Does Mobility Impact the Spread of COVID-19?

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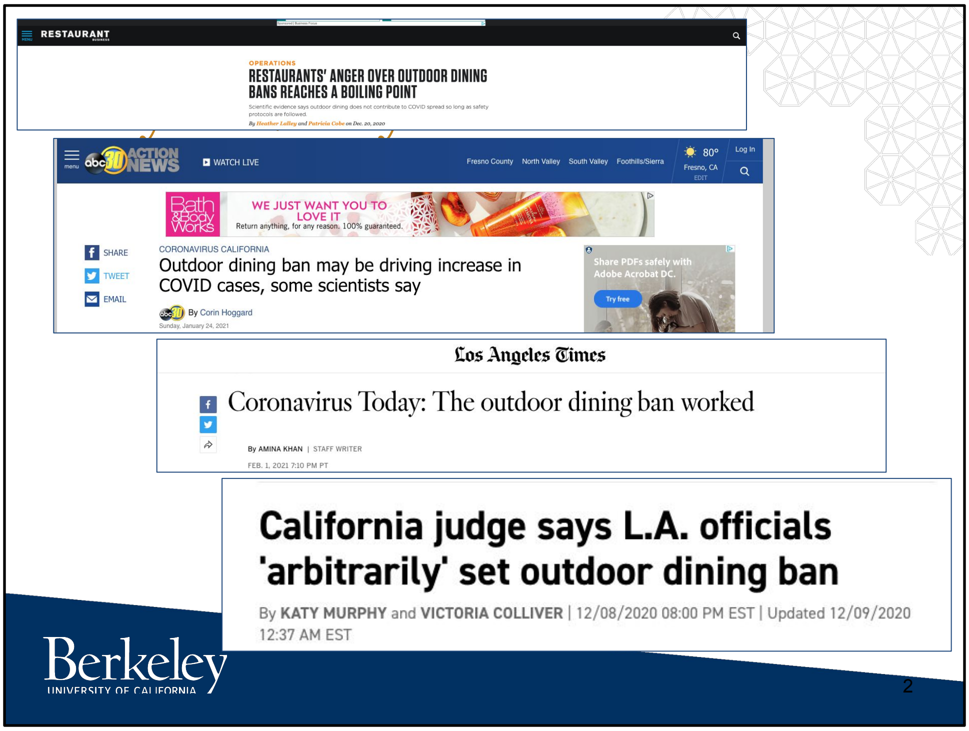
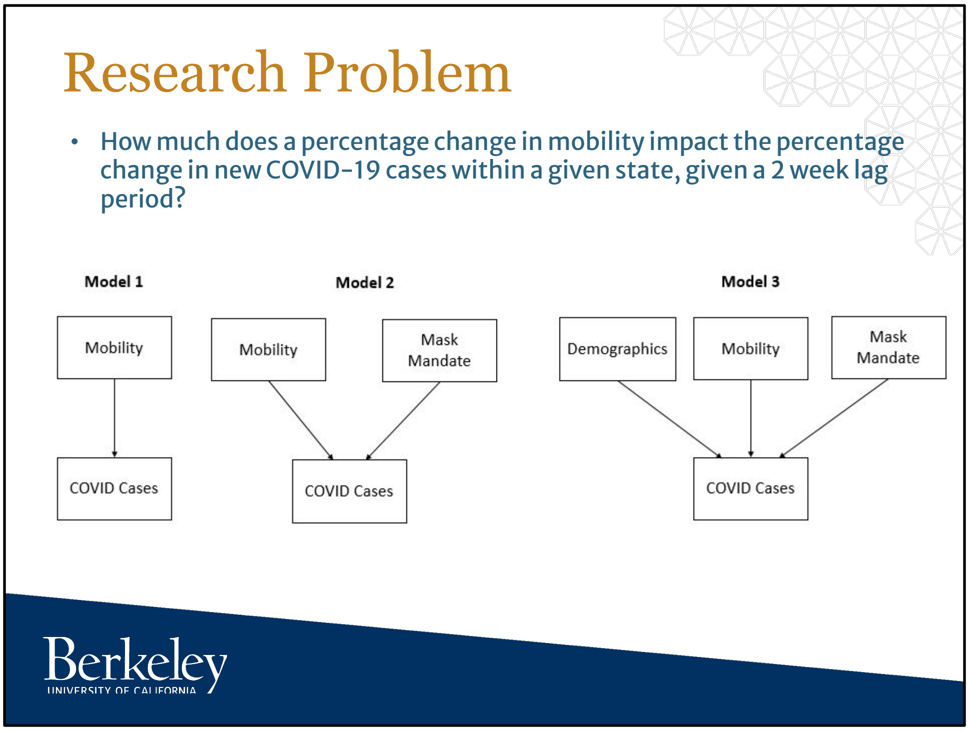


