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ECON 474

December 16, 2020

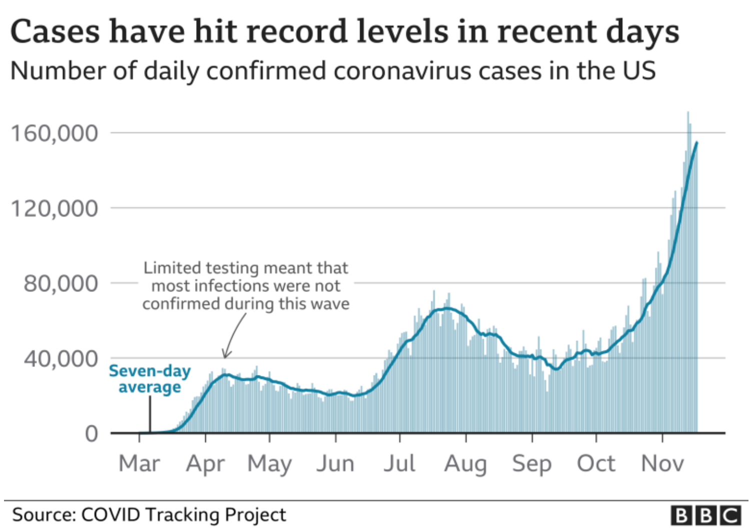
Analyzing the Efficacy of Mask Mandates

1. Question

Coronavirus became the deadliest virus of all time. It's important to lower the number of cases in order to lower the number of deaths from the coronavirus. Our goal is to test whether face mask policy would have an effect on the number COVID-19 cases in the United States.

2. Motivation

On January 19th 2020, the first case of COVID-19 appeared in the United States. Since then the daily number of COVID-19 cases has been increasing. Below is a graph that shows the daily number of COVID-19 cases since March 1st 2020.



According to the BBC News graph, the United States has reached the highest number of COVID-19 cases (Hills). The United States has reached 160,000 cases in November 2020. As the number of COVID-19 cases increases, the number of deaths increases in the United States. Unstopping the virus could possibly lead to human extinction which is what motivated us to see if mandating masks could possibly lower the number of COVID-19 cases in the U.S. It is also important to see if mask mandating could possibly lower the number of cases in the U.S. since Coronavirus has no cure so far. Many people have also lost their jobs due to COVID-19. Not to mention, some people were unable to socialize due to COVID-19. If mandating masks is effective in lowering the number of cases in the U.S., people would start wearing their mask so they return back to their jobs and socialize again. Lately, there was the news about COVID-19 vaccines coming to lower the number of COVID-19 cases. We decided to keep working on testing the face mask mandation instead of vaccines because we know that many people would prefer to wear a face mask than taking the vaccine since vaccines have long term side effects.

3. Relevant Literature

Andrew Bacon and Jan Marcus wrote an article called, "Using Difference-in-Differences to Identify Causal Effects of COVID-19 Policies." The article is about testing all COVID-19 policies to see if they were effective in lowering the number of cases in the U.S. The article is so important for many reasons. First, it was mentioned in the article that they used the difference in difference method which is the method we used in our testing to test and see if COVID-19 policies could lower the number of cases in the U.S. Second, according to the article, the testing proved that COVID-19 policies are effective in lowering the number of COVID-19 cases in the U.S. The reason we picked mandating face masks policy is to see if it was the reason that COVID-19 policies in the article were effective in lowering the number of COVID-19 in the U.S.

Wei Lyu and George Wehby wrote an article called, "Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US: Health Affairs Journal." In that article, they just focused on testing the effectiveness of face masks on the number of COVID-19 cases in the U.S. which is the same as our testing. There are two things that were done in that testing that were different than our testing. First, the event study method was used to test the effectiveness which is different from our testing method since we used difference in difference methods. Also, the event study testing that was done in the article focuses only on the states that mandates masks. Our testing focuses on states that mandate and states that don't mandate face masks. The reason we decided to continue our testing is that the result that came back from the testing in the article showed that mandating face masks were effective in reducing the number of COVID-19 cases in the U.S.

