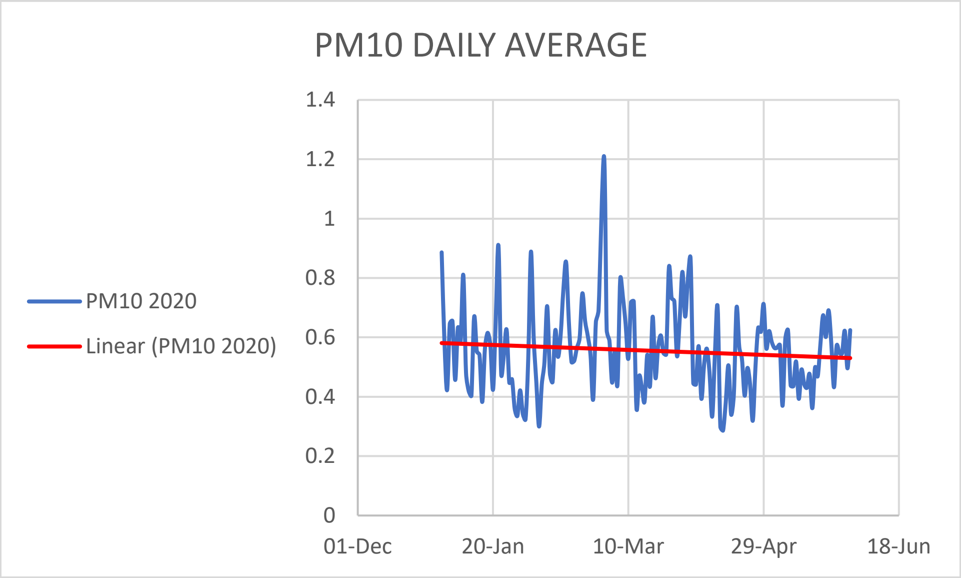
Author's calculation for average concentration of PM2.5 pre/ post treatment in USA. PM2.5 has reduced in terms of daily average after first lockdown issued on March 19, however the decrease is not drastically.

Figure 6. SO2 Pre/post Treatment



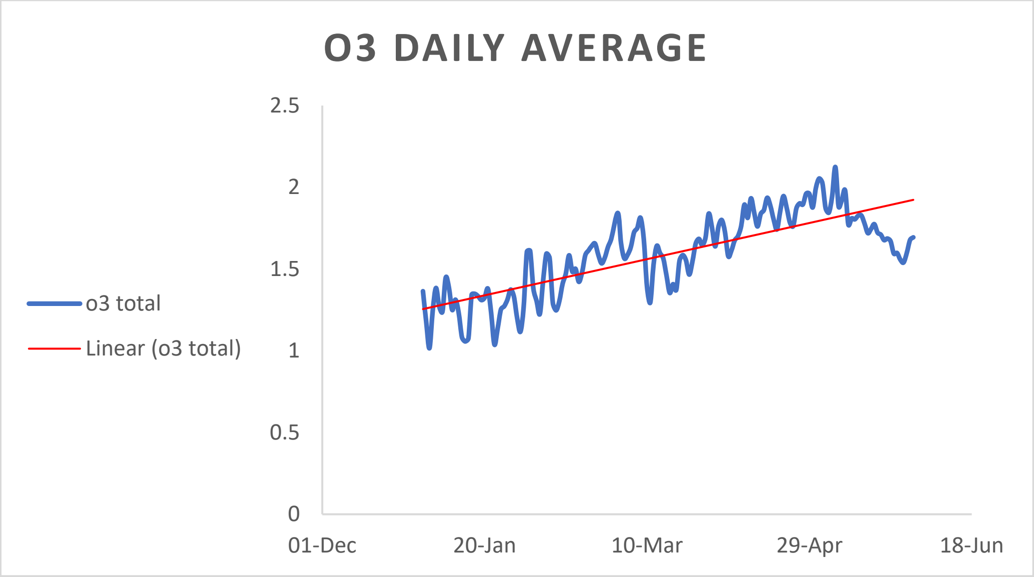
Author's calculation for average concentration of SO2 pre/ post treatment in USA. It could be seen that changes in daily concentration of So2 has experienced a steady trend before and after implementation of first lockdown on March 19 .