The first question is “Why do we care about mobility”.

We think the effect of mobility on covid-cases is interesting to study because there are many conflicting opinions about whether or not policies to reduce mobility is necessary. For example, here are a few references to arguments on LA’ outdoor dining ban.



Public health guidance during the pandemic has centered on the importance of limiting mobility and mask wearing as the most effective methods available to stop the spread of the virus. Although policies have been implemented at the state and federal level to address this guidance, the effectiveness of these measures depend upon individual compliance. Since Google has made mobility reports available, we sought to address the impact of changes in mobility upon percent changes in COVID-19 cases in a causal model. For our model progression, we chose to implement the presence of a state public mask mandate and demographic variables as controls.

Variables

- **Dependent Variable:**
  - Percent Change in new COVID-19 cases (comparing to previous week)
- **Primary Independent Variables:**
  - Percent Change in Mobility (comparing to previous week)
- Control Variables:
  - Public Facemask Mandate
  - Demographics

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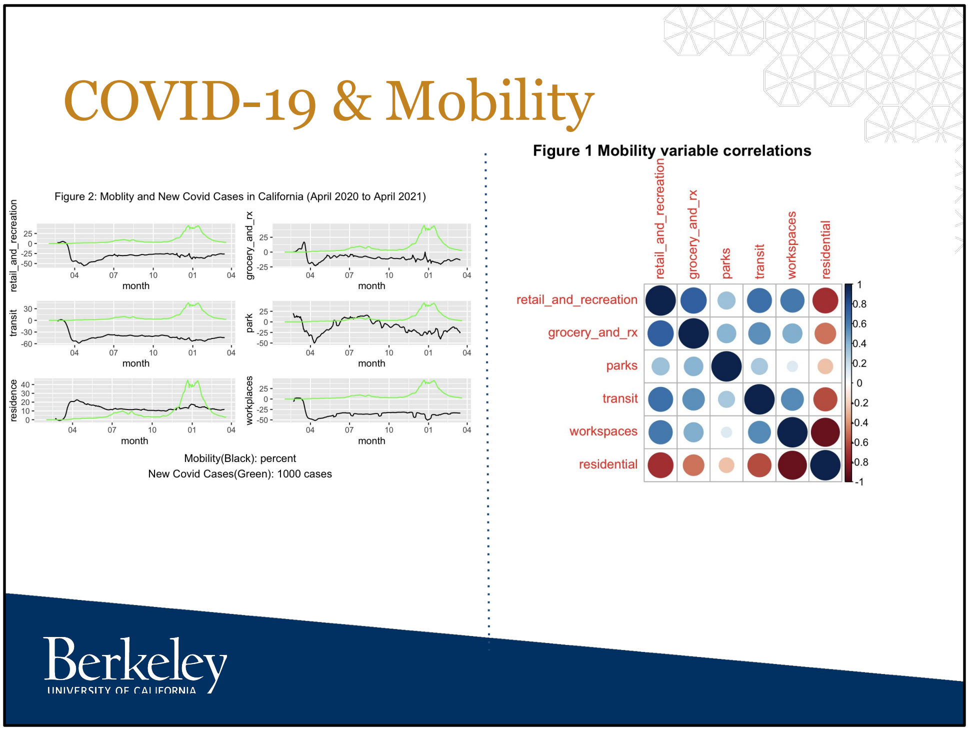
Briefly talk about the variables high level. Read through the slides and explain in more details later.



Two main points:

(1) No visual correlation between mobility and new covid cases over the entire time period.
(2) Talk about correlation between different mobility variables. Retail and transit move in the same direction, negatively correlated with residential.