Muhammad Salar Khan wrote an article called , "Evaluating the Effectiveness of Regional Lockdown Policies in the Containment of Covid-19: Evidence from Pakistan." In this article, a testing was done on the effectiveness of lockdown policy on the number of cases in Pakistan. In this testing, a regression discontinuity design method was used which is different from the method we are using; difference in difference. Also, the testing that was done in the article wasn't done in the United States like our test. The testing was done in three areas in Pakistan:Punjab, Sindh, and Khyber Pakhtunkhwa (KPK) regions. The reason we see this article important is because the result from the testing showed that lockdown policy has no effect on the number of cases in Pakistan. This was also one of the reasons we picked a mandatory mask policy to do the testing on instead of the lockdown policy or any other COVID-19 policy.

4. Data

The policy we focused on is the face mask mandate in Indiana, effective since July 27th. The executive order 20-37 stated that all individuals within the state of Indiana were required to wear a face covering over the nose and mouth in public space (Holcomb 2).

The data we used comes from the New York times. In this dataset, the number of COVID cases is organized by state and by county, which is preferable since we can treat each county as a data point. We used the counties of Indiana for our treatment group. And for the control group, we chose Florida, a state that had no state-wide face covering requirements around the same time period. Because each county has a different population, we adjusted the number of cases with the population of each county. The descriptive statistics for the dependent variable $\log(\text{cases/population})$ for both before (Jun 6) and after (Sep 6) the mask mandate are shown in Table 1.

Besides mask mandate, we also wanted to consider other government policies, so as to eliminate other confounding factors that contribute to our outcome. Oxford COVID Policy Tracker provides info on all government regulations such as social gathering, closing of public spaces. And in their study, they created a government response index to assess these policies.

In Figure 1, we can see that both Indiana and Florida's state governments have similar strategies around the same time. For the time period we focus on, they are both relaxing regulations and attempting to open up.

5. Strategy

Intuitively, we chose the difference in differences method to evaluate how this policy affects the number of cases by comparing data from two different time periods. The key assumption we make, before we use this method, is the same time trend effect, which suggests that the two outcomes follow the same trend before the policy becomes effective and are expected to continue in the same trend IF the policy had not existed.

From Figure 2, we find that they do follow the same trend. The difference between them is relatively constant until the mask mandate was in place.

Hence, we arrive at this DID model for regression:

$$log(\frac{cases_{it}}{population_{it}}) = ß_0+ß_1 treat_i+ß_2 time_t+ß_3 treat_i*time_t+\varepsilon_{it}$$

treat represents the group, i.e., the state a given county is in. $treat_0$ for the control group, Florida counties, and $treat_1$ for the treatment group, Indiana counties. *time* is another dummy variable that indicates the date when the case count is recorded. $time_0$ for a date before the policy change (Jun 6) and $time_1$ for after the change (Sep 6). We divide the number of cases by the population of a given county. Since the initial growth of pandemic cases tends to be exponential, we took the logarithm to prepare it for the linear model.

The model assumes that during the time period, the executive order for mask mandate was the only significant difference between Florida and Indiana's response in government policy, which was confirmed by the government response indices, as mentioned in Section 3. However, the Oxford COVID policy tracker also has its limitations. For instance, the tracker might not have a comprehensive evaluation of the responses on a county level.

6. Initial Results

By running the regression, we obtained the coefficient estimates and significance levels for $ß_0$, $ß_1$, $ß_2$, and $ß_3$ as shown in Table 2 (see Figure 3 for the expected value equations for the intercept and coefficients). In addition to the intercept and all of the coefficient estimates being statistically significant, our DID estimate ($ß_3$) was reported as -1.49837. Since our dependent variable had been logarithmically transformed in the model to linearize the exponential growth of COVID-19 cases in our data, the initial DID estimate could not be meaningfully interpreted in order to explain the causal effect of mask mandates on COVID-19 case counts. To remedy this, we exponentiated our β_3 estimate such that

$$(e^{-1.49837}-1)*100 = -77.65058.$$

By subtracting one and then multiplying by 100, we found the percentage change in our dependent variable given that our interaction term $treat_i*time_t$ had a value of one (i.e when $treat_i = 1$ and $time_t = 1$). We interpreted the meaning of our DID estimate to be that the implementation of a mask mandate resulted in almost seventy-eight percent fewer cases (adjusted for population) in our treated group of Indiana counties versus our control group of Florida counties. The difference between the Indiana and Florida counties is particularly striking in Figure 4. On this plot, pre-treatment ($time_t = 0$) COVID-19 cases adjusted for population in Indiana and Florida counties appear to be similarly distributed, while in the post-treatment period ($time_t = 1$) Florida's counties have worsened notably and there is a clear difference between the case count distribution of counties in Indiana compared to those in Florida.