Figure 7. PM10 Pre/post Treatment



Author's calculation for average concentration of O3 pre/ post treatment in USA. trendline shows that daily average of PM10 has shown a fixed trend before and after the lockdown.

Figure 8. O3 Pre/post Treatment



Author's calculation for average concentration of O3 pre/ post treatment in USA. diagonal line shows that the lockdown reduces almost all the pollutants but ozone (O3). This is probably because of the reduction in NOx slows down its interaction with O3 and consequently the O3 concentration increases. (Sillman,S.(1999)- Seinfeld, J. H.(2016))

7. Tables

Table 1. Pollutants' and metrological parameters' measurement units and main sources.

<table>
<tr><th>Parameter Name</th><th>Units of Measure</th><th>Sample Duration</th></tr>
<tr><td>O3-Ozone</td><td>Parts per million</td><td>8-hour average[5]</td></tr>
<tr><td colspan="3">O3 is not emitted directly into the air but is created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC). This happens when pollutants emitted by cars, power plants, industrial boilers, refineries, chemical plants, and other sources chemically react in the presence of sunlight.</td></tr>
<tr><td>CO- Carbon monoxide</td><td>Parts per million</td><td>8-hour average</td></tr>
<tr><td colspan="3">The greatest sources of CO to outdoor air are cars, trucks and other vehicles or machinery that burn fossil fuels.</td></tr>
<tr><td>SO2- Sulfur dioxide</td><td>Parts per billion</td><td>1-hour and 3-hour average[6]</td></tr>
<tr><td colspan="3">SO2 is produced from the combustion of coal or oil. Although coal is falling into disuse and vehicle fuels are becoming more sophisticated, the emission of those gases into the atmosphere by the industry remains very high.</td></tr>
<tr><td>NO2- Nitrogen dioxide</td><td>Parts per billion</td><td>1-hour average</td></tr>
<tr><td colspan="3">The emission of No2 come from industrial actions the most, as they are generated from combustion at very high temperatures</td></tr>
<tr><td>PM2.5</td><td>Micrograms/cubicmeter(µg/m3)</td><td>24-hour average[7]</td></tr>
<tr><td colspan="3">Emissions from the combustion of gasoline, oil, diesel fuel or wood produce much of the PM2.5 pollution found in outdoor air</td></tr>
<tr><td>PM10</td><td>Micrograms/cubicmeter(µg/m3)</td><td>24-hour average[8]</td></tr>
<tr><td colspan="3">In addition to primary sources of PM2.5, PM10 also includes dust from construction sites, landfills and agriculture, wildfires and brush/waste burning</td></tr>
<tr><td>Temperature</td><td>Degrees Fahrenheit</td><td>1-hour average</td></tr>
<tr><td>Wind speed</td><td>Knots</td><td>1-hour average</td></tr>
<tr><td>Humidity</td><td>Percent relative humidity</td><td>1-hour average</td></tr>
<tr><td>Pressure</td><td>Millibars</td><td>1-hour average</td></tr>
</table>

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[5] First 8-hour averages have been calculated then the daily maximum of these 8-hour averages are reported. Thus, reports are based on the daily maximum of 8-hour average.

[6] First 1-hour or 3-hour averages have been calculated then the daily maximum of these 1-hour or 3-hour averages are reported. Thus, reports are based on the daily maximum of 1-hour or 3-hour average.

[7] Average of 24 hours are reported as daily data.

[8] Average of 24 hours are reported as daily data.

Table 2. Statistical summary of Pollutants' and metrological parameters for 2018-2019-2020