Covid-19:

1) We chose to use percentage change in COVID-19 cases rather than case counts in order to study the impact of mobility when states have very different population sizes, since total case count is related to a state's population size.
2) The time period of the dependent variable is 2 weeks lagged from the mobility variable. We choose the 2 weeks lagging period based on the CDC suggestion that an individual is likely to incubate the disease 2-14 days after initial symptoms appear (which could be up to 10 days after initial infection).

We chose to use this specific time period for the following reasons:

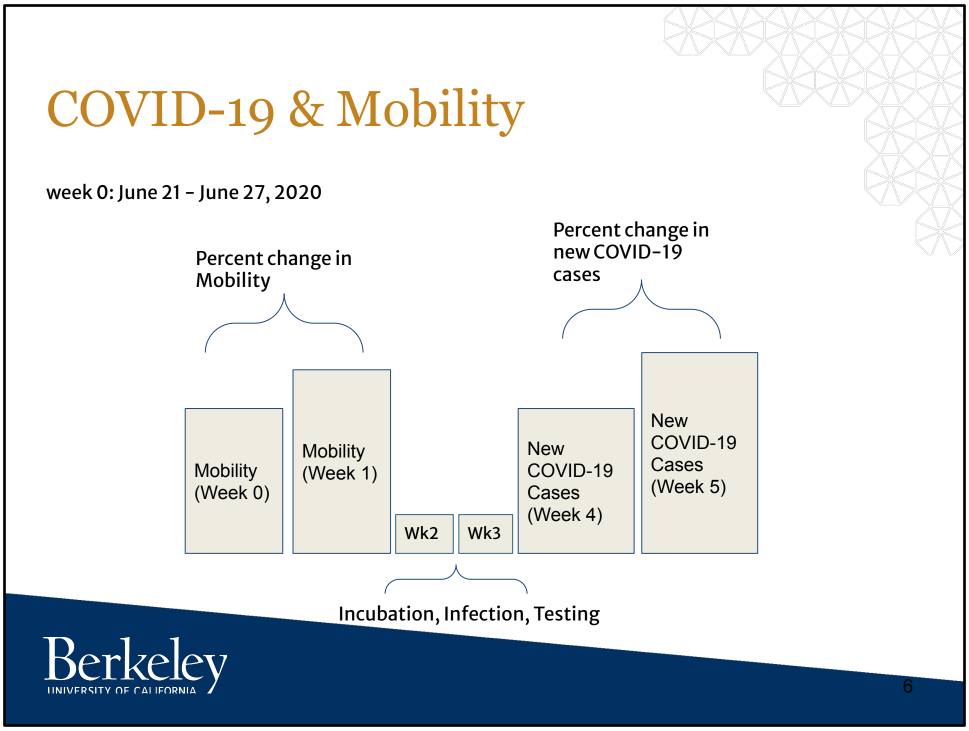
- Captures the big return towards baseline mobility after the initial lockdown dip (quarantine fatigue) which is an interesting time period to study (Figure 2).
- A week in which 31 states did not have public face mask mandates vs 20 states did (policy variation and balanced n-count of groups).
- Is a counter to the seasonal nature of the disease (i.e. weather may play less of a role in transmission during this summer time period which helps our causal question.
- It's also early enough in the pandemic that we'd expect a much lower

- proportion of the population to have contracted the disease already and develop antibodies, which gives us a clearer picture of our causal question since antibodies / disease resistance could be a potential confounding variable

Mobility

Retail, transit and grocery have positive correlation of > 0.70 (figure 1) and they tend to move in the same direction (from the figure 2). Retail and residence has a negative correlation of -0.75 and they tend to move approximately in the opposite direction.

