# Estimating the Effect of COVID-19 Lockdowns on Changes in Air Quality

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**Abstract**

Polluted air from man-made activity poses a global threat to health and safety for humans and other species. COVID-19 lockdowns reduced mobility and visibly improved air quality for a portion of 2020 in several high polluting countries. I sought to quantify this improvement: I estimate the effect of COVID-19 lockdowns on national changes in PM2.5, PM10, SO2, and O3 levels over 15 countries. PM10 levels were reduced the most during lockdowns. There were slight improvements to PM2.5 levels and virtually no improvement to SO2 levels. O3 levels fared worse in the immediate days following a lockdown, compared to historical levels. Datasets and code are on Github (*Jennahh/covid_airqual*, n.d.).

## Introduction

The consequences of prolonged exposure to air pollution are dire to human health and safety. Fine particulate matter (PM2.5) refers to particles that have diameters of less than 2.5 micrometers. These particles remain in the air for long period and reduce visibility. There are long term health effects associated with over-exposure to elevated PM2.5 levels. Poor lung performance is one (Xing et al., 2016). Elevated PM2.5 levels are even positively associated with slightly higher levels of carbon emissions(**?**Anenberg et al., 2019). PM10 air particles are more coarse, with diameters of less than 10 micrometers. PM10 is a combination of particles like dust, dirt, smoke, and soot. PM10 is linked to aggravated asthma symptoms and lung cancer. SO2, or sulfur dioxide is a by-product of fossil fuels burning and volcanoes erupting. SO2 can harm the eyes and also make one susceptible to lung infection. The colorless, ordorless gas reacts with water and air to make acid rain (Queensland;, n.d.). Finally, Ozone or O3, has positive and negative effects. In the upper atmosphere, it protects the earth from ultraviolet rays. However, Ozone on the ground can severely pollute the air, leaving airways damaged thus making breathing more difficult (US EPA, 2015).

Transportation largely contributes to elevated air pollution (Sun et al., 2019). The burning of coal and other fossil fuels is the next contributor. However, in the face of COVID-19, vehicle use has dropped substantially. The pandemic caused many to begin working from home; commuting to work has almost diminished to nil. Many countries imposed severe travel restrictions, reducing air travel and factory operatios. Some countries even went under severe lockdowns--wherein citizens could only leave their home for essential items.

I investigate the effect of COVID-19 lockdown on national changes in air quality. I consider four outcome variables: changes in levels of PM2.5, PM10, SO2, and O3. I use a standard Ordinary Least Squares (OLS) regression on extensive panel data, comprising daily observations of 15 different countries. PM10 levels were most affected by the lockdown. There were slight improvements to PM25 levels and virtually no improvement to SO2 levels. O3 levels fared worse in the immediate days following a lockdown, compared to historical levels.

Negative outcomes generally characterize lockdowns. Stay at home orders dampen economic activity. Small businesses often do not survive, and even massive corporations take a big hit. Youth development can stall when learning goes remote. On a micro level, lockdowns can have an impact on people's mental health. Staying in isolation for months on end can lead to anxiety or depression. The Centers for Disease Control and Prevention found elevated mental health challenges and substance use associated with COVID-19 (Czeisler, 2020).

One positive outcome to lockdowns are the environmental effects. From pictures alone, air quality levels improved drastically at the onset of lockdowns. People reported being able to see the Himalayas for the first time in decades(CNN, n.d.). Folks from New Delhi reported breathing easier. Several countries might not reach herd immunity or have a widespread vaccine for another several years. Lockdowns could be commonplace, so understanding their environmental and health consequences will be invaluable.

Existing literature examines the effects of covid-19 lockdowns on one specific region. Sharma et al. (2020)considers a number of air pollutant species, but only focusing on New Delhi, India. Chang et al. (2020) looks at two major cities in Taiwan that did not experience any economic or social lockdown COVID-19 restrictions. Chang finds that air pollution here actually worsened this year. I wanted to build off this research by analyzing more countries over a longer span of time.

Section I discusses background, data sources, and mechanisms for which lockdowns affect air quality. Section II overviews the design. Section III discusses results. I conclude in Section IV. Section V is the appendix with additional tables and figures. Data/code is documented on GitHub *Jennahh/covid_airqual* (n.d.).

