**The Effect of COVID Lockdowns on CO2 Emissions**

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Air pollution is a global concern. According to the NIH, it can contribute to negative health outcomes such as asthma, COPD, heart attacks, and strokes. It is a continual source of policy debate, in the domestic and international theaters, as nations struggle to balance industry, regulation, and accountability at home and abroad.

COVID-19 lockdowns give a unique opportunity to examine human impact on air quality. As the entire United States locked down in a roughly one-month window, human activity such as driving and manufacturing were drastically reduced. Photos of clear skies in normally smoggy cities and dolphins in waterways went viral. In a sense, we can view this short period as representing an extreme change in human behavior; if we severely curtail our activity, how much can we improve air quality?

From the Environmental Protection Agency’s Air Quality System database, we will be utilizing trends in the Air Quality Index (AQI) to look at the effects of COVID-19 lockdowns on air quality. We utilize data ranging from March 1st, 2019, up until January 1st, 2022, to capture the effect of the lockdowns on the AQI levels. We selected eleven of the most densely populated counties. Highly populated areas are more likely to have poor air quality to begin with, and, with more people staying home, they are likely to have a more pronounced change than rural areas.

To measure the effect of COVID lockdowns, we developed an ARIMA model for each county. Trained on data from before the COVID lockdowns began, our forecast represents a counterfactual in which the COVID-19 pandemic and lockdowns never occurred. We utilized the R package “fable”, which selected the optimal ARIMA model to be used for each time series (i.e. for each county).

Even though we have data up until January 1st, 2022, our model is only be trained on data up until each county’s respective lockdown dates. We then use our model to forecast 90 days out, and compare to the real data to see the effect of the lockdowns on the air quality in each county.

State/Region Approx. Date of Lockdown

New York March 23, 2020 New Jersey March 16, 2020

Virginia March 30, 2020

Massachusetts March 15, 2020

California March 19, 2020

Pennsylvania March 23, 2020

District of Columbia March 16, 2020

Table A: Includes the states we pulled counties from, and their respective approximate lockdown dates.

The first models we created using fable’s ARIMA function looked at data from every day to create a forecasting model. We found the models were unable to capture day to day variation in air quality, and essentially could only forecast a mean out. However, plotting the forecast against the true data, while noisy, appeared to show that the true air quality index was lower than the forecast.







Figure 1: A selection of air quality forecasts plotted against the true air quality index at the daily level. Counties shown are San Francisco County, CA, Suffolk County, MA, and Queens County, NY

To provide a clearer picture of the relationship, we aggregated the data to the monthly level, and present the same three counties below:

**(I)**

A graph showing a graph of a graph

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**(II)**

A graph showing the number of months

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**(III)**

A graph showing the number of months and months

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Figure 2: Air quality forecast at the monthly level for (I) San Francisco County, CA, (II) Suffolk County, MA, and (III) Queens County, NY. Note the discontinuity reflects two observation groups for March: the first half of the month, before lockdowns began, and the latter half of the month, after lockdowns began. The exact date of the split varies by county, pursuant to Table A.

By our judgement, these three counties are roughly representative of the eleven counties we chose; plots of other counties are elided either due to their similarity to the above plots or missing data. Aggregation at the monthly level more clearly displays that air quality index was lower than the AQI predicted by our counterfactual ARIMA model, suggesting COVID lockdowns improved air quality.

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Table B: Shows the order of each Arima model created for each county.

Above we can see that there was a different order chosen for each Arima model created for almost every county. This is a sign of having no time trend with respect to AQI because if there was, we would expect the processes to be similar across all counties. Slight differences in the models may be tolerable, but having one model that is AR(1) and another that is AR(5) raises an eyebrow.

Given that the ARIMA models we constructed essentially do no better than simply forecasting a mean, there is no trend over time, and working with the eleven counties individual is tedious, a regression-based approach is more appropriate.

To do this, we performed a regression of AQI on discrete monthly time periods. In effect, this aggregates our data for the eleven counties. The trend over time is modeled with comparison to March 2020, the reference group. Standard errors are clustered at the county level, which calculated more accurate standard errors with the within cluster variation, instead of throwing away all that information. A symbolic representation of the regression equation, as well as results presented as a graph and table, are available below.

**AQI = β0 + βt + ε**

Where:

AQI is air quality index; β0 is an intercept; βt is a unique value for each time period (i.e month); and ε is an error term.

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Figure 3: Linear regression approach with March 2020 used as the reference group.

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Table C: Table including the estimated coefficients for each month.

Our findings are perhaps clearer in the coefficient plot; the two months immediately following March 2020 have near zero coefficients, which were not statistically significant. This would seem to reflect that April and May of 2020 had an air quality that was quite similar to March. Ideally, we would’ve found a negative coefficient, but, given that COVID lockdowns began in the middle of March, the effect is somewhat muddled. Considering that the months before March 2020, as well as the summer months of 2020, have much larger, statistically significant coefficients, it would seem that COVID lockdowns did indeed improve air quality for a period of about two months.

It is difficult to account for certain situations in our model. People did not always comply with COVID lockdowns. In a less compliant area, we might expect air quality to remain elevated. In future research, we may want to incorporate data on people’s movement (Google publishes one such dataset) to try to estimate compliance.

The idea of a “lockdown” is a somewhat vague term as well. Actual restrictions and enforcement vary by jurisdiction. We chose lockdown dates by the issuance of stay-at-home order where available, but in some cases identifying the “start” of a lockdown is more art than science.

Lastly, our rather small selection of counties may make it difficult to generalize our results. We chose only 11 counties, and they are densely populated, urban counties. Do these results hold in suburban areas? In urban areas? Perhaps a better approach would be to simply use all the data available in the EPA’s API.

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