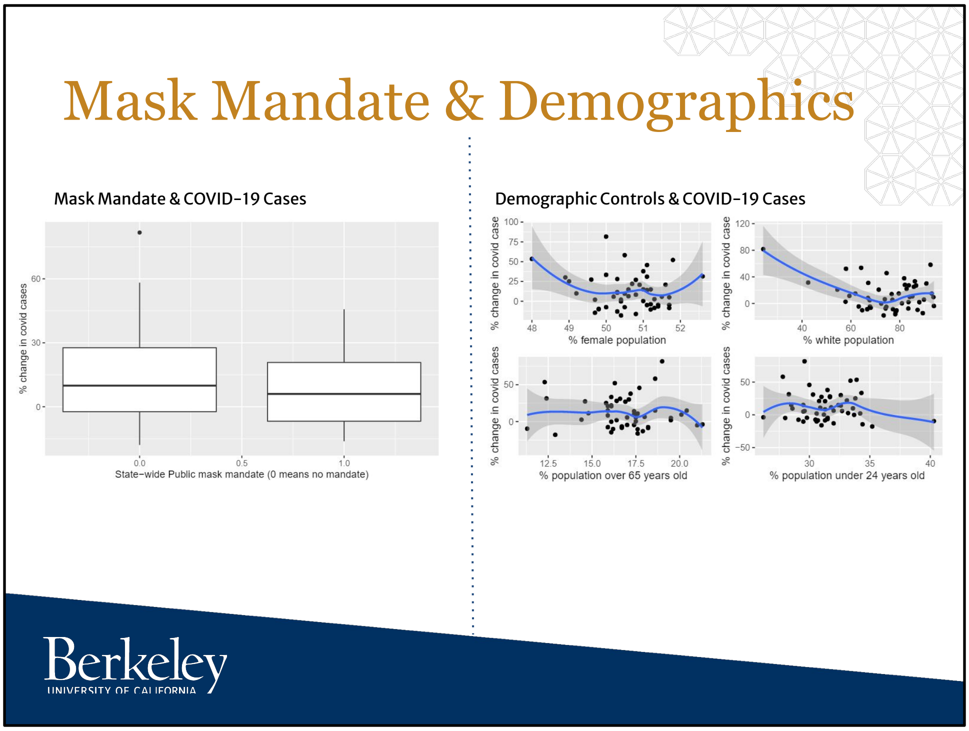
Since retail mobility is positively correlated with transit and grocery and negatively correlated with residence mobility, we decide to only include one of them as our independent mobility variable. We decide to use retail mobility because we think its practical meaning is the most interesting among all the mobility variables, given the political focus on restaurants and storefronts. We decide not to use workspaces and park mobility variable because (1) park is outdoor and easier to maintain 6-feet social distances, and therefore, we don't expect change in park mobility will cause change in new covid cases and (2) for workplaces, generally speaking people have less control of whether to go to workplaces or not, and therefore, this variable doesn't not have sufficient practical impact.



Two important points:

(1) the time period (best mask mandate separation)

