COVID Information Commons (CIC) Research Lightning Talk

Transcript of a Presentation by Courtney Baird (Brown University) January 30, 2024

Title: The Impact of Non-Pharmaceutical Interventions on the Rate of Growth of COVID-19

Pedro Gonzalo CIC Database Profile

NIH Award #: 3R01AG053307-04S1

YouTube Recording with Slides

Winter 2024 CIC Webinar Information

Transcript Editor: Lauren Close

Transcript

Slide 1

All right. Lauren, Can you see my slides? Great. So hi everyone, my name is Courtney Baird. I'm a fifth year doctoral candidate in the Health Services Research Ph.D. program at Brown. My main area of interest and expertise is in evaluating the effectiveness of public health policies. So naturally, during the pandemic I developed an interest in figuring out whether any of the COVID-19 mitigation policies were effective, and if so, which ones were most effective. And that's what I'll be talking about today.

Slide 2

So before I get started, I'd just like to quickly acknowledge all of my co-authors and also thank the NIH for funding this important work. The work that I'm presenting today is actually in press at Health Affairs [journal] and will be published sometime in February or March.

Slides 3-4

So first, I'd like to start off by providing some context on what really motivated this study. Given the initial lack of vaccines and therapies to address COVID-19, the country adopted several non-pharmaceutical interventions, also known as NPIs, to slow down COVID-19 transmission and prevent health care systems from reaching full capacity. Early evidence has been mixed about whether these NPIs have been effective. Some studies have found a significant association between NPIs and slower COVID-19 growth rates while other studies have also found that NPIs had no effect on COVID-19 transmission. These mixed findings may be due to several factors, but mainly most of these studies were conducted at the state level and did not account for county-level differences in the adoption and repeal of NPIs, infection burden, testing levels, and population - socio-demographic characteristics. Additionally, most of these policies only covered the first one or two waves of the pandemic and only studied one NPI (not all of them).

Slide 5
So to address these shortcomings, we use daily county level data to evaluate the joint effect of five different NPIs on the speed of COVID-19 transmission over the course of the first four waves of the pandemic. We also describe policy implementation and county level characteristics associated with policy implementation during the pandemic.

Slides 6-7
Now, I'll move on to talk about the data and the methods that we used. We used CDC data sets to obtain daily county level data for all five policies and for COVID-19 testing and vaccination rates. We obtained daily county-level COVID-19 cases from the USAFacts COVID-19 dashboard. We obtained data on numerous county-level characteristics such as the distribution of age, sex, race, and educational attainment from the U.S. Census Bureau and the Department of Commerce. We also obtained county-level 2020 presidential election results from the results published by Fox News, Politico, and the New York Times.

Slide 8
We evaluated the potential of the policies to reduce the COVID-19 transmission rate separately for each of the four national COVID-19 waves for which policy data was available and which are shown on this graph. We also conducted the analysis with all of the waves combined. Ultimately, we decided to exclude wave five from the analysis because the CDC policy data sets ended on August 15th [2021] so we were not able to evaluated the entire upward slope of wave five.

Slide 9
We evaluated the impact of five different policies on the growth of COVID-19, including large gathering bans, stay-at-home orders, face mask mandates, and bar and restaurant closures.

Slide 10
Now I'll just review the steps that we took to model the policy exposure. First, for each policy, we calculated a five day lag to seven-day rolling average of cumulative policy days because people who test positive on a given day were on average exposed to the virus five days earlier. That's based on prior research. Second, we created a composite NPI variable calculated as the sum of cumulative policy days for all four policies. We decided to use a composite policy variable because counties implemented and repealed most of the NPI policies at the same time, which leads to a high degree of muli-colinearity among policies. That makes it really difficult to identify individual policy effects when you're including them all in the model at the same time.

In our regression models, we evaluated two different versions of this composite policy variables: a continuous version and also a binary version that compares high policy counties versus low policy counties.

Slide 11
We evaluated the impact of this composite variable on seven outcomes which are defined as the number of days counting from the county's at-risk start date that it took for the county's COVID-19 seven day rolling average case rate to reach or surpass 50, 100, 200, 400, 600, 800, or 1,000 infections for 100,000 people. The at risk start date for each county in each wave began on the first day in which the county exceeded 10 new COVID-19 cases for 100,000 people. The follow-up period ended either when the county reached the specified threshold or on the day in which the wave peaked in that county.

Slide 12
For our statistical approach, we performed multivariable Cox Proportional Hazards regression models. We excluded counties that never reached 10 cases per 100,000 during a wave because we didn't consider them to be at risk. Also, counties in the bottom 5% of county population size because small populations can lead to overinflated case rates that would result in imprecise estimates.