From a policy perspective, these results serve as an indicator that mask mandates can be a useful component in the arsenal of tools to fight the COVID-19 pandemic. As economists and policymakers have pointed out, the negative externalities of more cases are staggering. Economists from the National Bureau of Economic Research have determined that "the true social cost [of an additional case] is around $268k...If [policymakers] cannot make policy contingent on the epidemiological status of individuals...then optimal policy still sharply reduces the number of infections but at significantly larger initial economic cost" (Bethune and Korinek 33). The mask mandate appears to be a good example of an 'optimal policy' in that it is efficient at slowing the increase of infections, especially when considering "the asymptomatic nature of COVID-19 [and] the lack of sufficient testing" (Bethune and Korinek 33). In the United States, which has the unfortunate distinction of topping global charts for its high number of cases and deaths from the coronavirus, mask mandates could become ever more vital as the country enters a season of colder temperatures and vaccines are making their way through emergency approval processes and into the arms of patients. In recent days, there have been alarms raised about widespread mask 'complacency' as vaccines are approved. Activist investor Bill Ackman, CEO of the Pershing Square Capital Management hedge fund, said to the *Financial Times* that "[Vaccine] news was 'actually bearish for the next few months'...because it was likely to make people more complacent about wearing masks and less likely to view the virus as a threat" (Aliaj). Per our analysis, there is a significant and beneficial effect of mask mandates on case counts, with the emphasis that mask wearing must be a collective effort. Without a large portion of the population being vaccinated, mask mandates are one of the most proactive approaches that policymakers can take, keeping in mind that every new case is a potential hospitalization and death, putting only more strain on burdened healthcare systems.

Although we demonstrated the same time trend effect assumption in Section 5, there are other robust checks that can be performed to test this assumption. We chose to conduct a placebo test on our data by moving the time of treatment to a random date before the actual treatment took place, and subsequently ran a regression based on the new placebo treatment date and infection data to find our placebo DID estimate. In this case, given that we had observed a similar time trend in COVID-19 infections in both Indiana and Florida prior to the actual treatment date, our expected treatment effect was zero. After choosing the random placebo treatment date of May 17th, 2020 we set $placebotime_0$ as April 17th, 2020 and $placebotime_1$ as June 17th, 2020. After collecting the proper county level data for those dates as in Section 4, we repeated the regression at the beginning of this Section with the new data:

$$log(\frac{cases_{it}}{population_{it}}) =$$

$$ß_0+ß_1 placebotreat_i+ß_2 placebotime_t+ß_3 placebotreat_i*placebotime_t+\varepsilon_{it}.$$

Running the new 'placebo' regression yielded the coefficient estimates and significance levels for $ß_0$, $ß_1$, $ß_2$, and $ß_3$ in Table 3. This time, per our expectations, not only was the DID estimate $ß_3$ not statistically significant, but it had a miniscule value of -0.017098, which when exponentiated to reverse the logarithmic transformation in the same manner as the first DID estimate, revealed that

$$(e^{-.017098}-1)*100 = -1.695266.$$

This meant that there was a less than two percent difference in population adjusted COVID-19 case counts in the post-placebo-treatment period (when the interaction term $placebotreat_i*placebotime_t = 1$) between Indiana and Florida. This was in agreement with our expectation that the treatment effect would be insignificant. This placebo test is visualized in Figure 5, which reiterated our findings that there was no discrepancy in the COVID-19 case trend prior to the actual treatment taking place between Indiana and Florida.