# 1 Background and Data

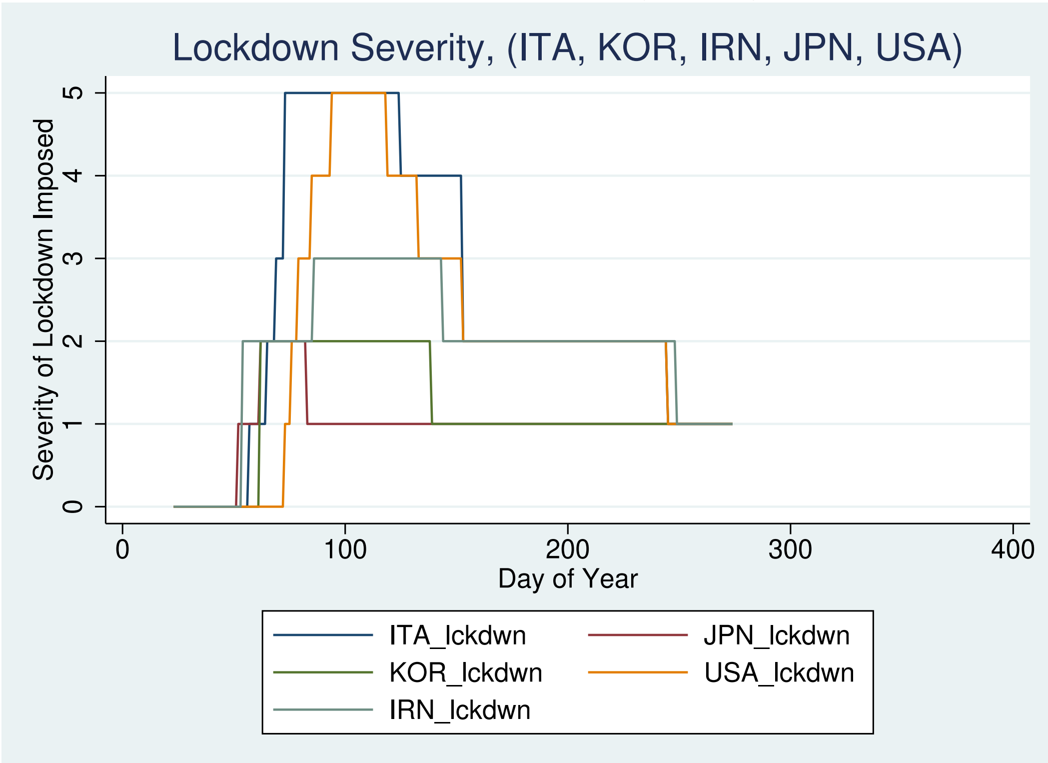
## 1.1 Summary of Data

I observe the following countries: Sweden, Japan, South Korea, India, Iran, China, Russia, Germany, Italy, UK, France, Spain, Peru, Mexico and the US. I chose this subset of countries for a varying severity of lockdown and historical precedence of air pollution. Lockdown data comes from Olivier Lejeune, an energy and weather analyst (Lejeune, 2020). Data is first observed from January 23rd, 2020, when China imposed the first lockdown, until September 23rd, 2020. Lejeune codifies the severity of the lockdown on a scale of 0-6 everyday as follows:

0: Very few or no restrictions to daily life.

1: Ban on large public gatherings.

Figure 1: Lockdowns, by Country (Group A)




2: Schools and universities closed.

3: Non-essential services (e.g bars, restaurants, shops) closed or available for carry-out only.

4. Partial lockdown or night curfew in place.

5. Severe lockdown. Government has prescribed staying at home all day except for essential trips to grocery store of pharmacy.

6. Harshest lockdown possible. Government has prescribed staying at home all day, no exceptions.

The data is described at the country level for all countries except for the US, wherein data is observed at the state level. I aggregated the US data by taking the average lockdown score across each state daily. See figures below for lockdown severity for each country.

Fine Particulate Matter, or PM2.5, is the strongest indicator of air quality. Air quality data comes from the Air Quality Open Data Platform Worldwide COVID-19 and is observed daily at the city level(project, n.d.) . To aggregate this data to the country level, I average median species count for all observed cities for the day. I have done the same for PM10, SO2, and O3.

Finally, death count from COVID-19 data comes from the Center for Systems Engineering and Science at Johns Hopkins University (JHU). JHU has been one of the leading institutions for tracking the spread and outcomes from the global pandemic. Once again, the data is publicly available on GitHub (*CSSEGISandData/COVID-19*, n.d.). The data is described daily since January 23rd at the country level, with the exception of China. However, I have aggregated all Chinese provinces for country level

Figure 2: Lockdowns, by Country (Group B)

