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The Effect of Mask Mandates on States' Covid New Case Rates

Introduction

Pondering upon the distress and strife that covid-19 and its associated repercussions caused for the United States, we asked the question: What was the average effect of state mask mandates on the growth covid-19 case rates in the US? Though there is much research that seeks to establish the effectiveness of mask usage in the context of covid-19, many people still do not believe that masks made any substantive difference. This became a central topic of both political and ethical division in the United States. Fearing another comparable pandemic, some may still question the legitimate efficacy of mask mandates. Ultimately, if one were to come to a statistical conclusion concerning the causal impact of mask mandates, many could be better prepared for another potential and comparable virus.

Many studies have attempted to conclude whether mask-wearing was efficacious in reducing covid case rates. Some have found that mask mandates were extremely effective. In the studies of (Leech et al 2022), a 20 million-person survey was conducted to measure the overall efficacy of mask-wearing in impeding the spread of covid; their results indicated a 19% decrease in transfer rates. Other studies have aimed to measure the impact of a mask mandate on wearing masks (Binka et al 2023); these studies show significant increases in mask utilization in response to such a mandate. (Huang et al) ask similar questions as we do concerning the effect of mask mandates on county case rates; they find that though there might have been an immediate period of no effect after treatment, eventually, mandated counties experienced a 25%-35% decrease in covid case rates compared to unmandated counties. Though inspired by such research, we are unique in that we approach this question using a difference-in-differences and quantile regression methodology, estimating the effect of mask mandates on the percentage change in new case rates at the state level for the US in 2020.

Data

Our data is from the CDC, US Census Bureau, and the AARP. The US Census Bureau is a reputable source that consistently records the nation's population, producing reliable data. We also used data from CDC; they gathered daily data concerning covid cases to measure the general development of the pandemic. Under legal state disease laws, hospitals and laboratories sent covid case rates to the state's health department. Thereafter, states transferred the data to the CDC. It should be noted that states did not report their findings all at the same time; states also possess different standards of what qualifies as a covid case (Mcphillips 2022). All of this data is used to generate a variable indicating daily covid case rates, measured as the ratio of new cases in a given state and day over that state's population. Due to the inconsistencies in the data reporting and generating process, there may likely be inaccuracies in our data; however, it was the most reliable data available to us. We also managed to gather data on the time intervals in which a state had an active stay-at-home mandate, intending to control for this potential confound. Lastly, the AARP produced data on whether a state possessed an active mask mandate. We leverage this as the place and time in which treatment occurs for our DiD approach. We include a table of summary statistics about these critical covariates next.

Summary Statistics

Variable	Obs	Mean	Std. Dev	Min	Max
Duration of Stay at Home Mandate	37	49.95	41.729	0	251
Daily Cases Per 100,000	13628	16.00	24.393	0	501.9749
Population	5.00E+01	6.56E+06	7.32E+06	5.79E+05	3.95E+07
Daily Cases, Raw	13628	947.4662	1678.894	0	19863