There are confounding factors that could affect the number of cases within the time period that we observed. For example, it is important to note that in each of the states we studied, in addition to the state and county governments, there are countless more regional, district, municipal, and township authorities that can implement their own health restrictions, such as business closures or social distancing guidelines. Given that these regulations and ordinances take place in such a micro-environment when compared to mandates implemented at the state level, the fragmented nature of local governments could certainly represent a confounding factor in our analysis. Perhaps more significantly, we could not control for the risk-tolerance levels of individuals in our model. While mask-mandates are a collective action, ultimately it is individuals who wear them. NBER economists wrote that "individually rational infected agents recognize that they have nothing to lose from further social interaction and do not internalize that their economic activities impose externalities upon others by exposing them to the risk of infection" (Bethune and Korinek 3). Because we could not quantify the level of care that individuals take on following or not following precautions and protocols, risk-tolerance also presented itself as a possible factor for confoundedness in our study.

7. References

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Table 1: Descriptive Statistics for the number of Covid cases

	Count	Mean	Standard deviation	Standard error	Minimum	Maximum
Before (control)	67	-6.376749	0.9176315	0.1121065	-9.695725	-3.731053
After (control)	67	-3.5879	0.4752165	0.05805693	-4.476503	-2.006004
Before (treat)	92	-5.753492	0.7977386	0.08317	-7.646991	-3.172159
After (treat)	92	-4.46301	0.4785527	0.04989257	-5.972017	-2.446166

Table 2: Inferences for Estimated Coefficients in the Original Model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-6.37675	.11127	-57.3105	< 2.2e-16
treat	.62326	.13864	4.4954	9.782e-06
time	2.78885	.12530	22.2570	< 2.2e-16
(*treat * time*)	-1.49837	.15813	-9.4756	< 2.2e-16

Table 3: Inferences for Estimated Coefficients in the Placebo Treatment Model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-7.627320	.097302	-78.3884	< 2e-16
placebotreat	.336364	.136106	2.4713	.01399
placebotime	1.690166	.141459	11.9481	< 2e-16
(*placebotreat* * *placebotime*)	-0.017098	.188294	-0.0908	.92771

Figure 1. Government response index vs. time

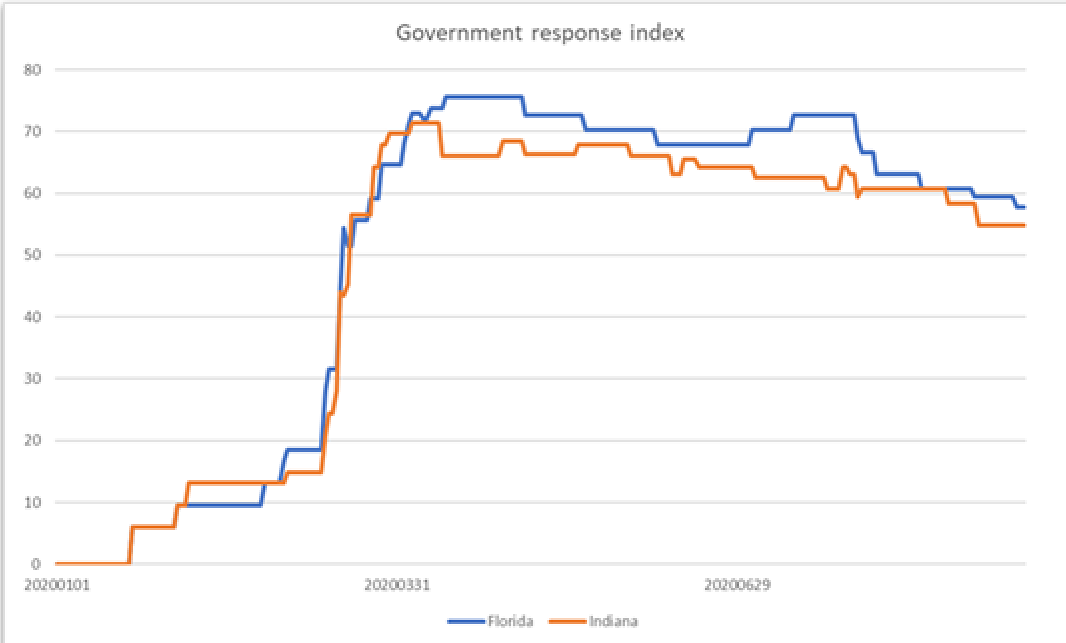

Figure 2. Logarithm of Cases vs. time. Same time trend effect.

