Estimating the impact of public policy interventions on the spread of Covid-19

Abhishek Saini

Introduction

The Covid-19 pandemic has had a devastating impact on both public health and the economy. Policymakers have faced a difficult challenge in trying to balance the need to protect public health with the need to minimize the economic impact of their decisions. In this analysis, we seek to quantify the impact of masking mandates and stay-at-home policies on the spread of the virus. We use a combination of data from Johns Hopkins University, the Centers for Disease Control and Prevention, and Google Community Mobility Reports to answer this question.

Our analysis uses SIRS model and correlation analysis to quantify the impact of historical public health interventions during the pandemic. Our analysis finds that the beta values were very similar whether or not masking mandates were in place, indicating that the mandates did not have a clear impact on the spread of the virus. However, we found that the infection doubling rate increased as relative mobility decreased, suggesting that stay-at-home policies have an impact on the spread of the virus.

This analysis is important because it provides policymakers with a data-driven approach to understanding the impact of their decisions on the spread of the virus. By quantifying the impact of different interventions, policymakers can make more informed decisions that take into account the broader impacts of their policies. However, it is important to note that this analysis has its limitations, and we need further research to fully understand the impact of different policies on the spread of the virus.

Background/Related Work

Recent studies by Karaivanov et al, Lyu et al, and Adjodah et al show positive benefits of masking mandates. These studies use data from multiple geographies, unlike our scenario, where we use only a single county for our analysis. The methods employed by these studies include difference-in-differences design, event study frameworks, statistical tests, smoothing using moving averages, SIR model, and more.
Other recent studies by Al-Jubory et al, Hâncean et al, and Cheshmehzangi et al show that Covid spread is reduced as mobility reduces. These studies also use multiple regions and employ techniques such as the use of epidemiological models, simulation studies, social network analysis, statistical modeling, and more.

I haven't looked at these studies prior to my analysis, but I can note that there are some similarities in using epidemiological models, statistical tests, curve smoothing, etc.

Research Questions and Hypothesis

The broader research question that I have tried to answer is how do we quantify the impact of interventions like masking mandates, stay at home policies on the spread of Covid-19?
The particular question and hypothesis are shown below.

Part 1
How impactful are masking mandates in reducing the spread of Covid-19?
Hypothesis: SARS-CoV-2 transmits faster without masking mandates

Part 2
How did restrictions on the movement of people affect the spread of Covid-19?
Hypothesis: SARS-CoV-2 transmission is reduced when community mobility decreases

Methodology

Part 1
To quantify the impact of masks, I have used a basic SIRS model to model the spread of SARS-CoV-2. I have fit the model to the data to estimate the transmission parameter beta. As the beta parameter controls how fast the virus spreads, a higher beta implies faster transmission. If our fit estimates a higher value of beta, it means that the virus was spreading faster.
On looking at the data, I noticed that there were 4 waves of infections, of which two fell when masking mandates were in place, and the other two when they weren't. I estimate the beta parameters by fitting the data to when masking mandates were present and were not present, and then compare the two.

The reason for choosing a SIRS model approach was that it incorporates certain underlying mechanics of how diseases spread which vanilla time-series based approaches cannot.
This design decision was also guided by the human-centered factor that most public policy professionals who forecast the trend of disease are aware of epidemiological models. Further, the use of beta parameter makes the results explainable to the end user.

Part 2
To quantify the impact of community mobility, I have used an approach that tries to estimate the infection doubling rate. The infection doubling rate is nothing but the number of days it takes for the infections to double and gives a really nice physical interpretation to policymakers.
For this analysis, I first estimate the infections from the daily deaths to get the trend of infections. I use this to estimate the infection doubling rates at the start of different infection waves throughout the