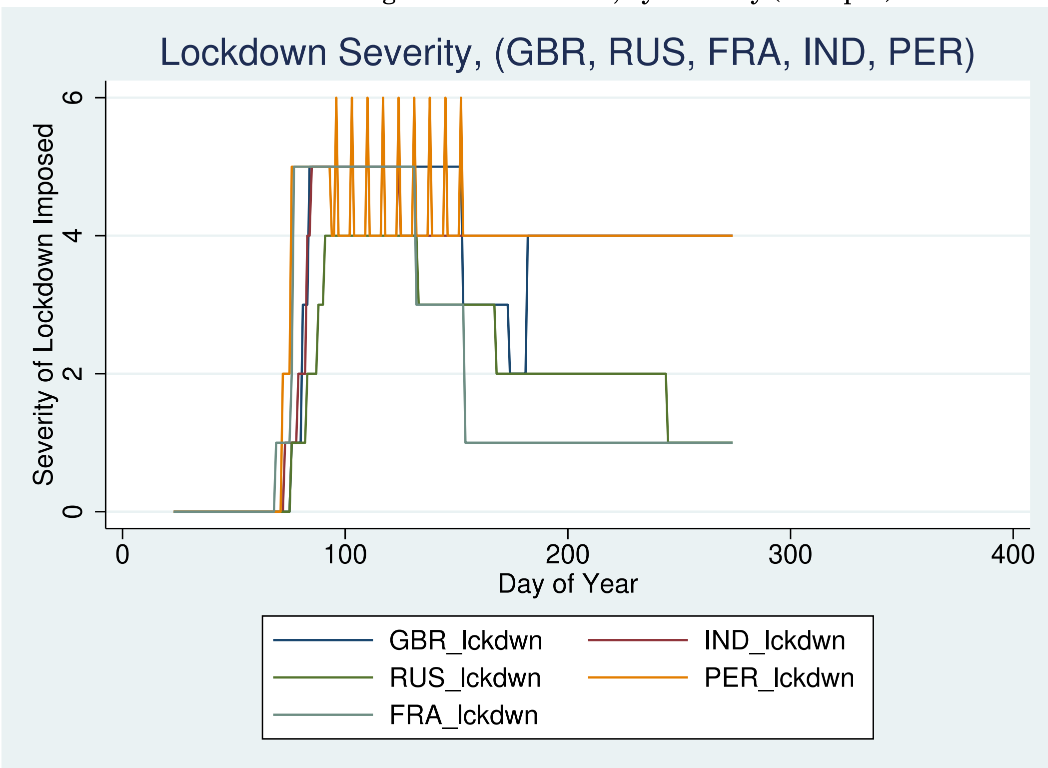



Figure 3: Lockdowns, by Country (Group C)

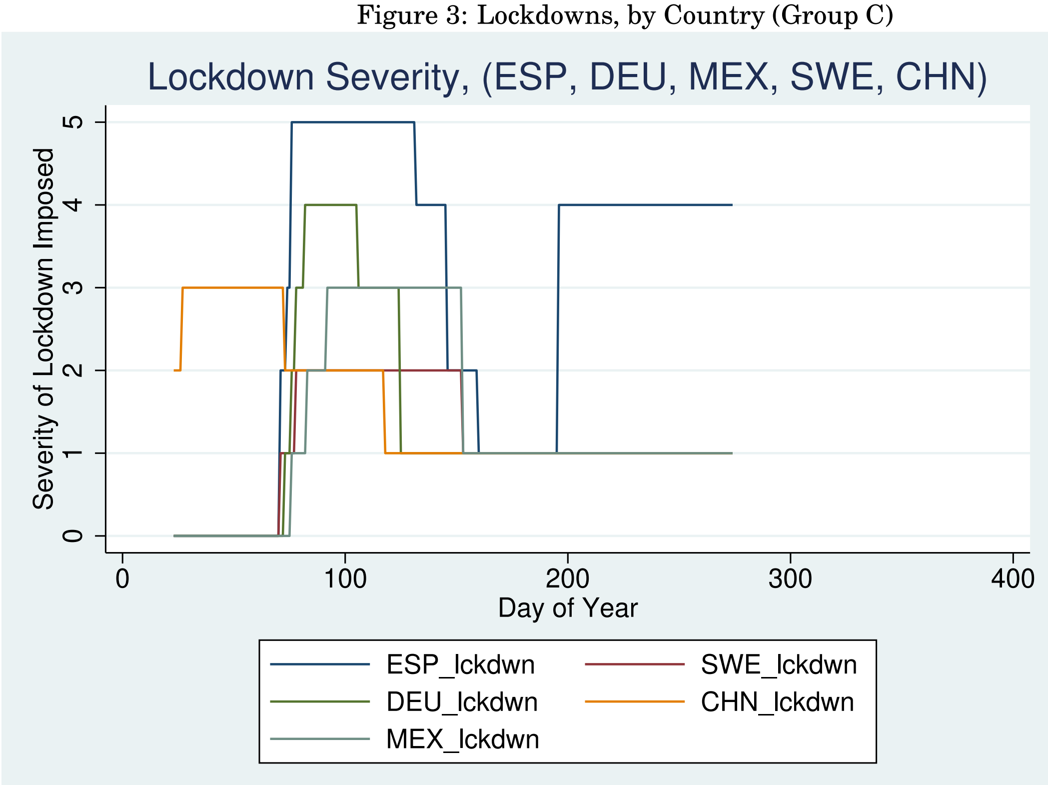
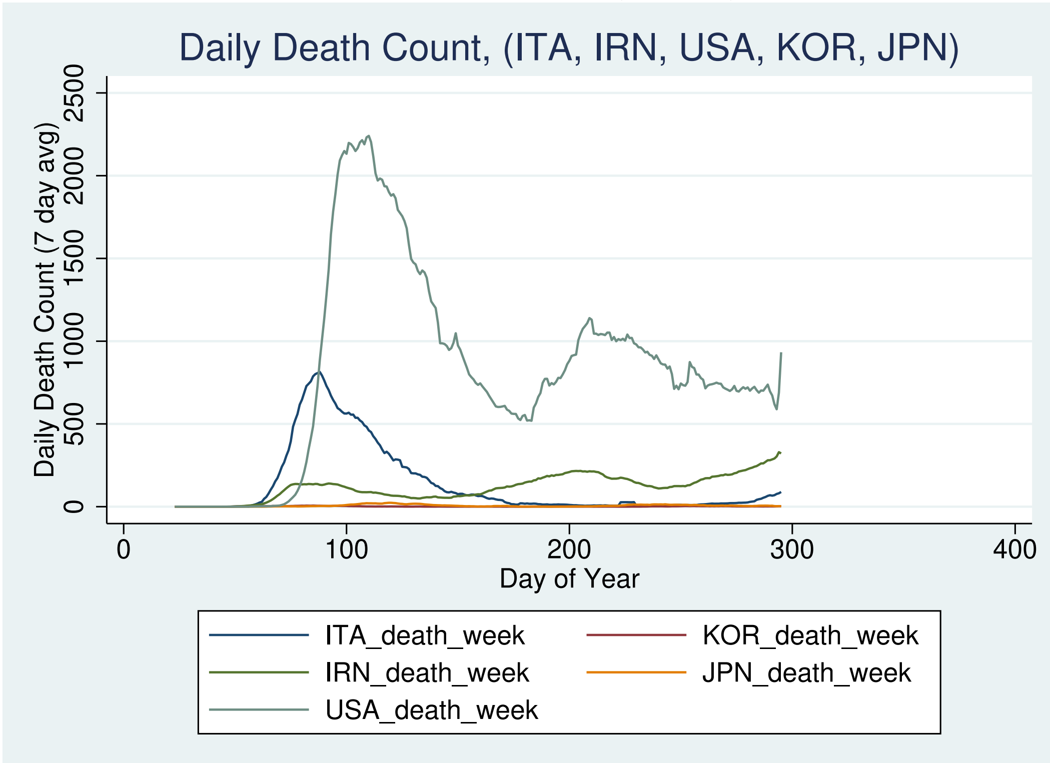