Variable	*Obs*	*Mean*	*Std. Dev.*	*Min*	*Max*
PM2.5-2018	32,082	7.389341	4.076183	0.0071	156
O3-2018	29,582	.0395321	.0097533	.002353	.086294
CO-2018	20,690	.240767	.1465332	0.012	2.3
NO2-2018	14,471	7.355645	6.453839	0.0038	53
S02-2018	22,382	.8265121	3.351106	0.0041	178.9565
PM2.5-2019	36,476	6.46768	4.014967	0.00178	63.49167
O3-2019	29,320	.0371407	.0086736	.001	.070765
CO-2019	19,012	.2313145	.1075912	0.0143	1.1625
N02-2019	14,507	6.818706	5.836279	0.0004	44.8
S02-2019	22,086	.651036	1.350144	0.0013	37.4625
PM2.5-2020	36,156	5.9842	3.719305	0.0066	59.99583
O3-2020	25,291	.0366005	.0086201	.003118	.082
CO-2020	13,750	.2095905	.0999669	0.0184	.979167
NO2-2020	12,473	4.8086	4.299206	0.0029	38.38696
SO2-2020	19,480	.6033723	1.390753	0.0056	42.00833
Temperature-2018	32,082	59.39778	14.81394	-.604167	93.91667
Wind-direction-2018	32,082	190.6727	62.80963	1	350
Windspeed-2018	32,082	4.689519	2.794574	.225	26.06667
Temperature-2019	36,476	58.57309	12.48673	17.375	90.79167
Wind-direction-2019	36,476	188.196	62.1322	5.875	348.1417
Windspeed-2019	36,476	5.032561	19.44611	.316667	1620.8
Temperature-2020	36,156	57.92735	14.61179	3.958333	97.45833
Wind-direction-2020	36,156	186.8179	67.75348	7.916667	347.75
Windspeed-2020	36,156	4.696003	2.835363	.158333	29.90833

Note: For all the pollutants, "mean" in 2020 is smaller than 2019 and 2018 in the given period. To report statistics for Temperature and wind, we have referred to PM2.5's datasets as they include most of the observations.

Table 3. U.S Gross Domestic Product by State 2019 categorization

	U.S. Gross Domestic Product (GDP), by state 2019 (billion US dollars)	*average*	*417.79*
1	*California*	*3,137.47*	*High-GDP*
2	*Texas*	*1,886.96*	*High-GDP*
3	*New York*	*1,731.91*	*High-GDP*
4	*Florida*	*1,093.35*	*High-GDP*
5	*Illinois*	*897.12*	*High-GDP*
6	*Pennsylvania*	*813.51*	*High-GDP*
7	*Ohio*	*698.46*	*High-GDP*
8	*New Jersey*	*644.84*	*High-GDP*
9	*Georgia*	*616.33*	*High-GDP*
10	*Washington*	*599.61*	*High-GDP*
11	*Massachusetts*	*595.56*	*High-GDP*
12	*North Carolina*	*587.71*	*High-GDP*
13	*Virginia*	*554.21*	*High-GDP*
14	*Michigan*	*541.55*	*High-GDP*
15	*Maryland*	*428.34*	*High-GDP*
16	*Colorado*	*390.28*	*Low-GDP*
17	*Minnesota*	*380.85*	*Low-GDP*
18	*Tennessee*	*380.14*	*Low-GDP*
19	*Indiana*	*377.1*	*Low-GDP*
20	*Arizona*	*366.19*	*Low-GDP*
21	*Wisconsin*	*347.31*	*Low-GDP*
22	*Missouri*	*332.08*	*Low-GDP*
23	*Connecticut*	*285.64*	*Low-GDP*
24	*Louisiana*	*263.86*	*Low-GDP*
25	*Oregon*	*251.6*	*Low-GDP*
26	*South Carolina*	*246.31*	*Low-GDP*
27	*Alabama*	*230.97*	*Low-GDP*
28	*Kentucky*	*214.67*	*Low-GDP*
29	*Oklahoma*	*206.06*	*Low-GDP*
30	*Iowa*	*194.79*	*Low-GDP*
31	*Utah*	*188.5*	*Low-GDP*
32	*Nevada*	*177.61*	*Low-GDP*
33	*Kansas*	*173.14*	*Low-GDP*
34	*District of Columbia*	*146.19*	*Low-GDP*
35	*Arkansas*	*133.18*	*Low-GDP*
36	*Nebraska*	*127.04*	*Low-GDP*
37	*Mississippi*	*118.78*	*Low-GDP*
38	*New Mexico*	*104*	*Low-GDP*
39	*Hawaii*	*97.28*	*Low-GDP*
40	*New Hampshire*	*88.6*	*Low-GDP*
41	*Idaho*	*80.91*	*Low-GDP*
42	*West Virginia*	*78.19*	*Low-GDP*
43	*Delaware*	*75.42*	*Low-GDP*
44	*Maine*	*67.52*	*Low-GDP*
45	*Rhode Island*	*63.54*	*Low-GDP*
46	*North Dakota*	*57.04*	*Low-GDP*
47	*Alaska*	*55.41*	*Low-GDP*
48	*South Dakota*	*53.31*	*Low-GDP*
49	*Montana*	*52.17*	*Low-GDP*
50	*Wyoming*	*39.65*	*Low-GDP*
51	*Vermont*	*34.78*	*Low-GDP*