Research Design

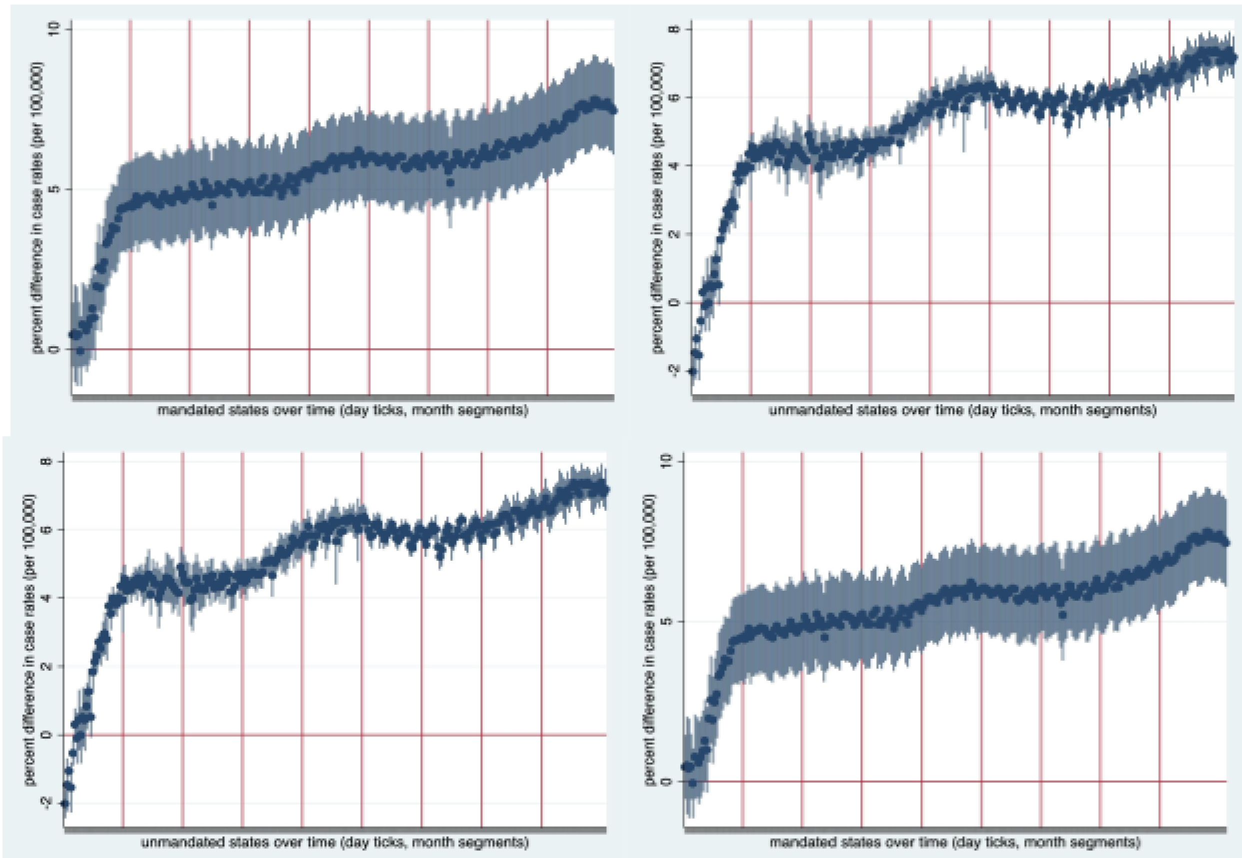
As mentioned in the introduction, we use both a quantile regression and difference-in-differences strategy where we effectively compare differences in the percentage change or growth in new covid case rates (per 100,000) between states that did and did not institute mask mandates, with respect to days since mask mandate implementation. Our general estimating equation is:

$$ln(CaseRates_{it}) = A_o + A_1 StayAtHome_{it} + \beta_{t\text{-}k} ActiveMandate_{it} + \pi_i + \partial_t$$

Here, the dependent variable is the natural log of *CaseRates,* yielding the daily percent change in new case rates (per 100,000) for a given state. *ActiveMandate* is a binary variable that equals 1 if a mask mandate is active in a given state and day, and 0 if otherwise. The coefficient of interest is $\beta_{i\text{-}k}$, which quantifies the time-dependent effect of the mandate since the time the mandate was imposed (k). *StayAtHome* is simply a binary control, equalling 1 when a given state has an active stay-at-home mandate; we feared that omitting this control might produce a contemporaneous shock. If it were the case that there exists a strong correlation between having an active mask mandate and having a stay-at-home mandate, we would receive biased results, seeing that stay-at-home mandates directly relate to the propagation of covid. Since this approach leverages two-way fixed effects, we include both group or state fixed-effects (π_i) and time or day fixed-effects (∂_t).

The identifying assumption here is the existence of parallel trends between treatment and control, absent the occurrence of treatment. Of course, this is only verifiable indirectly. If there are parallel pre-treatment trends between treatment and control, we assume that the control group is an adequate counterfactual of what would have happened to the treatment group, had they not been treated. To informally assess the remote plausibility of this, we begin by comparing daily new case rates between mandated states and unmandated states throughout the year (see Figures 1-3).

Figure 3: Relative Plausibility of Parallel Trends



Next, to statistically verify the assumption, we conduct an event study, plotting the average difference between the treatment and control groups in the days leading up to the day that a mask mandate is instituted. Our results show that throughout the 90 days previous to a mask institution day, after controlling for time and group fixed-effects, treatment and control groups were not statistically different, consistent with the identifying assumption (see Figure 4).

Concerning our inference strategy, we must account for some autocorrelation. Typical standard errors assume independence between observations; because covid case rates within a state are inherently correlated from day to day, we must not treat each day of state data as independent. We address this by clustering our data at the state level. Thus, we assume that though covid cases might be correlated across time within a given state, case rates within one state are independent of other states. To execute valid inference, the conventional threshold for the minimum number of clusters is 50. It happens to be that this number is the exact number of states in the US, and thus the exact number of clusters in our data. Thus, we are enabled to estimate the causal effect of mask mandates on new case rates using reliable standard errors.