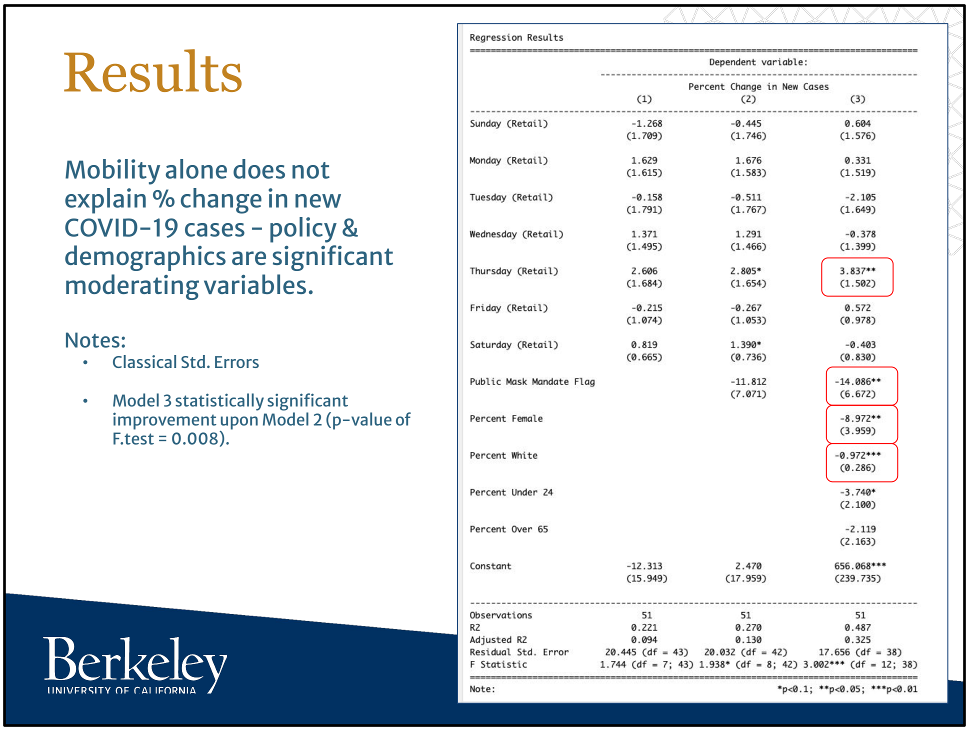
(2) one variable to each week day



Our inclusion of mask mandate and demographic control variables is largely based on academic research to justify our causal theory, which is discussed in detail in our write-up. I'll quickly walk through the distribution of each of these, as plotted against % change in COVID-19 cases, which nearly all give a compelling reason to include, even without the academic support.

Simple view between mask mandate and change in COVID cases appears to be negative. We see Hawaii has a high change which was driven by a combination of delays in testing due to Hurricane Douglas and known superspreader events at 2 bars. Since we can't unpair the impact of the two we decide to include Hawaii in our analysis, and discuss the difficulty of testing as an omitted variable bias.

Moving to the right of the slide, % female appears slightly negative, but tough to tell in the simple relationship. % white appears negative. % over 65 and % under 24 don't appear to have a clear relationship with COVID cases, but we include in our full model given the ongoing public discussion around differences in mobility and mask compliance between different age groups.



Regression Results

	Dependent variable: Percent Change in New Cases (1)	(2)	(3)
Sunday (Retail)	-1.268	-0.445	0.604
	(1.709)	(1.746)	(1.576)
Monday (Retail)	1.629	1.676	0.331
	(1.615)	(1.583)	(1.519)
Tuesday (Retail)	-0.158	-0.511	-2.105
	(1.791)	(1.767)	(1.649)
Wednesday (Retail)	1.371	1.291	-0.378
	(1.495)	(1.466)	(1.399)
Thursday (Retail)	2.606	2.805*	3.837**
	(1.684)	(1.654)	(1.502)
Friday (Retail)	-0.215	-0.267	0.572
	(1.074)	(1.053)	(0.978)
Saturday (Retail)	0.819	1.390*	-0.403
	(0.665)	(0.736)	(0.830)
Public Mask Mandate Flag		-11.812	-14.086**
		(7.071)	(6.672)
Percent Female			-8.972**
			(3.959)
Percent White			-0.972***
			(0.286)
Percent Under 24			-3.740*
			(2.100)
Percent Over 65			-2.119
			(2.163)
Constant	-12.313	2.470	656.068***
	(15.949)	(17.959)	(239.735)
Observations	51	51	51
R2	0.221	0.270	0.487
Adjusted R2	0.094	0.130	0.325
Residual Std. Error	20.445 (df = 43)	20.032 (df = 42)	17.656 (df = 38)
F Statistic	1.744 (df = 7; 43)	1.938* (df = 8; 42)	3.002*** (df = 12; 38)
Note:			*p<0.1; **p<0.05; ***p<0.01

I first want to note that we present classical standard errors here and for our coefficient tests, given we observe homoscedastic variance in our models and classical standard errors are larger, and thus more conservative, than robust standard errors in our models.

We chose to use a general linear F-test for nested models to determine if there is a statistically significant improvement in our F-statistic between reduced and full models.

Finally we choose to use an alpha level of 0.05 for all statistical tests due to the popularity of this threshold value and since we do not have a preference, given our limited background in the study of COVID-19 case analysis.

So to the results..

Model 1 in the regression table above demonstrates that there is not a statistically significant weekday mobility change that explains changes in statewide COVID-19 cases.As a whole, we fail to reject the null hypothesis that Model 1 has a significantly higher F-statistic than an intercept only model (p >0.05). We also observe that adding a control for a public mask mandate flag in Model 2 does not significantly improve our model compared to Model 1 (we fail to reject the null hypothesis that Model 2 has a statistically different F-statistic than Model 1 since conducting an F-test to compare models1 and 2 results in a p-value greater than our α of 0.05). In Model 2, the public mask mandate variable is not significant at an α level of 0.05.