Figure 4: Deaths, by Country (Group A)




observations. I smooth the data so that each day represents the average deaths per day over a 7 day period. See figures below for daily death count.

There are four final datasets I use. Each air pollutant species gets its own dataset, with observations for each country for each day of the year. On each day, I encode the number of days since a lockdown of severity 3 or higher was first imposed. I also include the rolling death count for that day, and the air pollutant species median count on that day, and on the same day of the year in both 2019 and 2018. I will discuss how each variable will be used in 2.

## 1.2 Mechanisms

There are many possibilities in which lockdowns impact a country's overall change in air quality. The first is mobility. Under lockdowns, travel becomes severely limited. People are using cars, buses, trains, and planes much less often compared to standard benchmarks. Google mobility is tracked through smartphone data based on indicators related to retail, grocery, transport and workplaces. Mobility plummets for several countries with strict lockdowns, and remains stable for countries without lockdowns (*COVID-19 Community Mobility Report*, n.d.). This suggests a decrease in air pollution.

Another mechanism in which lockdowns would change air quality is through residential heating. Typically, there is an uptick in electricity output and overall heating usage when people are in their homes. There is a large dip during the day when people go to work or school. However, if the majority of people are working from home or attending school remotely, residential heating and electricity would go up. This suggests an increase in air pollutant species.

Figure 5: Deaths, by Country (Group B)