Results

Our main results were the following: mask mandates had no significant effect immediately after implementation. However, within three months after implementation, there is a statistically significant reduction in the change of new case rates for mandated states, compared to unmandated states. This statistically significant reduction (under a rejection region of 5%) was nearly 3/4ths of a percentage point lower for the treated states by the 90th day after implementing the mandate (Figure 4 & Event Study Regression Table). By the 60th day after implementation, treated states' daily new covid case rates were, on average, growing at a rate that was nearly 2/3rds of a percentage point lower than unmandated states; this was significant under a 5% rejection region, seeing that the p-value for this estimate was 1%. By the 30th day after implementation, treated states' daily new covid case rates were, on average, growing at a rate that was nearly half of a percentage point lower than unmandated states; this was significant under a 5% rejection region, seeing that the p-value for this estimate was less than 1%. Estimates concerning the discrepancy of this growth between treated and untreated states for 90, 60, and 30 days before the mandate are also all negative but insignificant with p-values of 45%, 34%, and 36%, respectively. Though it was the case that on the day of mask mandate implementation, this discrepancy was positive, implying that the growth of daily case rates for treated states might be higher than the control group, the associated p-value was about 95%, settling our concerns that trends between treatment and control would not be conducive to intuitive causal interpretation.

Event Study Regression Table

Variable	Coefficient	Standard Error	T-Score	P-Value	95% CI LB	95% CI UB
stay at home	0.5907	0.1445	4.09	0.000	0.3004	0.8810
90 days before	-0.2071	0.2747	-0.75	0.455	-0.7591	0.3449
60 days before	-0.2445	0.2558	-0.96	0.344	-0.7584	0.2695
30 days before	-0.1442	0.1580	-0.91	0.366	-0.4616	0.1733
day of mandate	0.0041	0.0772	0.05	0.958	-0.1510	0.1591
30 days after	-0.5437	0.1954	-2.78	0.008	-0.9364	-0.1510
60 days after	-0.6292	0.2402	-2.62	0.012	-1.1118	-0.1465
90 days after	-0.7773	0.2690	-2.89	0.006	-1.3179	-0.2367

Furthermore, in all three of our regressions, the coefficients for the time before a mandate were statistically significant. We note that there were two days in Figure 4's pretreatment differences that were statistically significant. However, because there are over 80 days in that period of presumed "no difference", we would expect about 4 days (5%) to be statistically significant by random chance; considering that our results yielded only half of that, our results are still impressively consistent with the identifying assumption. The coefficients for the time after mandates were consistently significant, and not seemingly due to random chance. Ultimately, these results substantiate the hypothesis that there were parallel trends between states that received treatment and states that didn't receive treatment (Figures 4, 5, & 6).

Concerning the coefficients of our aforementioned event study, there is a possibility that using days since a mandate may possess qualities that do not hold in a more aggregated approach, such as statistical significance or lack thereof. We explored this possibility by conducting another event study where we used months, instead of days, to measure time since a mask mandate implementation day. Furthermore, this new approach used weekly dummy variables rather than daily dummy variables to increase the degrees of freedom and precision of our regression. Our event study results remained robust.

Moreover, using the same model, we performed another analysis leveraging quantile regression, specifically, at the 85th percentile of the dependent variable. Perhaps, mask mandates may have a statistically significant impact on average but not for states with covid case rates that are much higher than average. This regression, therefore, estimates the effect of mask mandates on states with above-average covid cases. Due to the computational complexity of quantile regression, we used monthly dummy variables to represent time-fixed effects. Here, we used the command *qregpd* in Stata to receive standard errors that are corrected for the group fixed effects and serial correlation of panel data (Powell, D 2022). The quantile regression for the 85th percentile gave very similar results to our regressions that used OLS (Figure 6), further reinforcing the robustness of our results.

We note that our dataset has the weakness of non-extensive controls. For example, we do not control for average mask mandate compliance levels per state. We also do not control for the average magnitude of misreporting of new cases per state, measured as the probability of false positives or false negatives per state. We expect that imperfect compliance would cause our results to be biased towards 0 when in reality they are more extreme. Since we do not know the proportion of false positives to false negatives across states, our results can be biased such that there is an exaggerated difference between treatment and control if the control group systematically reports more false positives; alternatively, our results can be biased towards 0 if the control group systemically reports more false negatives. The inverse of each situation is also plausible, as is a combination of all of these possibilities and the associated bias that they introduce.