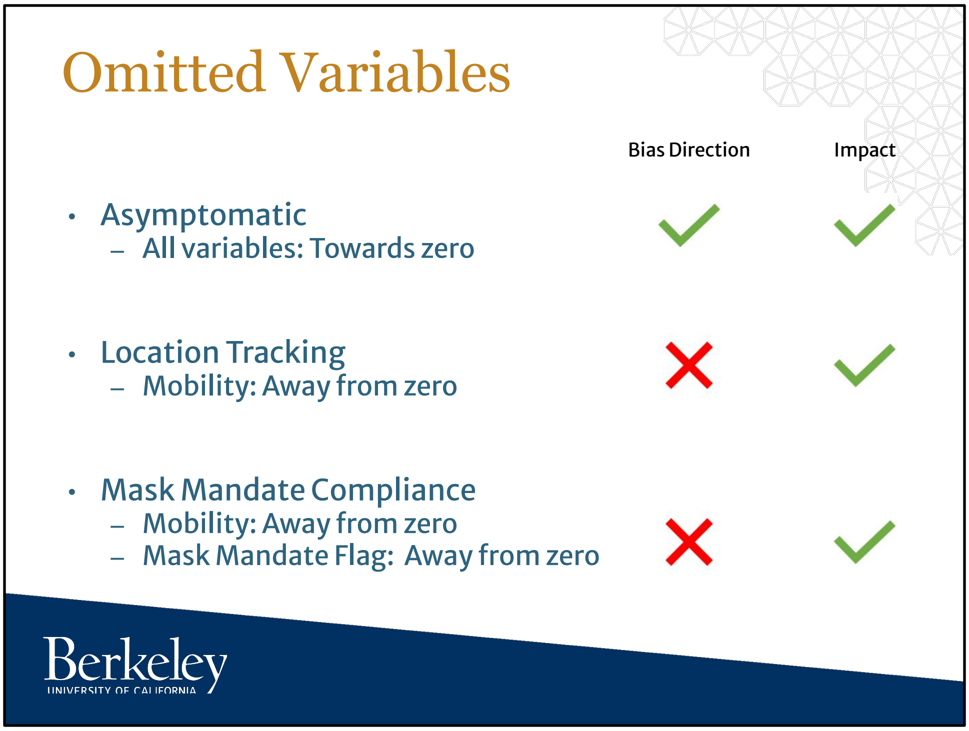
Interestingly, we see significant improvements in our explanatory model as a whole features in Model 3. We reject our null hypothesis that Model 2 and Model 3 have the same F-statistic (since the resulting p-value from the F-test of models 2 and 3 is less than our α of 0.05), and conclude that Model 3 is a statistically significant improvement upon Model 2 and an intercept only model.

Although we see one mobility variable, Thursday retail, is statistically significant we deem this a practically insignificant finding regarding mobility more generally since only one out of seven mobility variables was associated with a non-zero change in COVID cases.