Table 4. Main regression results of equation 1, No Fixed Effects.

Main Regression-Cluster State Level							
	CO	NO2	PM10	O3	PM2.5	SO2	AQI
City-treatment2020-2019(Strict-SHO 25March-31May)	-.0024355 (.015999)	-1.726955*** (.4063863)	-2.740884** (1.286227)	-.000085 (.0007229)	-.2541488 (.3713461)	-.1538213 (.1397966)	-.5650497 (.6343251)
SHO	-.0026998 (.0191375)	3.66383*** (.6120194)	4.384472 (2.637606)	.0003234 (.001126)	-.1057044 (.4773101)	-.09137 (.190202)	-2.058382 (1.526262)
Time	-.0238462 (.01132)	-.7596469** (.2676982)	-.0093012 (1.14508)	-.0005033 (.0005754)	-.2428891 (.2700627)	.0487566 (.1023983)	-1.557119** (.430595)
Temperature	.0009327* (.0005339)	.0586803** (.0155319)	.3823007*** (.0436558)	.0000636 (.0000385)	.2700627*** (.0172889)	-.0017307 (.0038828)	
Wind-Speed	-.0001004 (.0001208)	-.0086216 (.0138232)	.9492698 (.5869922)	.0000422 (.0000449)	-.0028561 (.0036975)	.0006716 (.0012428)	
Wind-Direction	-.0001809 (.0000703)	-.0105856* (.003692)	-.0027228 (.0043652)	.0000147** (.000039)	-.0073267** (.0016456)	-.0001324 (.0005411)	
constant	.2123184*** (.0346373)	2.933404** (1.223196)	-12.46782** (5.718441)	.0301755*** (.0025672)	1.901131** (.8380541)	.8314929 (.2044397)	40.5912*** (.8917994)
observations	32762	26980	20977	54611	72632	41566	130421
Time fixed effects	NO	NO	NO	NO	NO	NO	NO
County fixed effects	NO	NO	NO	NO	NO	NO	NO
R-Squared	0.0355	0.1364	0.0281	0.0233	0.1519	0.0444	0.0043
F-Statistic Prob > F	2.71 0.0250	101.31 0.000	37.01 0.000	17.91 0.000	10.22 0.000	0.88 0.5173	13.86 0.000

Table 4 Note: The impact of COVID-19 Strict Stay-at-home orders on US main air pollutants. Columns represent the dependent variable. City_treatment is the interaction term between the treated group (states which implemented Strict-SHO policies) and the time dummy variable . Fixed effects have not been considered in regressions. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 5. Main regression results of equation 1, With Fixed Effects.