Conclusion

In the end, we discover a statistically significant effect of instituting a mask mandate on reducing the growth or percentage change in daily new covid case rates when observed within 3 months of implementation. This finding validates that our government played a pivotal role in mitigating the propagation of covid in the year 2020. Accordingly, we can be assured that there might be an effective policy that can be implemented to slow the progress of another comparable pandemic. This analysis raises several new questions, such as: “How do mask mandates affect compliance with social distancing protocol? How do mask mandates affect compliance with stay-at-home mandates? What is the unique effect of a mask mandate on each given US state's covid case rates?”. With this research, one might potentially juxtapose our nationwide perspective alongside a more granular one to produce unique procedures for each given state’s optimal response to a comparable pandemic. We note that our current paper could be greatly improved by including more controls, having more accurate data from testing centers, and having covid data specific to urban versus rural areas to further verify the robustness of our event study, especially with regard to heterogeneous treatment effects.

Graphs and Table

Figure 1

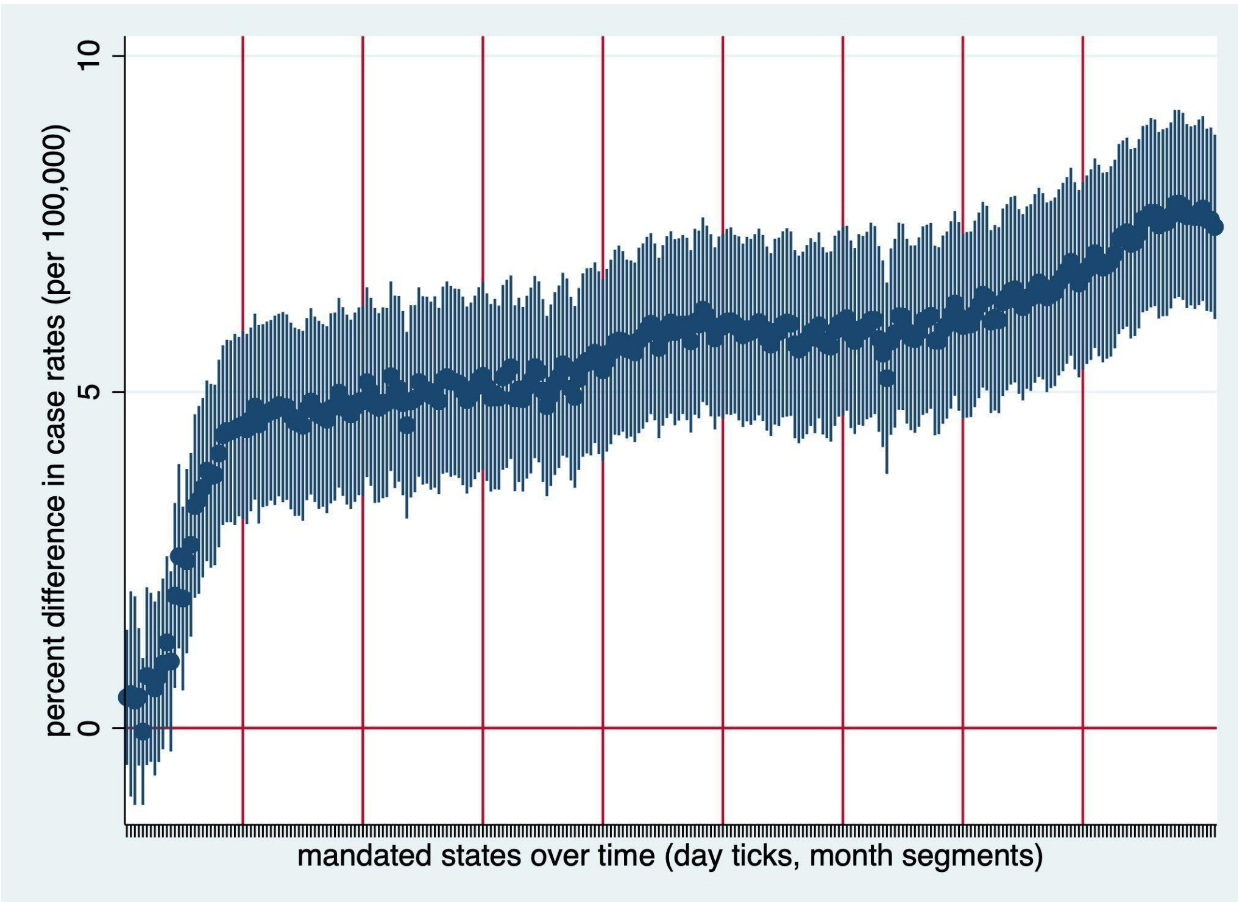
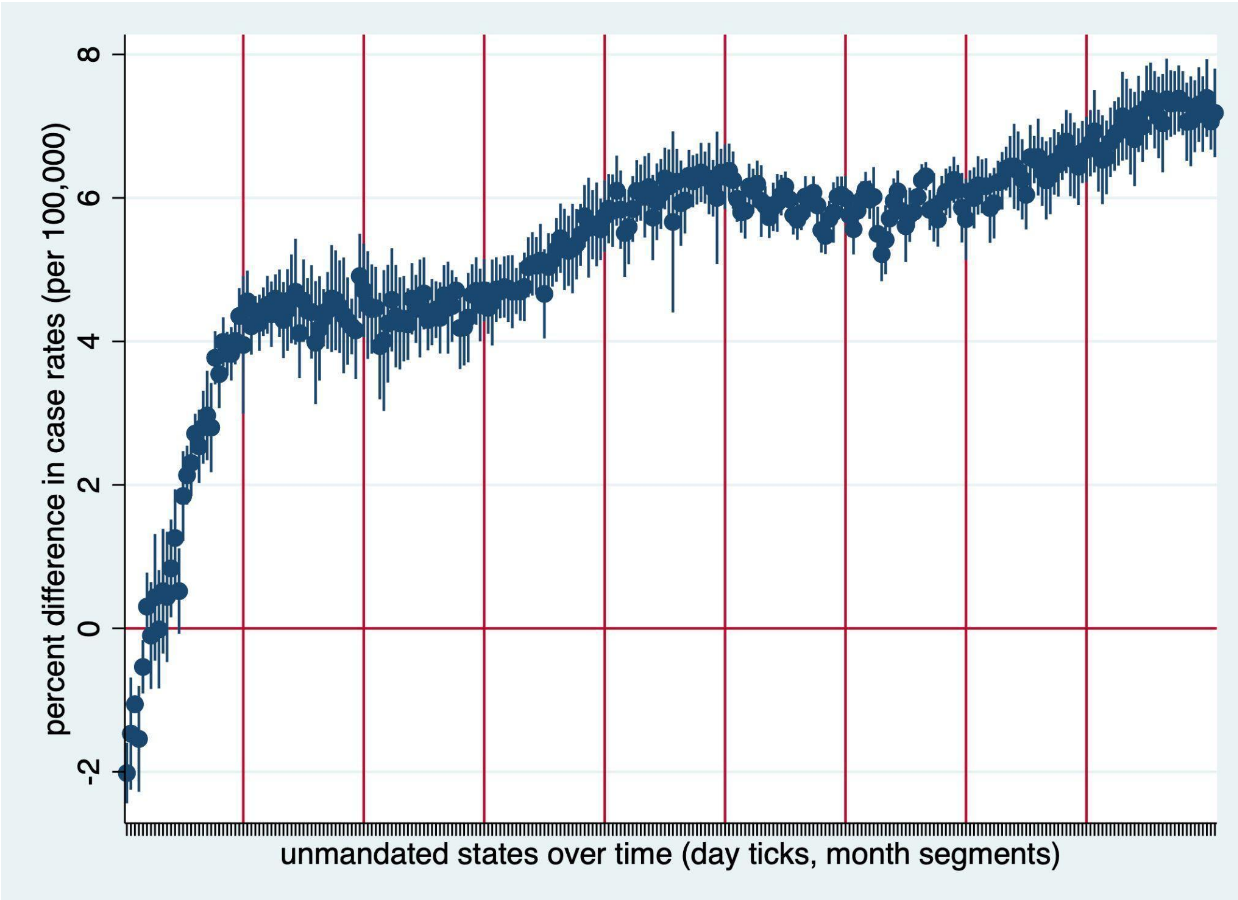


Figure 2



percent difference in case rates (per 100,000)
8
6
4
2
0
-2
unmandated states over time (day ticks, month segments)

Figure 3: Relative Plausibility of Parallel Trends: Comparing Mandated to Unmandated States Over Time