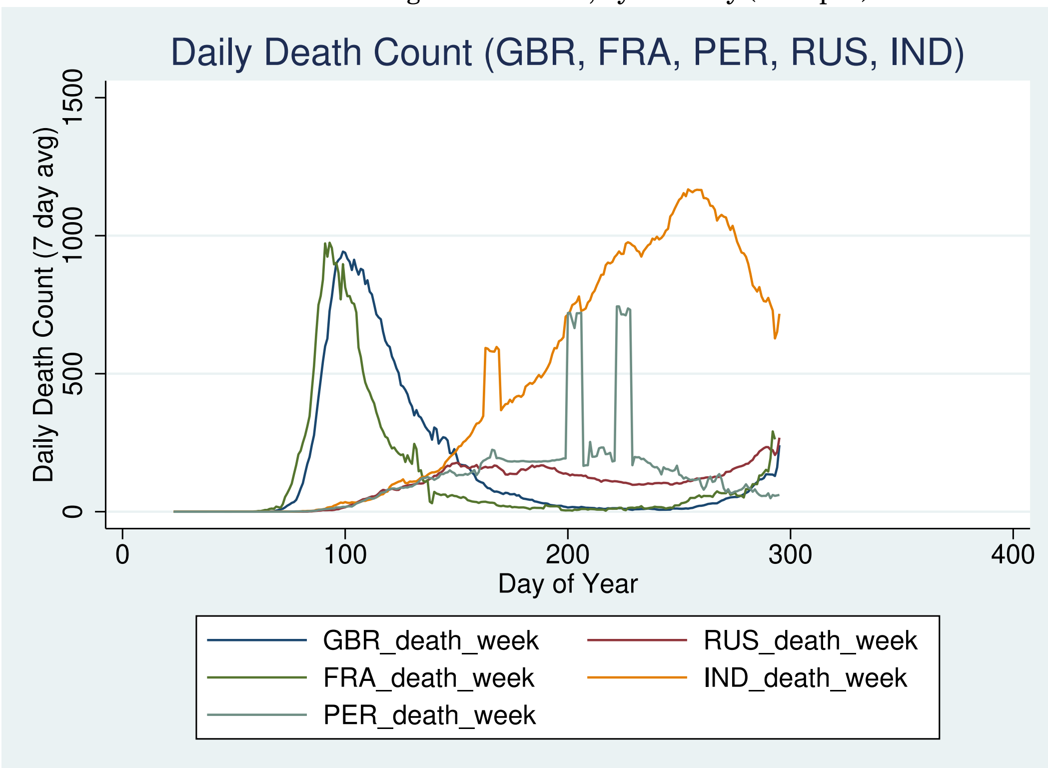
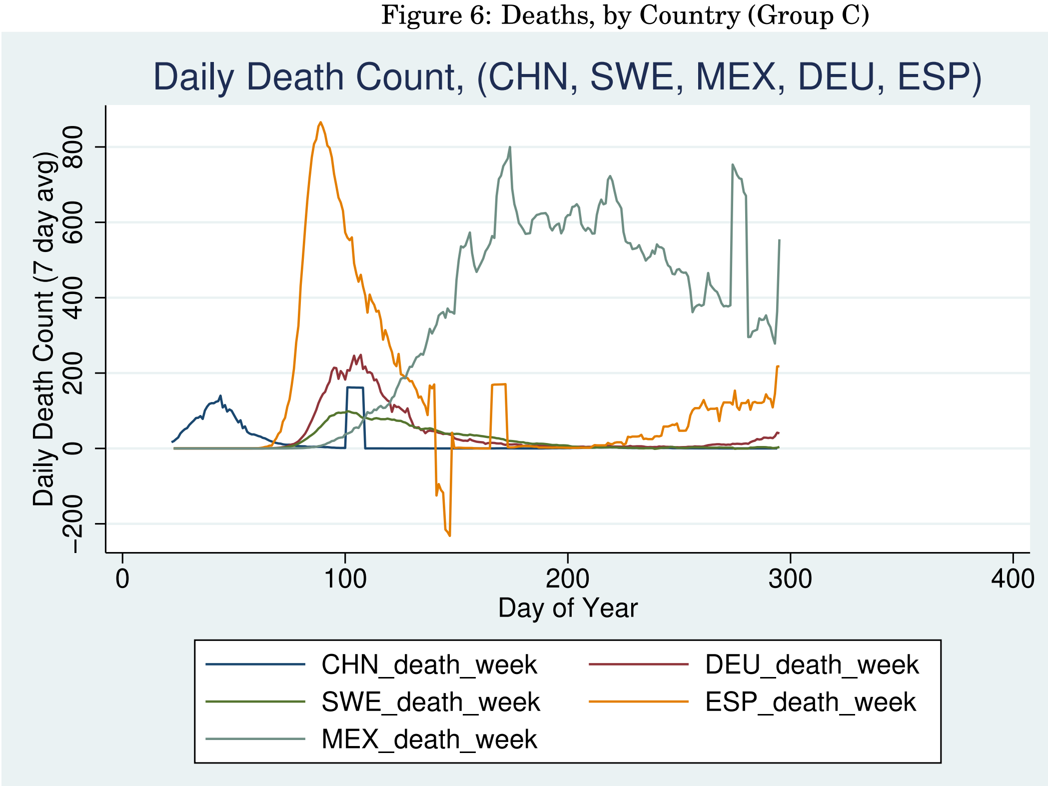



Figure 6: Deaths, by Country (Group C)



The third mechanism to consider is factory closures. Manufacturing production largely stalled in the early months of the pandemic. All US automakers in Detroit elected to temporarily close all their factories in America, Mexico, and Canada after positive test cases were confirmed at various plants. Many European manufacturers followed suit, some closing for good. Factories burn coal and fossil fuels, suggesting lower levels of air pollution.

# 2 Design

## 2.1 Identification Strategy

I use a panel event study, related to the difference in differences approach, to answer my research question. This proved to be the best strategy since I observe the effect of several different types of lockdowns across 15 countries for almost a year. A few threats should be mentioned. A key assumption is the standard difference in difference parallel trends assumption. The control group and treated group should have the same outcomes if it were not for the lockdown. That would mean countries areidentical. This is obviously not true regarding population, climate, economic development, etc. More related to this research, certain countries already have higher levels of pollution and would likely see the biggest change. Event leads do, however, allow for examination of trends in the pre-treatment period. Country fixed effects are encoded. I also account for seasonality by using air quality data from 2019 and 2018.

There are controls since a few countries, like Sweden and South Korea, never imposed a formal lockdown. Each lockdown is also not identical and has its own provisions. I address this threat by declaring the day of the lockdown as the first day in which a lockdown of severity 3 or higher is imposed. If a country immediately jumps from severity 2 to severity 4, I choose the day in which a 4 was imposed as the onset of the lockdown. The next threat is that the timing of the treatment is likely not random. Most lockdowns were imposed when countries started to see an uptick in cases within their own borders or nearby. I attempt to account for non-random timing by including a number of lags and leads for my model.

## 2.2 Empirical Details

There are concerns of omitted variable bias when examining the effect of lockdowns on air quality. The most obvious is that lockdowns themselves may not will people to stay at home. The decision to quarantine may have been voluntary and separate from government restrictions. The nature of panel data remedies this problem. I have observations on air quality levels ranging from 80 days before the lockdown was put in place to 200 days after. The immediate few days following the lockdown order is most likely when the people staying at home are doing so to comply with government regulation. The next threat is that countries may impose severe lockdowns but perhaps people are not in compliance. Alternatively, people may choose to stay at home and reduce overall mobility (thus improving air pollution) when there is an uptick in cases, regardless of the severity of the lockdown imposed. To account for this, the daily average death count is added as a control.