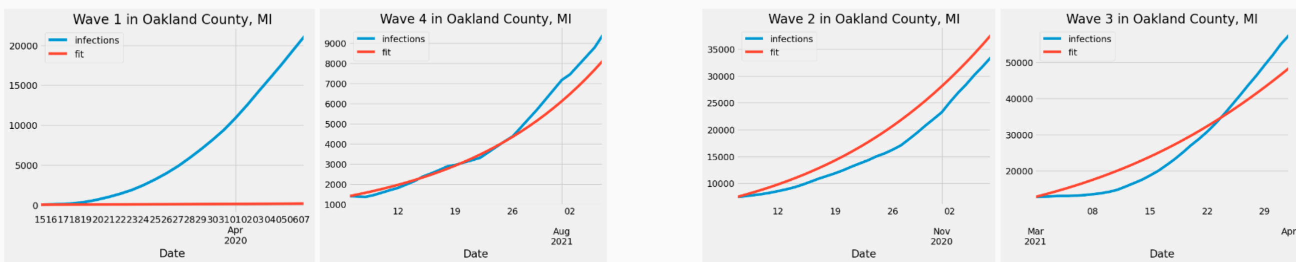
pandemic and check if there is any correlation with changes in mobility.

The reason for choosing the infection doubling rate was that it has a very easy and practical interpretation that is easily understood by the end users. This metric can also be easily extended for other downstream tasks, such as planning hospital capacities, and is thus extremely useful for public health policymakers. Another human-centered benefit of this design is that the linear regression gives an expected target for policymakers to decide how severe stay-at-home policies should be.

Findings

Part 1

The fitted values vs actual values for the two waves are shown in the figure below.



Fit on two waves **without** masking mandates

Fit on two waves **with** masking mandates

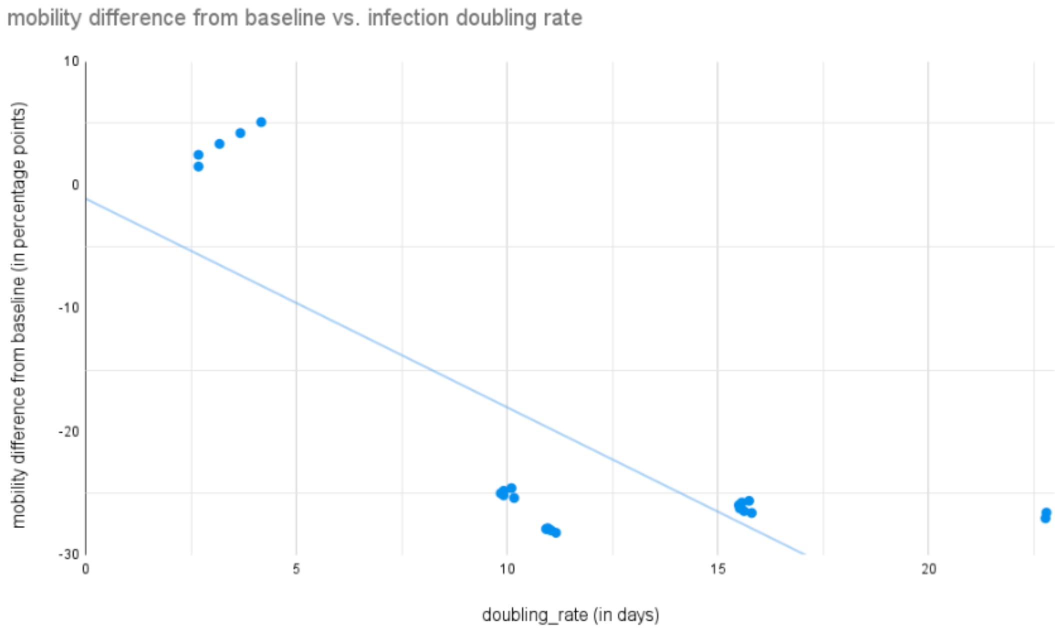
The two beta parameters that we estimate are shown below:

```
{'beta_mask': 0.1623748633423853, 'beta_wo_mask': 0.1625971183690065}
```

The result show both betas are similar in value and we thus cannot say whether masks have helped reduce the spread of Covid-19.

Part 2

On plotting the doubling rate vs mobility difference we get the plot show below. It shows that as the mobility reduces, the spread of Covid-19 reduces as well.



This was also validated to be statistically significant by the bootstrap test to give a 95% CI correlation coefficient between -0.47 and -0.87. This confirms our hypothesis that reducing mobility also reduces the spread of Covid-19.

Discussion/Implications

Our findings are important because they provide a data-driven approach to understanding the impact of various public health interventions during the pandemic. By quantifying the impact of different policies, policymakers can make more informed decisions that take into account the broader impacts of their policies.