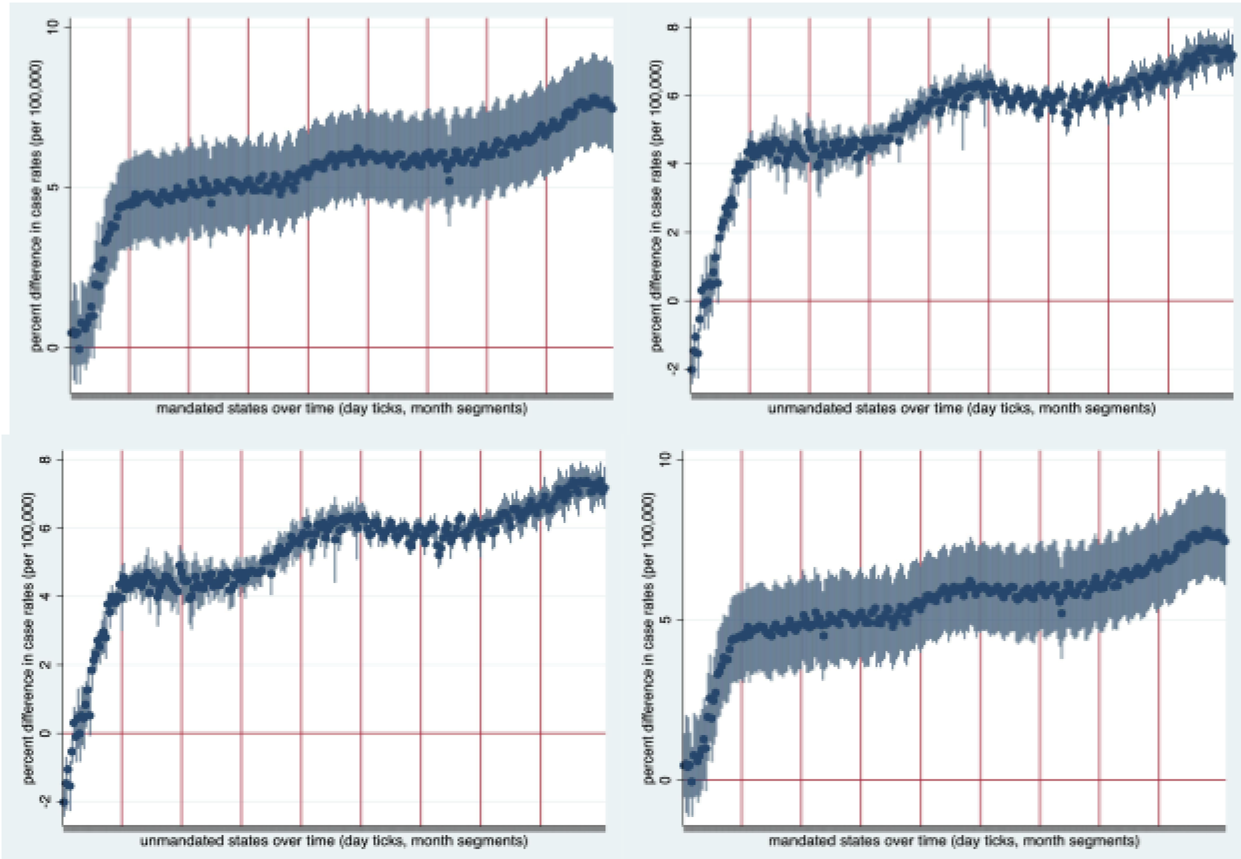


Figure 4: Event Study by Day (daily fixed effects)