I run a standard Ordinary Least Squares (OLS) regression. The outcome variable is change_pm25, indicating the change in PM2.5 species count from 2020 to 2019. This accounts for time fixed effects and seasonality. I generate another variable days_since_lckdown, which subtracts the day a lockdown of severity 3 was imposed from the current day of the observation. If a lockdown doesn't reach severity 3, the country is treated as a control group. If a country immediately skipped from a 2 to 4 lockdown severity, then the day a 4 was imposed is encoded as the start of the lockdown. I also account for country fixed effects since the historical air pollution levels as well as length and timing of the lockdown varies widely country to country. Standard errors are clustered at the country level since observations among the same country are much more closely related than observations of differing countries. I also simulate a placebo lockdown to see how much of the change in air quality is due to seasonality versus the actual lockdown put in place. Finally, I repeat all these regressions for the other 3 dependent variables of interest: change_pm10, change_so2, change_o3.

Equation: change_pollutant = a*country_fe + b*days_since_lckdwn_fe + c*average_death_day + d*pollutant_19 + constant

Placebo equation: change_pollutant_placebo = e*country_fe + f*days_since_lckdwn_fe + g*average_death_day + h*pollutant_18 + constant

# 3 Results

Of the four species of pollutants, PM10 levels saw the biggest reduction from the lockdown, followed by slight changes in PM25 levels. SO2 sees no real change, and O3 counterintuitively saw a positive change. This may be because PM is largely associated with cars and other forms of transportation, while SO2 stems from the burning of any fossil fuel. O3 levels can even be elevated in warmer temperatures. See the tables in the appendix for exact coefficients for the countries and immediate days following the lockdown. In all species, the average_death_day variable has little to no effect in either the real lockdown or the simulated one.

First, examine PM2.5 levels. In the first few days after a lockdown, the change in PM25 levels from 2020 to 2019 shrinks. On Day 1, there is an average 6.6301 change in median PM2.5 species count from the previous year; this represents an increase from the 4.343 change under the placebo lockdown in 2019. However, the standard error on all of these coefficients are incredibly high. Examining the placebo lockdown simulated in 2019, Days 2-4 after the lockdown was imposed, the change in PM2.5 from 2020 to 2019 is slightly smaller than the change in 2019 to 2018, though both coefficients still representative a positive increase from the former year. But again, there is no statistical significance to these numbers at the 90% confidence level nor the 95% level. This may indicate again that all the pollution at the beginning of the year in 2020 may have not been completely offset from the lockdown. It could be that there needs to be a longer period of immobility until pollution levels actually start to decrease. As you extend beyond 10+ days after the lockdown was imposed, the changes become much more pronounced. In the normal lockdown, there a typical reductions anymore from -5 to -10, while the placebo lockdown sees positive gains from historical levels. However, the longer the period after the lockdown, the less clear it is that people are staying at home directly to comply with government orders. Looking at the country fixed effect coefficients, many countries like Germany, France, the UK, and the US see a massive reduction in PM2.5 levels. This information is somewhat useful since no country has reverted to a lockdown of 0 yet; however, again it should be interpreted with caution since after a certain amount of time people may only be voluntary staying at home and not acting to comply with government mandates.

I consider PM10 next. The ensuing days after a lockdown the change in PM10 levels from 2020 to 2019 gets smaller and smaller. This indicates that the presence of a lockdown does improve air pollution, however these results are not statistically significant. Looking at the placebo lockdown held in 2019, however, one can see coefficients are vastly different. On the first day after a lockdown in 2020, there is an estimated 2.674 increase in PM10 species count compared to 2019 levels. However, a placebo lockdown in 2019 increases the change PM10 species count compared to 2018 levels by 20.611. Mexico and Italy see large reductions in PM10 levels. China sees heightened levels of PM10 by more than 27 species count.

Next, I look at SO2 species count. There is no real change in SO2 levels upon inspecting the few days after lockdown severity in both the real lockdown and the simulated one. In fact, the day after a lockdown saw a greater change in SO2 levels compared to the change during the placebo lockdown. Day 2 after the lockdown the change was smaller than in the placebo lockdown, however in Day 3 or 4 the gap widens once more. Again, very few of these results are statistically significant at the 10% or 5% level. Iran saw an increase in SO2 species count by nearly 12, but virtually every other country saw SO2 levels decrease. China, USA, and India saw the biggest changes. The coefficient for China went from 4.380 for the placebo lockdown to -5.064 in the real lockdown. The coefficient for India went from 5.921 to -5.671. The USA went from 0.458 to -8.577. Nearly all these results were significant at the .1% level too.

Finally, I examine O3 species count. O3 levels largely increased under the real 2020 lockdown compared to if we were to simulate a placebo lockdown in 2019. In the few days after the placebo lockdown in 2019, changes in O3 levels range from -13.1 to -14.9, all significant at the .1% level. However in 2020, these changes rise to 0.07 to 1.7, not statistically significant at any level. This demonstrates that O3 levels actually fared worse when there was a lockdown compared to historical trends. Country-wise, I also find some interesting patterns. Every single country sees a decline in the level of O3 from 2020 to 2019 compared to 2019 to 2018. A few countries, such as India, Italy, Peru, and Russia, even see these changes with statistical significance (see table below).