Main Regression-Fixed effects

	CO	*NO2*	*PM10*	*O3*	*PM2.5*	*SO2*	*AQI*
City-treatment2020-2019(Strict-SHO 25March-31May)	-.0193546 (.0191395)	-1.264982*** (.318885)	-2.239959** (1.054951)	-.0001877 (.0003095)	-.0681944 (.3234613)	-.0992293 (.0927917)	-1.113674* (.5703207)
SHO	.0669615*** (.0052812)	5.471422*** (.2918545)	2.529456*** (.5379833)	.0006748 (.0005137)	-.431649 (.5406964)	.1015023** (.0500617)	-14.62** (6.923671)
Time	-.0206709 (.0168751)	-.1745767 (.254447)	17.1245*** (1.795156)	-.0008275** (.0002604)	-.2804015 (.2252149)	.0512578 (.0825688)	-1.47*** (.5049122)
Temperature	.000561** (.0001755)	.0082265 (.006363)	.1669012** (.0156021)	.0001216*** (.0000106)	.0829079*** (.0060874)	.0066377*** (.0021698)	
Wind-Speed	-.0000389 (.0000586)	-.0025617 (.004566)	.1938446 (.1237536)	.0000231 (.0000116)	-.0007404 (.0015762)	-.0001024 (.0001403)	
Wind-Direction	-.0000798* (.0000225)	-.0029808** (.0013108)	-.0024292 (.0026504)	.0000103*** (.0000344)	-.0047083** (.0005357)	.0004636 (.0004356)	
constant	.1391332 *** (.0094078)	2.409225 *** (.5066732)	-6.101441 ** (2.080976)	.0274757 *** (.0008389)	1.894275*** (.6302405)	.0224022 (.2044397)	51.39482 (5.569935)
observations	11230	14408	11230	30231	20319	16106	131298
Time fixed effects	YES	YES	YES	YES	YES	YES	YES
County fixed effects	YES	YES	YES	YES	YES	YES	YES
R-Squared	0.0160	0.0477	0.0672	0.0356	0.0556	0.0399	0.0057

Table 5 Note: The impact of COVID-19 Strict Stay-at-home orders on US main air pollutants. Columns represent the dependent variable. City_treatment is the interaction term between the treated group (i.e. US states which implemented Strict-SHO policies) and the Time dummy . Standard errors are not clustered at the state level. Instead, time invariant and county invariant fixed effects have been considered. (*** p<0.01, ** p<0.05, * p<0.1).

Table 6. Falsification Test for Main regression results of equation 1, No Fixed Effects.

Falsification Test-Cluster State Level	*CO*	*NO2*	*PM10*	*O3*	*PM2.5*	*SO2*	*AQI*
city treatment 2019-2018(SHO-Strict)	*-.0103199* *(.0160127)*	*.4527646* *(.3104035)*	*-.287794* *(1.763489)*	*-.0004458* *(.0006022)*	*-.1602311* *(.2518807)*	*-.0015208* *(.1967731)*	*1.455856* *(1.070324)*
SHO	*.0087917* *(.0194877)*	*3.22499**** *.7846428*	*4.370751* *(4.099496)*	*.0007381* *(.001045)*	*.0343644* *(.4491167)*	*-.0715654* *.2784448*	*-3.514237** *(1.724683)*
Time	*-.0006487* *(.0116107)*	*-.7530758**** *.1542319*	*-2.546431* *(1.684215)*	*-.0020191*** *(.0005082)*	*-.7256522* *(.1757118)*	*-.17757* *.1083322*	*-5.696*** *(.8173783)*
Tempreature	*.0012925*** *(.0003966)*	*.0672025** *.0230281*	*.4465594*** *(.0803546)*	*.0000675* *(.0000346)*	*.1142174**** *(.0137145)*	*.0034705* *.0045314*	
Wind-Speed	*-.0001379* *(.0001634)*	*-.0122896* *.0175639*	*1.199735** *(.6144658)*	*.0000466* *(.000049)*	*-.002049* *(.0029089)*	*.0015363* *.0023245*	
Wind-Direction	*-.0002662** *(.0000688)*	*-.0115876* *.0043811*	*.0021794* *(.0052435)*	*.0000178* *(.000066)*	*-.005134**** *(.0011365)*	*-.0016898* *.0010513*	
constant	*.206786 **** *(.0272297)*	*3.369486 *** *(1.404747)*	*-15.70249 ** *(8.299753)*	*.0313559 **** *(.001745)*	*1.567831 ** *(.8493843)*	*.970299* *(.302832)*	*46.287**** *(1.146521)*
observations	*39702*	*28978*	*22665*	*58902*	*68598*	*44468*	*132733*
Time fixed effects	*NO*	*NO*	*NO*	*NO*	*NO*	*NO*	*YES*
County fixed effects	*NO*	*NO*	*NO*	*NO*	*NO*	*NO*	*YES*
R-Squared	*0.0339*	*0.0958*	*0.0429*	*0.0233*	*0.1644*	*0.0444*	*0.0123*
F-Statistic *Prob > F*	*3.58* *0.004*	*17.39* *0.000*	*18.31* *0.000*	*44.35* *0.000*	*36.17* *0.000*	*0.97* *0.002*	*28.93* *0.000*