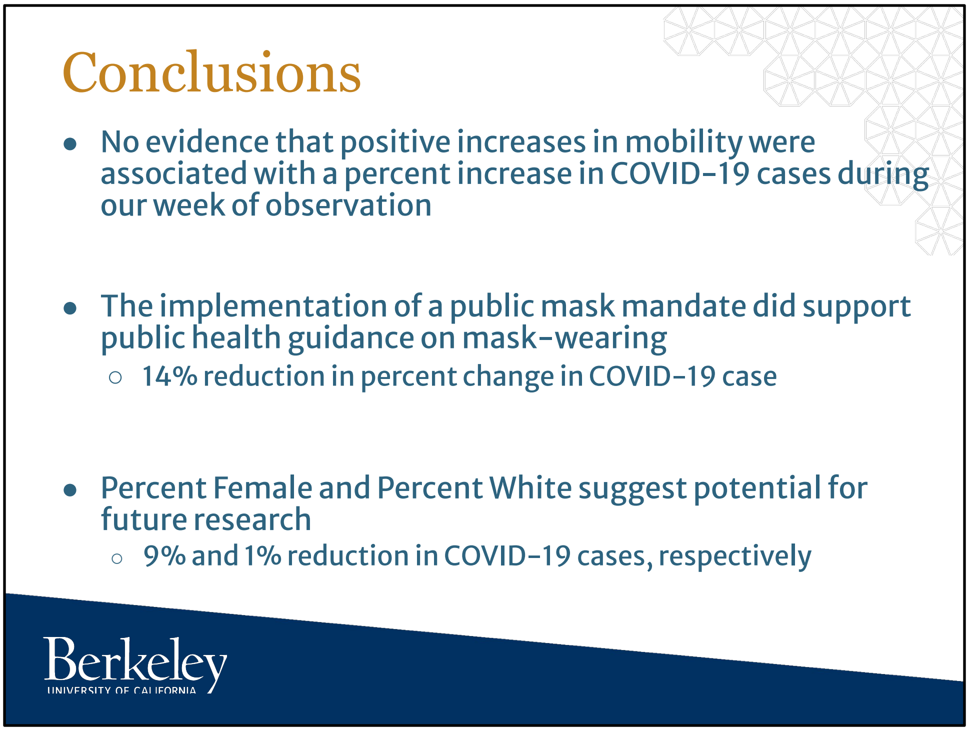
In our observation period, state's with a public mask mandate flag in place as of July 1st, 2020(i.e. the majority of the week that includes the July 4th holiday) saw 14% fewer new COVID-19 cases week-over-week, two weeks after the mobility time period than states with no public mask mandate flag in place, holding mobility and demographics constant.

We also observe that percent female ($p= 0.03$) and percent white ($p= 0.002$) are statistically significant at an α level of 0.05 in our Model3. A 1 percentage point (ppt) increase in a state's proportion of female residents was associated with 9% fewer new COVID-19 cases week-over-week, when holding mobility, publicmask mandate flag, and other demographic variables constant.

A 1 ppt increase in a state's proportion of residents who identify aswhite was associated with 1% fewer new COVID-19 cases week-over-week, when holding mobility, publicmask mandate flag, and other demographic variables constant.



- The omitted variable of Asymptomatic individuals has a bias Towards zero for all our coefficients, so it underestimated and we can have some confidence in the results of their coefficient
- The omitted variable of location track is taking into account the individuals who do not have smartphones or have their location tracking turned off. This OV has a bias away from zero for mobility, so it is overestimated and we should be careful trusting the results of this coefficient if we believe the impact could be large.
- The omitted variable of mask mandate compliance is taking into account the individuals who do not follow the correct guidelines of wearing a mask. This OV has a bias away from zero for mobility and the mask mandate flag, so it is overestimated and we should be careful trusting the results of this coefficient if we believe the impact could be large.
- However, since we are measuring percent changes in COVID-19 cases in each state over a short window of time, we believe that all of these omitted variables will experience little change from our starting time period to our final time period, so it will be consistent within each state and have minimal impact.



Federal and state policies have focused on face mask mandates and limiting mobility to combat covid spread. We sought to determine if changes in mobility (proxied by changes in retail and recreation mobility) impacted the % change in Covid cases following July 4th, 2020.

We failed to find statistical evidence that positive increases in this metric resulted in a % increase in COVID cases. Although the change in Thursday mobility demonstrated a statistically significant result in the 3rd model, this finding lacks practical significance - the day does not coincide with the holiday and we have not found evidence of widespread holiday closures on Thursday the 2nd. Mobility may still explain changes in COVID cases in different time periods or if the impact of changes in mobility has been suppressed by omitted variables.

However, face mask mandates, percent female, and percent white were observed to result in a reduction in covid cases, when demographic controls were added. These findings may be artifacts of omitted variable bias, but they do support other studies on the relationship between mask-wearing, gender, race, and the spread of COVID. Therefore, further research in this area may prove valuable.

Thank you for listening.

Image References

1. Title Image: https://pixabay.com/photos/people-crowd-busy-streets-699160/
2. Restaurant Business Online: https://www.restaurantbusinessonline.com/operations/restaurants-anger-over-outdoor-dining-bans-reaches-boiling-point
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6. Stargzer Table: Hlavac, Marek. 2018. “Stargazer: Well-Formatted Regression and Summary Statistics Tables. R Package Version 5.2.2.” Computer Program. https://CRAN.R-project.org/package=stargazer.

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