Applications of Causal Inference

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Causal Inference Tutorial

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Introduction

On March, 11th, the World Health Organisation declared the Coronavirus outbreak as a global pandemic. The pandemic is growing in a climate of unprecedented political polarization, both globally and nationally. As a result, the effectiveness of public health regulations to contain the pandemic is still bipartisan globally. Thus, there is a growing need for empirical evidence to support the effectiveness of certain policies, such a s lockdown or travel ban, on the number of COVID-19 cases and deaths. Luckily, researchers Thomas Hale, Andrew J. Hale, Beatriz Kira, Anna Petherick, Toby Phillips, Devi Sridhar, Robin N. Thompson, Samuel Webster, and Noam Angris developed the Oxford COVID-19 Government Response Tracker (OxCGRT) which collects data on COVID-19 taken by governments across the world. In their Global Assessment of the Relationship between Government Response Measures and COVID paper, researchers measured the causal effect of government stringency policies on the number of deaths in each country. This paper explains the context of OxCGRT, and it extends to the original casual model proposed in (*Hale et al., 2020).*

Oxford COVID-19 Government Response Tracker (OxCGRT)

OxCGRT is a publicly available, real-time-updated dataset that has measures of policies implemented globally. There are main 3 types of measures:

1. C - containment and closure policies
2. E - economic policies
3. H - health system policies

C - Containment and Closure Policies

These are the policies that governments adopted as preventive measures of virus transmission. OxCGRT summarizes all of these policies into eight sub-policies. School Closing

1. Workspace Closing
2. School closing
3. Cancelation of Public Events
4. Restrictions on Gatherings
5. Stay at home requirements
6. International travel controls

Each of the policies has an ordinal scale to measure the scope of the policy. For example, the School closing policy has a value between 0 and 3, where 0 indicates no implementation of such policy, 1 indicates recommendation closing schools, 2 indicates closing schools for certain levels and 3 indicates closing schools for all levels.

H - Health System Policies

These are policies that governments adopted within the healthcare system to limit the rise of new cases and deaths.

1. Public information campaigns
2. Testing policies
3. Contact tracing
4. Emergency investment in healthcare
5. Investment in vaccines

6. Facial Coverings

Similar to the C policies, all of the H policies do have an ordinal scale to measure the strictness/broadness in the policies, except for emergency investment in healthcare and investment in vaccines that are measured in United States Dollars (USD).

Aggregate Stringency Index

OxCGRT introduces several aggregate indices that incorporate the values of different policy measures like the Stringency Index (SI). This index aggregates the values of all policies under the C - Containment and Closure Policies category in addition to Public information campaigns, a policy under the Health System Policies. SI has a range between 0 and 100, and it reflects the strictness/stringency of government policies.

Causal Effects of Delays in Government Responses

In (*Hale et al., 2020)*, the authors measured the effect of delays in government responses on the number of deaths nationally. For 170 countries, the authors argued that the delay in implementing strict policies to contain the spread of the infections contributed to an increased number of deaths. For instance, a two-week delay could lead to 3.4 times as many deaths overall (*Hale et al., 2020)*.

To measure the delay for government response, the authors calculated the time, measured in days, each government took to have a SI of 40 since it recorded its first COVID-19 case. In other words, the delta days show how fast governments were to implement containment policies when the first case was recorded.

The authors used a linear regression model to estimate the effect of delays on the number of deaths per million in 170 countries. Although researchers didn't share their code, I was able to implement their causal model in DoWhy.

Replication of Original Model

The Directed Acyclic Graph (DAG) of the model as seen in Figure 1 shows the effect of delay, measured in days, on the number of deaths per million in a country. Researchers did not include unobserved confounders nor other covariates/independent variables that could affect the outcome of COVID-19 related deaths. Using DoWhy, I was able to estimate the average treatment effect (ATE) of days on the outcome.

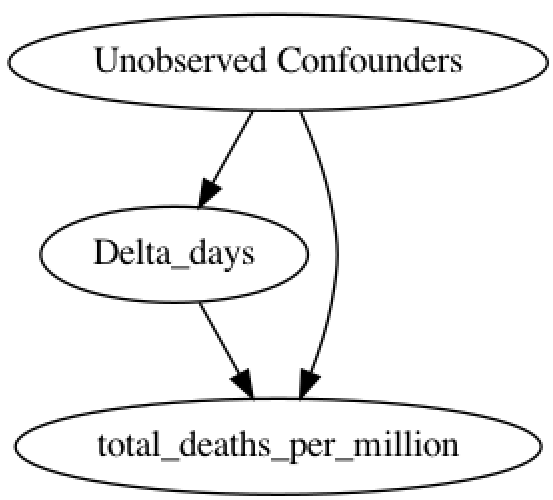

Figure 1. DAG of the original model was proposed by (*Hale et al., 2020).* The graph was generated using DoWhy. The code link.

Using backdoor linear regression, I was able to estimate the coefficient of the following equation, to be 2.576 with a p-value of 0.02729174.

$$Number\ of\ Deaths\ =\ C\ (Delta\ Days)$$, where C is the ATE.

Although my replication supports that author's claims about the association between delays, and the number of deaths, Figure 1 does not capture all confounders that affect the treatment and the outcome which makes the causal claims about the relationship invalid, under the proposed model.