Table 6 Note: The impact of COVID-19 Strict Stay-at-home orders on US main air pollutants. Columns represent the dependent variable. City_treatment is the interaction term between the treated group (US states which implemented Strict-SHO policies) and the Time dummy variable . Fixed effects have not been considered in regressions. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 7. Secondary results, Equation 2 (Triple Differences)

Secondary results-Cluster State Level

2020-2019*(Strict-SHO 25March-31May)*	*CO*	*NO2*	*PM10*	*O3*	*PM2.5*	*SO2*	*AQI*
SHO	-.0022103 (.0253446)	4.806679*** (.9134133)	2.963806 (2.555686)	.0003186 (.0017385)	.2433648 (.5510656)	.0775914 (.1308865)	-15.18* (7.14715)
Time	-.0409777 (.0140142)	-.7976734 (.9134133)	.3097303 (1.301579)	-.00153*** (.000431)	-.089929 (.4591021)	.1250863 (.160025)	-1.9238** (.69600)
High_Gdp	.0421377 (.0258971)	1.187647 (.924743)	5.918581 (3.459251)	-.0026065 (.0016006)	1.750609** (.5042798)	.561979*** (.0917011)	-3.3443* (2.7650)
SHO_High_Gdp	-.0084849 (.0292928)	-1.998162** (.924743)	-2.61148 (3.656184)	.0004065 (.0018104)	-1.13009* (.6674108)	-.404167 (.288809)	1.434513 (4.41271)
Time-Gdp	.0196873 (.0139255)	-.0622645 (.7023842)	-4.39057 (2.541124)	.002*** (.0004459)	-.637655 (.4615989)	-.209494 (.159989)	1.321052 (.908313)
City_Treatment	.0336437 (.0204575)	-1.34699** (.7292398)	-.583524 (1.378548)	.0015314** (.0007281)	-.050482 (.5102853)	-.116114 (.174388)	-.31353 (.78624)
City_Treatment_High_Gdp	-.0429685* (.023282)	-.7510662 (.822394)	.4023932 (2.772293)	-.00346*** (.0007679)	-.095945 (.590503)	-.047357 (.2187515)	-2.0081** (1.052598)
Tempreature	.0006124 (.0005396)	.0457846* (.0228127)	.367661 (.0457459)	.000088* (.0000407)	.0900991 (.0155609)	-.005984* (.0034837)	
Wind-direction	-.000198** (.0000765)	-.008495* (.0033855)	-.004402 (.0042318)	.0000158*** (.0000311)	-.006944** (.0015882)	.0000876 (.0006014)	
Wind-speed	-.0001068 (.0001171)	-.0086961 (.0141487)	.9567781 (.5845804)	.0000406 (.0000428)	-.003366** (.0039103)	.0005727 (.0011702)	
constant	.2160302*** (.0352746)	2.677779** (0.002485)	-11.92** (5.627397)	.0298118*** (.0024856)	1.906307** (.8155215)	.7935135** (.223204)	51.24714*** (5.379134)
observations	32762	26980	20997	54617	72632	41566	101547
Time fixed effects	NO	NO	NO	NO	NO	NO	YES
County fixed effects	NO	NO	NO	NO	NO	NO	YES
R-Squared	0.0578	0.1474	0.0294	0.0452	0.1624	0.0150	0.0068

Table 7 Note: The impact of COVID-19 Strict Stay-at-home orders on US main air pollutants considering states GDP. Columns represent the dependent variable. City Treatment _High_Gdp is the interaction term between the treated group (i.e. US states which implemented Strict-SHO policies) and High-GDP equal 1 if state is in High-GDP category and the Time dummy equal to 1 if the date is between 25 $March31May$ 2020 and 0 if the date is between 25 $March - 31May$ 2019. Fixed effects have not been considered in regressions. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).