Slide 13
Aside from the previously mentioned county level demographic characteristics, we also controlled for several other COVID-19 related confounders, including the county's COVID-19 testing rate, the percentage with at least one vaccine dose, the percent of fully vaccinated people, the COVID0-19 case rate at the start of the at risk period, and which national COVID wave was the the county's first wave.

Slides 14-15
Now I'll move on to sharing our descriptive results. This graph shows the percentage of the U.S. population covered by the four policies over the study time period. As you can see from the graph, bar and restaurant closures had the highest implementation level throughout the pandemic. We've combined them into one policy here because we realized that about 99% of the time bar and restaurant closures were implemented together so we just combined them into one. Face mask mandates were all largely implemented later on, starting in July to August of 2020. Then finally, all four policies dropped off significantly by May to June of 2021.

Slide 16
There were also some interesting findings when we compared 30 different county descriptive statistics in the high versus low policy groups. I've highlighted just some of the most interesting findings on this slide. Overall, counties that implemented policies more frequently had a higher

population density, a higher percentage of service job employees, a low lower percentage of work from home employees, a lower percentage of Republican voters, a higher percent of people living in housing with 20 or more units, and also a higher COVID-19 testing rate.

Slide 17
This slide displays a county level heat map illustrating regional variation and policy implementation where red represents a high policy intensity and yellow represents low intensity. You can see that, in general, counties in the Northeast and Northwest had more days with policies in place and counties in the Southeast and Central Plains had fewer policy days throughout the pandemic.

Slides 18-19
Now I'll just move on to the impact evaluation results. Across all four waves combined, high policy implementation counties were associated with a lower hazard rate for every single threshold and these results were all statistically significant. These results are most apparent in waves two and three and less apparent In waves one and four, which I'll touch on later in the discussion.

Slide 20
The Cox regression results for the continuous version were also similar. We see that all four waves combined a one- day increase in the policy is associated with a lower hazard rate for every single threshold. Again, we see that the results are most apparent In waves two and three and less apparent in waves one and four.

Slides 21-22
Overall, the different policy effect strengths across waves reflects the timing and prevalence of policies and also the presence of mediating factors that influenced COVID-19 transmission at different times during the pandemic. At the beginning of wave one there was confusion about the seriousness of the pandemic and about clinically important virus characteristics and a lack of specific early CDC guidance. These factors contributed to a delay in policy implementation and caused many counties to implement policies after already having an outbreak rather than proactively to prevent an outbreak. The reduced mask availability in the early stages of the pandemic may have also made enforcement more difficult. These early difficulties are likely the cause of the lack of statistical significance for the lower thresholds that take place earlier in wave one while the significance at higher thresholds may reflect longer policy exposure by that point.

Slide 23
Wave four was also unique for several reasons. By the end of wave four, 54% of the country had at least one vaccination shot and 78% of older adults had a complete vaccination series. As you can see in this exhibit, many counties dropped their policy mandates during wave four, but the

dropping of the policies was not at random. Counties with higher COVID-19 levels were more likely to keep their policies in place while counties with higher vaccination rates were more likely to drop their NPIs This selective revocation can lead to reverse causality where higher policy levels are associated with higher COVID-19 transmission, as we can see for the low thresholds in wave four. There was also a significant amount of pandemic fatigue at that point which is based on a lot of survey data research and that led to much lower rates of policy compliance.

Slide 24
Overall, our stratified wave findings highlight that the degree of NPI effectiveness depends on timing, dosage, and policy compliance. By waves two and three, county officials had a better understanding of COVID-19 transmission mechanisms and the array of possible mitigation strategies. There was also stronger policy compliance at this time and policies were implemented more proactively. All of these factors are likely what led to a higher level of NPI effectiveness during waves two and three. In conclusion, one of the greatest threats of rapid COVID-19 transmission is that hospitals and health care providers become overwhelmed with COVID-19 patients and reach their full capacity. This could lead both COVID and non-COVID patients without access to needed care and ultimately result in excess morbidity and mortality. We believe these findings in this study provide crucial evidence in support of the use of non-pharmaceutical interventions as a public health measure to flatten the curve of future waves of COVID-19 or similar infectious disease outbreaks.

Slide 25
I'll just mention again that there's a lot I couldn't share here because of time limits, so if you're interested in learning more - in the publication that's coming out in Health Affairs we've got sensitivity analyses, a thirty page appendix.. If you're interested finding out more, please look out for the Health Affairs publication. Thank you all for listening and I'm looking forward to answering questions later on.