# 4 Conclusion

In this paper, I estimated the effects of COVID-19 lockdown on national changes in air quality. I observed 15 countries with varying levels of lockdown severity. I find that lockdowns affected PM10 levels the most. There were slight improvements to PM25 levels and virtually no improvement to SO2 levels. O3 levels fared worse in the immediate days following a lockdown, compared to historical levels. Several countries, including high polluting ones like India and China, saw large drops in all species counts for the duration of the year. Even countries without historical air quality concerns like Italy and Spain faced large reductions in species count from the 4 pollutants. While it seems lockdowns only had a real causal effect on reducing PM10 levels and perhaps PM25 levels, it is quite clear that the lower mobility rates across these 15 countries, which may or may not have been because of lockdowns, has heavily impacted each country's environment.

The cost reduction from the improved air quality is substantial. (Muller et al., 2011)found that damages of pollution from small cars in the year 2002 cost $37 billion in the US alone. Residential heating amounted to an additional $17 billion in damages. That amounts to $54 billion. Given that I consider 15 countries in the year 2020, the amount saved could be anywhere between 5-10x that. 400 million people live with Asthma (*Chronic respiratory diseases: Asthma*, n.d.). Their symptoms may subside if lockdown air conditions continued. Lung cancer is the most common cancer across the world (*Lung Cancer Fact Sheet*, n.d.). This could drastically change if particulate matter were less prolific. This is further evidence that human activities impact our climate and safety. A global pandemic may help reduce mobility through stay at home orders, but eventually activity will resume and environmental conditions will worsen. Policymakers will have to implement reforms to incentivize citizens to reduce mobility, and get major corporations and factories to curb their fossil fuel burning. Economists widely agree the optimal solution is to Introduce a carbon tax. A cap and trade system is another option. Regardless, when lockdowns come to a halt, countries should act quickly to continue enjoying the safer health conditions and scenery.

# 5 Appendix

Table 1: Regression results PM25

| | (1) | (2) |
|---|---|---|
| | chng_pm | chng_pm_placebo |
| | b/se | b/se |
| CHN | 1.624 | 37.127*** |
| | (3.01) | (11.13) |
| DEU | -36.415*** | -11.817** |
| | (6.11) | (4.37) |
| ESP | -35.431*** | -10.580** |
| | (6.34) | (4.03) |
| FRN | -35.058*** | -9.145** |
| | (6.28) | (4.05) |
| GBR | -38.260*** | -10.052** |
| | (6.39) | (4.31) |
| IND | 0.000 | 53.252*** |
| | (.) | (15.32) |
| IRN | 2.448 | -61.943*** |
| | (7.04) | (7.85) |
| ITA | -21.519*** | 0.316 |
| | (5.20) | (5.18) |
| JPN | 0.000 | 0.000 |
| | (.) | (.) |
| KOR | 0.000 | 0.000 |
| | (.) | (.) |
| MEX | -15.231*** | 3.963 |
| | (4.57) | (6.31) |
| PER | -15.290*** | 4.525 |
| | (3.56) | (6.79) |
| RUS | -28.535*** | 0.000 |
| | (6.13) | (.) |
| SWE | 0.000 | 0.000 |
| | (.) | (.) |
| USA | -36.147*** | -20.365*** |
| | (6.16) | (5.09) |
| avg_death_day | 0.004 | 0.002 |
| | (0.00) | (0.00) |
| pm25_19 | -0.676*** | |
| | (0.08) | |
| 1day_since_lckdwn_ | 6.301 | 4.343 |
| | (6.08) | (3.32) |
| 2day_since_lckdwn_ | 3.309 | 4.846 |
| | (4.89) | (4.47) |
| 3day_since_lckdwn_ | 4.726 | 5.815** |
| | (5.60) | (2.20) |
| 4day_since_lckdwn_ | 3.027 | 7.263 |
| | (7.33) | (6.10) |
| N | 3442 | 2021 |
| R-squared | 0.68 | 0.68 |