Table 8. Falsification Test for Secondary results, Equation 2 (Triple Differences)

Falsification Test-Secondary Results-Cluster State Level							
2019-2018(Strict-SHO 25March-31May)	*CO*	*NO2*	*PM10*	*O3*	*PM2.5*	*SO2*	*AQI*
SHO	*.035127** *(.0192865)*	*4.771065**** *(1.202091)*	*6.783895* *(4.966173)*	*.0011263* *(.0013462)*	*.2524904* *(.6212896)*	*.426314* *(.2904894)*	*-14.05714* *(9.34315)*
Time	*.010747* *(.017999)*	*-.9214021*** *(.3001414)*	*-22.6532*** *(3.373481)*	*-.002242** *(.0010199)*	*-.813359** *(.2540097)*	*.0190749* *(.0366292)*	*-6.441*** *(.6882466)*
High_Gdp	*.0590181**** *(.016369)*	*.5097204* *(1.225431)*	*9.278979** *(5.475199)*	*-.003398**** *(.0012092)*	*1.363897*** *(.5609301)*	*.8425959**** *(.0961058)*	*4.240337* *(5.01550)*
SHO_High_Gdp	*-.058704*** *(.0220825)*	*-2.535417** *(1.271344)*	*-4.91095* *(5.643876)*	*-.0000586* *(.0015782)*	*-.7617552* *(.6683774)*	*-1.08215**** *(.3762321)*	*6.602** *(11.73879)*
Time-Gdp	*-.0254528* *(.0178671)*	*.3145052* *(.3000519)*	*-3.76835* *(2.578732)*	*.0005312* *(.0010319)*	*.177206* *(.2686737)*	*-.391125*** *(.0380205)*	*2.242404* *(1.02238)*
City_Treatment	*-.0406568* *(.0262431)*	*-.1554419* *(.437765)*	*-3.90506* *(2.855314)*	*-.0008822* *(.0011593)*	*-.066447* *(.3209273)*	*-.391220* *(.280963)*	*1.889** *(1.01695)*
City Treatment _High_Gdp	*.0599159** *(.0263035)*	*.9040173** *(.4700611)*	*2.480729* *(2.899104)*	*.0006258* *(.0011872)*	*-.2313627* *(.438779)*	*.8095051* *(.3006588)*	*-.7841* *(1.34401)*
Temp	*.0010434*** *(.0003988)*	*.06131** *(.0305217)*	*.1984986**** *(.0212383)*	*.0001031*** *(.0000353)*	*.1012737* *(.0119818)*	*-.001534* *(.0037376)*	
Wind-direction	*-.0002783*** *(.000082)*	*-.0096817*** *(.003995)*	*.0005164* *(.0048442)*	*.0000189**** *(.0000479)*	*-.0052919** *(.0011001)*	*-.001425* *(.0010909)*	
Windspeed	*-.0001478* *(.0001623)*	*-.0127719* *(.0183409)*	*1.06525* *(.6494862)*	*.0000459* *(.0000501)*	*-.002577*** *(.0030826)*	*.001344* *(.0021684)*	
constant	*.1976737**** *(.0254481)*	*3.097913*** *(1.515124)*	*7.661759*** *(6.342402)*	*.0306725**** *(.0015867)*	*1.842054* *(.8195811)*	*.8223367* *(2791259)*	*50.43521* *(8.59934)*
observations	*39702*	*28978*	*22665*	*58,902*	*68,558*	*44,468*	*103111*
Time fixed effects	*NO*	*NO*	*NO*	*NO*	*NO*	*NO*	*YES*
County fixed effects	*NO*	*NO*	*NO*	*NO*	*NO*	*NO*	*YES*
R-Squared	*0.0463*	*0.1060*	*0.0290*	*0.0659*	*0.1748*	*0.0098*	*.0122*

Table 8 Note: The impact of COVID-19 Strict Stay-at-home orders on US main air pollutants considering states GDP. Columns represent the dependent variable. City Treatment _High_Gdp is the interaction term between the treated group (i.e. US states which implemented Strict-SHO policies) and High-GDP equal 1 if state is in High-GDP category and the Time dummy equal to 1 if the date is between 25 $March31May$ 2019 and 0 if the date is between 25 $March-31May$ 2018. Fixed effects have not been considered in regressions. The standard errors are reported in parentheses and are clustered at the state level. (*** p<0.01, ** p<0.05, * p<0.1).