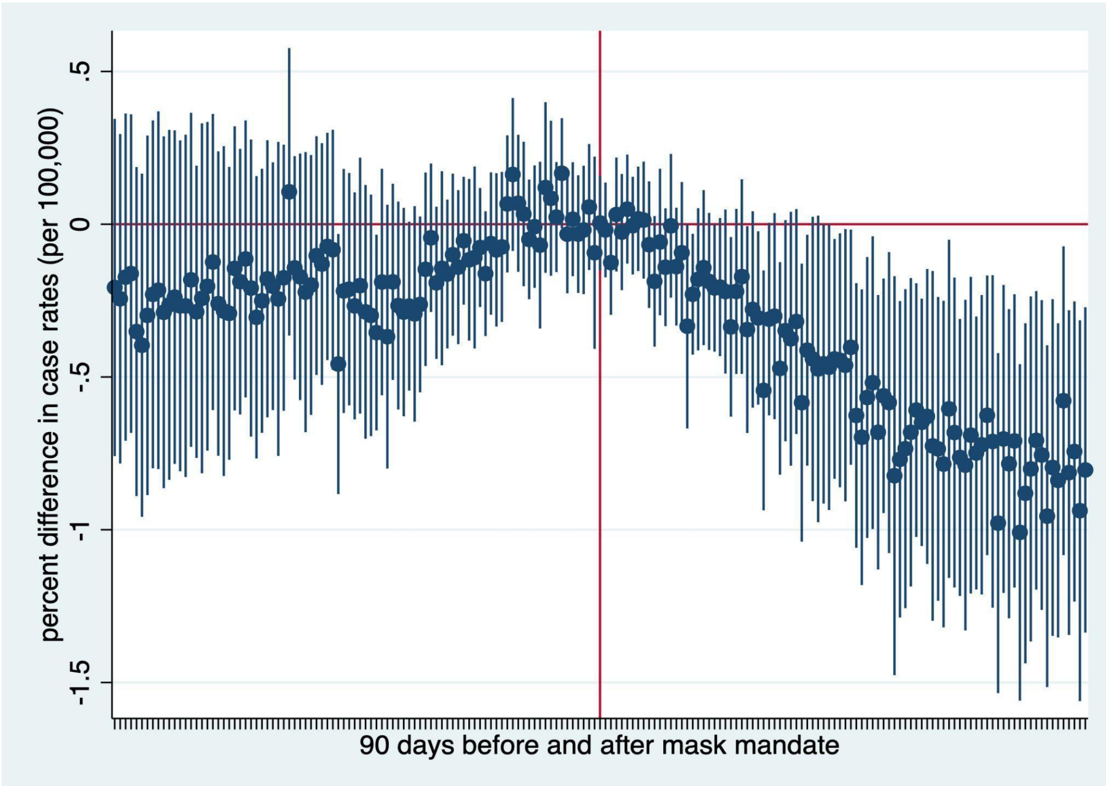


Figure 5: Event Study by Month (weekly fixed effects)