Table 2: Regression results SO2

| | (1) | (2) |
|---|---|---|
| | chng_so2 | chng_so2_placebo |
| | b/se | b/se |
| CHN | -5.064*** | 4.380*** |
| | (0.43) | (0.83) |
| DEU | -8.271*** | 0.246 |
| | (0.29) | (0.84) |
| FRN | -7.298*** | 1.244 |
| | (0.23) | (0.70) |
| ESP | -8.459*** | 0.088 |
| | (0.24) | (0.68) |
| GBR | -7.208*** | 1.436** |
| | (0.18) | (0.65) |
| IND | -5.671*** | 5.921*** |
| | (0.12) | (0.88) |
| IRN | 12.048*** | -0.880 |
| | (0.08) | (1.02) |
| ITA | -7.602*** | 0.943 |
| | (0.26) | (0.62) |
| JPN | 0.000 | 0.000 |
| | (.) | (.) |
| KOR | 0.000 | 0.000 |
| | (.) | (.) |
| MEX | -4.008*** | 10.993*** |
| | (0.10) | (1.07) |
| PER | 0.000 | 20.866*** |
| | (.) | (1.02) |
| RUS | -4.879*** | 0.000 |
| | (0.20) | (.) |
| SWE | 0.000 | 0.000 |
| | (.) | (.) |
| USA | -8.577*** | 0.458 |
| | (0.26) | (0.46) |
| avg_death_day | 0.000 | -0.001 |
| | (0.00) | (0.00) |
| so2_19 | -0.972*** | |
| | (0.01) | |
| 1day_since_lckdwn_ | 0.790** | 0.351 |
| | (0.32) | (0.47) |
| 2day_since_lckdwn_ | 0.425 | 0.811** |
| | (0.31) | (0.35) |
| 3day_since_lckdwn_ | 0.321 | -0.001 |
| | (0.30) | (0.51) |
| 4day_since_lckdwn_ | 2.638 | -0.816 |
| | (2.41) | (1.27) |
| N | 3419 | 2017 |
| R-squared | 0.88 | 0.81 |

Table 3: Regression results PM10

| | (1) | (2) |
|---|---|---|
| | chng_pm | chng_pm_placebo |
| | b/se | b/se |
| CHN | 54.692*** | 27.858*** |
| | (4.07) | (1.83) |
| DEU | -24.483*** | -10.839*** |
| | (5.83) | (1.77) |
| ESP | -23.018*** | -7.764*** |
| | (6.16) | (1.63) |
| FRN | -24.556*** | -9.902*** |
| | (6.45) | (1.64) |
| GBR | -25.723*** | -11.103*** |
| | (6.45) | (1.72) |
| IND | 0.000 | 59.863*** |
| | (.) | (3.01) |
| IRN | 6.784 | -30.510*** |
| | (5.84) | (2.53) |
| ITA | -19.507*** | -3.829** |
| | (5.98) | (1.45) |
| JPN | 0.000 | 0.000 |
| | (.) | (.) |
| KOR | 0.000 | 0.000 |
| | (.) | (.) |
| MEX | -12.827** | 7.455*** |
| | (4.24) | (2.35) |
| PER | -5.703 | 12.030*** |
| | (4.40) | (2.12) |
| RUS | -25.433*** | 0.000 |
| | (6.01) | (.) |
| SWE | 0.000 | 0.000 |
| | (.) | (.) |
| USA | -22.501*** | -11.516*** |
| | (5.05) | (1.59) |
| avg_death_day | 0.002 | -0.001 |
| | (0.00) | (0.00) |
| pm10_19 | -0.718*** | |
| | (0.09) | |
| 1day_since_lckdwn_ | 2.674 | 20.611*** |
| | (3.00) | (2.14) |
| 2day_since_lckdwn_ | 2.715 | 21.058*** |
| | (3.23) | (3.30) |
| 3day_since_lckdwn_ | 0.466 | 22.410*** |
| | (3.33) | (2.88) |
| 4day_since_lckdwn_ | 0.092 | 22.444*** |
| | (3.12) | (3.13) |
| N | 3441 | 2017 |
| R-squared | 0.77 | 0.80 |

Table 4: Regression results O3

| | (1) | (2) |
|---|---|---|
| | chng_o3 | chng_o3_placebo |
| | b/se | b/se |
| country_1 | 7.055 | 11.552*** |
| | (4.37) | (2.14) |
| country_2 | 4.899 | 14.272*** |
| | (3.58) | (1.68) |
| country_3 | 4.375 | 15.937*** |
| | (3.94) | (2.03) |
| country_4 | 4.798 | 15.392*** |
| | (3.91) | (1.92) |
| country_5 | 3.915 | 12.733*** |
| | (3.27) | (1.09) |
| country_6 | -4.561* | 7.524*** |
| | (2.44) | (1.04) |
| country_7 | 0.000 | -6.015*** |
| | (.) | (0.99) |
| country_8 | 10.278** | 17.296*** |
| | (4.64) | (2.28) |
| country_9 | 0.000 | 0.000 |
| | (.) | (.) |
| country_10 | 0.000 | 0.000 |
| | (.) | (.) |
| country_11 | -1.638 | 24.966*** |
| | (4.89) | (2.75) |
| country_12 | -11.216*** | 0.000 |
| | (2.17) | (.) |
| country_13 | -7.043* | 0.000 |
| | (3.31) | (.) |
| country_14 | 0.000 | 0.000 |
| | (.) | (.) |
| country_15 | 2.505 | 21.019*** |
| | (4.16) | (1.97) |
| avg_death_day | -0.002 | 0.001 |
| | (0.00) | (0.00) |
| o3_19 | -0.763*** | |
| | (0.13) | |
| 1day_since_lckdwn_ | 0.073 | -14.912*** |
| | (2.93) | (2.25) |
| 2day_since_lckdwn_ | 1.109 | -13.189*** |
| | (3.26) | (2.52) |
| 3day_since_lckdwn_ | 1.314 | -13.652*** |
| | (3.03) | (2.43) |
| 4day_since_lckdwn_ | 1.698 | -13.469*** |
| | (3.17) | (2.15) |
| N | 2953 | 1986 |
| R-squared | 0.73 | 0.65 |

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