Original Model Extension

To build upon the model in Figure 1, I incorporated more variables into the model to capture some of the confounders recorded for each country, Figure 2.

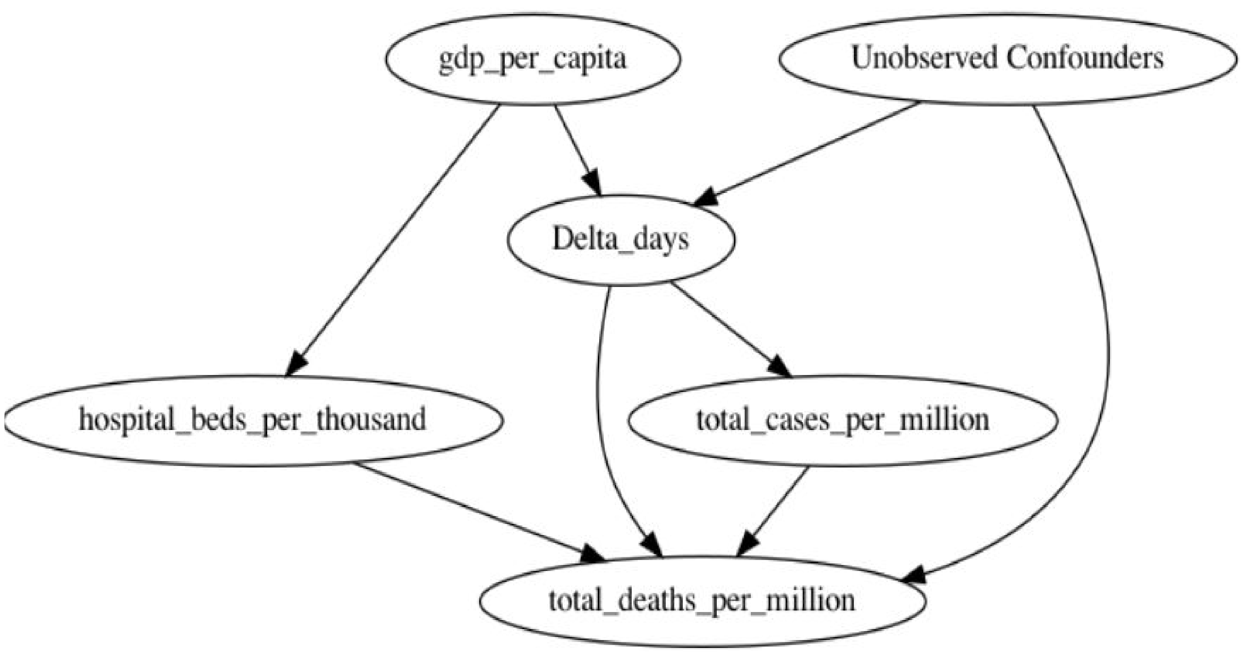

Figure 2. Extension to the original model.

I followed the same approach to calculate the number of days governments took to increase the SI to 40 after the first case was recorded. I used Our World in Data Dataset contained all of the additional factors in Figure 2. In my model, Gross Domestic Product per Capita might have affected how many days governments took to contain the virus. The assumption here is that the lack of resources in a specific country might have affected the speed of their response, due to the lack of infrastructure or medical supplies. GDP can affect the number of hospital beds that each country has. The number of hospital beds is a crucial factor in determining if the medical infrastructure can serve the infected population. Lastly, the delays of responses affect the number of cases in a country and the number of COVID-19 deaths. For instance, the number of cases when increased, there is a higher demand for medical care that can overconsume the medical resources making it harder for COVID-19 patients to get the proper care.

Measuring the Effects

Using DoWhy, I used backdoor linear regression to calculate the ATE of the delays on the number of deaths in millions in each country. Since we have a common cause/confounder of treatment and the outcome, we need to control for the backdoor path. Thus, I used the backdoor linear regression to estimate the causal effect. Unlike the original model, the linear regression model to estimate the causal effect was the following.

*total_deaths_per_million~Delta_days+gdp_per_capita+Delta_days*total_cases_per_million+ Delta_days*hospital_beds_per_thousand*

The estimated ATE is 3.136. Since I used linear regression to estimate the coefficients, I am assuming that that model has a linear relationship where effects are additive. Thus, we can interrupt the ATE to be that for each day delayed for SI to 40, the total deaths in millions are 3.1 times more overall.

Refuting the Model

The last step to test the robustness of the causal analysis to test if the outcome would have taken place if we got to observe some of the unobserved factors. Using DoWhy, I used the random sample refute method. This method uses bootstrapping to calculate a new treatment effect that would have happened if the treatment effects calculated earlier were the results of luck/sample. The new estimated effect was 3.12246 is more than the original estimate by 0.001, and the P-value of that difference is 0.45, which is not significant. Thus, the model is proven to be robust.

Conclusion

This piece shows the importance of incorporating available information to convey a story with the data. Although the original model proposed by (Hale et al., 2020) shows the importance of implementing non-pharmaceutical interventions to decrease the number of deaths nationally, it falls short when it comes to building a robust causal model that shows a causal mechanism that matches the world we live in. While my proposed approach is robust and inclusive of some key factors that determine the number of deaths nationally, it is not an accurate model after all. In my future work, I will use a country-specific model that captures the contextual factors within a specific country.

References

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Appendix A

Code Link