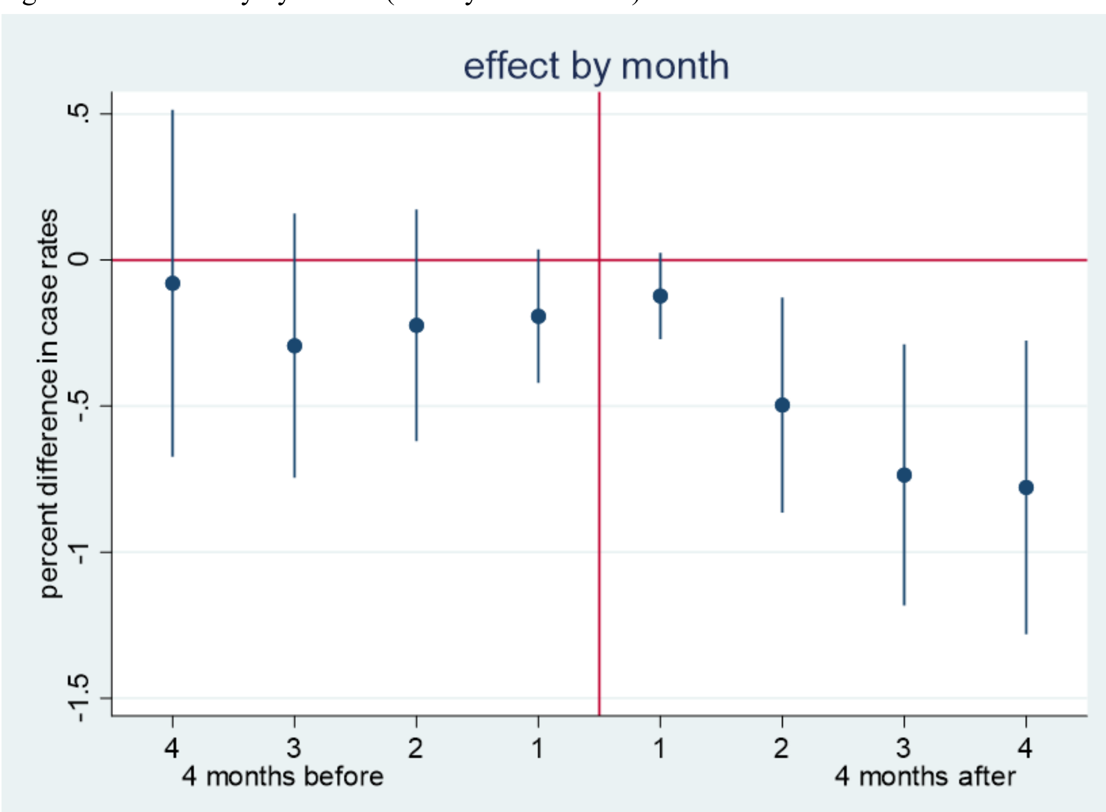
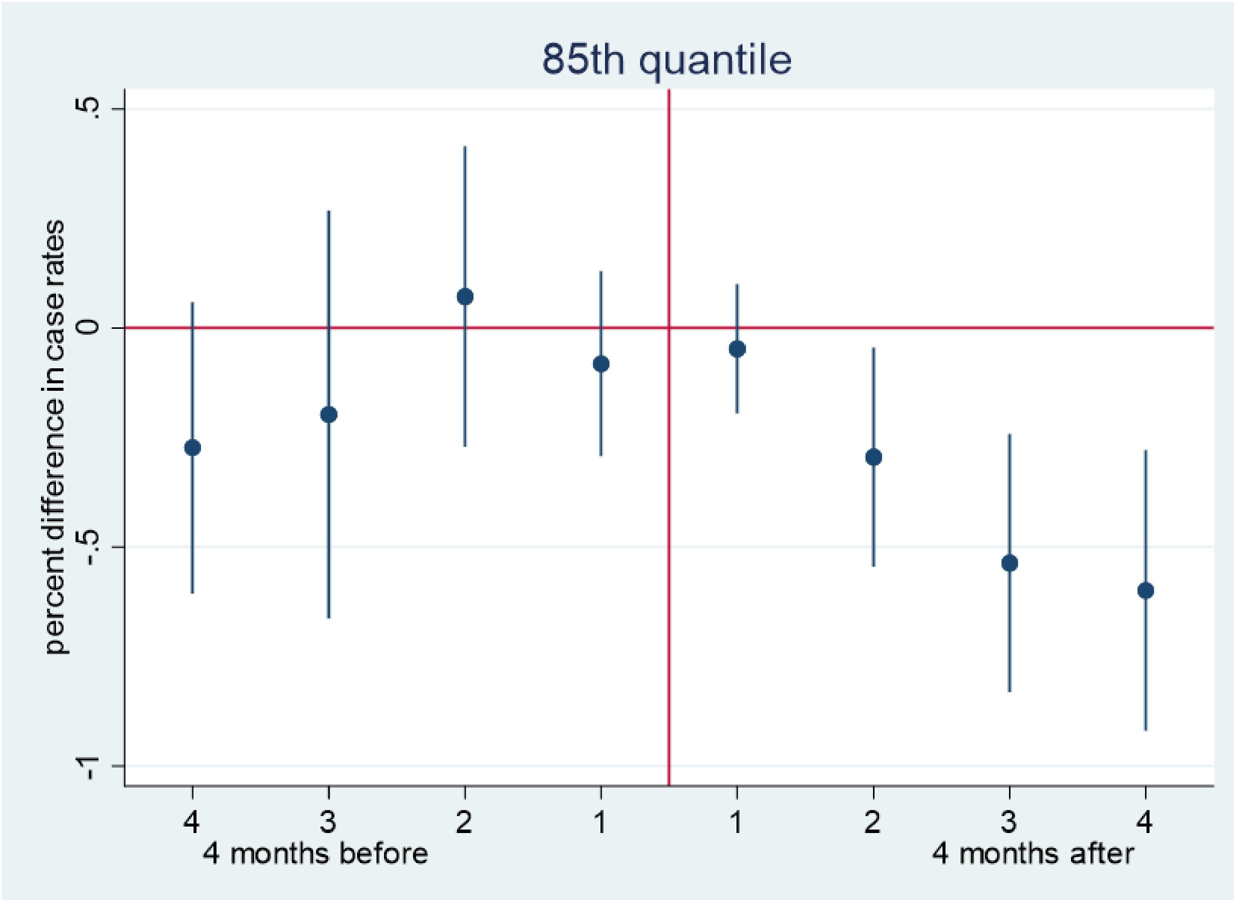


Figure 6: Event Study through Quantile Regression



Event Study (by day) Regression Table

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