Our study suggests that while the impact of masking mandates is not clear, stay at home policies do have an impact on reducing the spread of the virus. Our analysis also provides guidance for policymakers on how to set stay-at-home policies in order to most effectively reduce the spread of the virus.

Our analysis was guided by human-centered principles. We chose to use data-driven techniques such as SIRS model fitting and linear regression in order to make the results easily explainable for policymakers. We also sought to provide practical results that could be easily interpreted by policymakers, such as infection doubling rates and trends in mobility. The simplicity of the analysis also sets up a clear expectation for the end user about what to expect from the system. Further, the goal of our analysis is to assist policymakers in designing policies that consider the broader impacts on all humans.

As future work, we can consider the impact of multiple factors such as vaccinations, variant mutation and do the analysis on all the counties within the US.

Limitations

This analysis has several limitations. First, the data used in this analysis is limited to the US county of Oakland, MI and may not be generalizable to other regions. Second, our SIRS model has a number of assumptions that may not hold, such as a homogenous population and static transmission rate, which could lead to underestimating or overestimating the impact of interventions. Third, our analysis doesn't account for factors such as vaccination rates, viral evolution, population characteristics, availability of testing, masking adherence and more all of which would impact the spread of the virus. Finally, an important ethical limitation of our analysis is that it is consequentialist in nature. This is because we deal with aggregates such as cases, deaths, mobility, etc. which represent only the overall trend but fail to account for subgroups that may be particularly vulnerable to Covid-19 such as by age, underlying health status, and race.

Conclusion

In this analysis, we sought to quantify the impact of public policy interventions on the spread of Covid-19. We asked the following questions: 1) How impactful are masking mandates at reducing the spread of Covid-19? 2) How did restrictions on the movement of people affect the spread of Covid-19?

Our results showed that the beta values for both when masks were present and absent were very similar, indicating that the mandates did not have a clear effect on the spread of the virus. However, our analysis also found that the infection doubling rate increased as relative mobility decreased, suggesting that stay-at-home policies do have an impact on the spread of the virus.

Overall, this study demonstrated the importance of data-driven approaches and human-centered considerations when designing studies. Our analysis was guided by human centered data science principles such as using epidemiological models, linear regression, and interpretable metrics such as infection doubling rate. By incorporating these principles into our analysis, we were able to provide a clear, actionable set of results that can help inform the decisions of policymakers.

References

Lyu, Wei and George L. Wehby. “Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US.” Health affairs (2020)

Adjodah, Dhaval et al. “Association between COVID-19 outcomes and mask mandates, adherence, and attitudes.” PLoS ONE 16 (2021)

Karaivanov, Alexander et al. “Face masks, public policies and slowing the spread of COVID-19: Evidence from Canada.” Journal of Health Economics 78 (2020)

Al-Jubory, Dhuha H. and Eman Al-Shamery. “An Analysis of the Impact of Mobility on the Spread of the Covid-19 Pandemic.” 2021 1st Babylon International Conference on Information Technology and Science (BICITS) (2021)

Hâncean, Marian-Gabriel et al. “The impact of human mobility networks on the global spread of COVID-19.” Journal of Complex Networks 8 (2020)

Cheshmehzangi, Ali et al. “The Effect of Mobility on the Spread of COVID-19 in Light of Regional Differences in the European Union.” Sustainability 13 (2021)

Data sources

The following data sources were used in the analysis.
John's Hopkins Covid-19 data for daily cases and deaths
This dataset can be found here -
https://www.kaggle.com/datasets/antgoldbloom/covid19-data-from-john-hopkins-university
It is licensed under Attribution 4.0 International (CC BY 4.0).

CDC masking mandates dataset on when masking mandates were in place
This can be found here -
https://data.cdc.gov/Policy-Surveillance/U-S-State-and-Territorial-Public-Mask-Mandates-Fro/62d6-pm5i
Its licensing information can be found on the above link.

Google Community Mobility reports to get the trends in the relative changes in people's movement
This dataset is available at https://www.google.com/covid19/mobility/index.html?hl=en
To use this, one must accept the Terms of Services mentioned by Google here -
https://policies.google.com/terms?hl=en