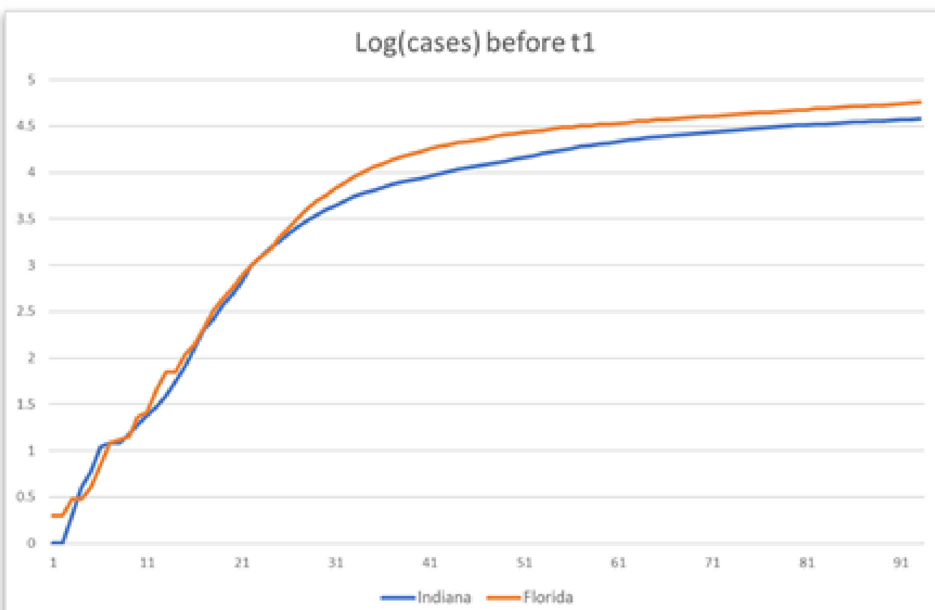

Figure 3: Expected Value Equations for the Intercept and Coefficients

$ß_0$= E[Y|D_i^{treat}=0, D_i^{time}=0]
$ß_1$= E[Y|D_i^{treat}=1, D_i^{time}=0]-E[Y|D_i^{treat}=0, D_i^{time}=0]
$ß_2$= E[Y|D_i^{treat}=0, D_i^{time}=1]-E[Y|D_i^{treat}=0, D_i^{time}=0]
$ß_3$= E[Y|D_i^{treat}=1, D_i^{time}=1]-E[Y|D_i^{treat}=0, D_i^{time}=1]-(E[Y|D_i^{treat}=1, D_i^{time}=0]-E[Y|D_i^{treat}=0, D_i^{time}=0])

Figure 4: Time vs. Log(cases/population) for the Original Model

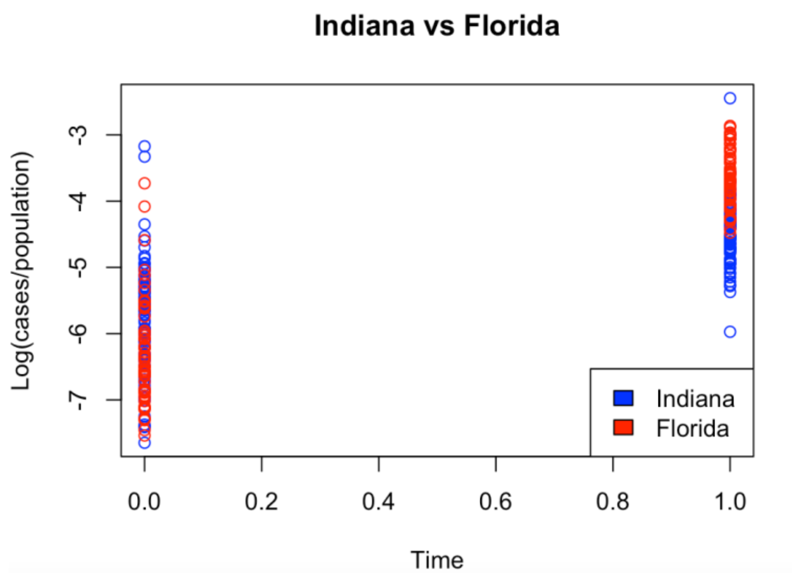

Figure 5: Time vs. Log(cases/population) for the Placebo Treatment Model