Hi everyone, I am Michelle Audirac. I will briefly introduce myself. I am a Data Scientist I have worked mainly as a Risk and Portfolio analytics specialist and currently I am interested in fraud and anomaly detection.

About two months ago more less Cory Zigler first presented our work, at that time we were exploring how to characterize county level death curves based on the heterogeneity of the US counties' anatomy and the timing of the stay-at-home orders.

The main goal of our work changed a bit and now it has more to do with providing insights for the following question:

which of the policy intervention that were first implemented had the greatest effect in reducing Rt?

It's been a while since the first interventions and the scientific communities have made significant progress understanding the relationship between mobility reductions and covid transmission, yet the way events unfolded poses major obstacles into answering this particular question.

- First, there was a close spacing of different policy interventions in time
- Also there is a strong correlation between the onset of interventions and reductions in mobility
- Third, state-level analysis in general mask the more granular and heterogeneous patterns found on a county-level

these three points I'm sure are not new to the group, but these are precisely the knots that our method aims to disentangle

I will breeze through our building blocks real quick. We use daily deaths of counties to quantify the impact of interventions and because we want to learn the immediate effects and not the long term effects we use observations from Mid March to early May and not later

An important pillar of our analysis is the use of the NCHS classification of counties. This classification is relevant in our analysis because it captures a lot of rural-urban factors that are typically associated with different levels of contact rate such as population density, modes of transportation and distance to major airports. There are 6 NCHS categories: 1 and 2 being metropolitan areas where 1 is more dense than two, 3 and 4 are micropolitan and 5 and 6 are mostly rural

In addition to NCHS, we incorporated other drivers of heterogeneity that have been reported to have a relationship with death mortality which are listed in the bottom

Taking all this in account and after the cleaning process we are left with 440 counties and we will focus our attention on isolating the effect of two interventions: one having a policy nature -stay home orders and another a mobility nature- 50% reductions in total visits to points of interest

- So after putting together all these data, to our surprise one of the first things we realized is that in most counties total visits had declined prior to stay-home orders
- For instance, in the plot we see that major metropolitan centers had already achieved a 70% decrease in their total visits the day stay-home was enacted and in non-core rural counties the average reached a 66% decrease although there is more variance within this group

- On the other hand, although the date distribution of policy interventions is mostly uniform across NCHS in calendar timing, when we look at the date distributions through the lens of the epidemic timing we see a cleaner differentiation across NCHS groups.
- Zooming into the plot in the middle, if time zero is determined by the day a county reaches the death threshold (given by 3 deaths per ten million residents) then we can see that metropolitan areas in nchs group 1 implemented stayhome orders later in epidemic time than the other groups and that at least 50% of non-core rural counties in groups 6 adopted stayhome orders way before reaching their death threshold, up to 20 days earlier.
- This is also true for the mobility decrease across NCHS groups

- Leveraging from the demographics heterogeneity in counties and also the heterogeneity in intervention timing captured by the epidemic time, our model finds the coefficients of a quadratic polynomial
- This curve fitting is mostly inspired by the Bayesian hierarchical model first introduced by the core team of the consortium
- But the major twist here is that our formulation captures changes in shape after introduction of the intervention and an intervention lag
- And because we are interested in differentiating the effects of interventions we fitted three variations of the model:
  - One that uses the timing of stay home orders
  - Another that uses the timing ot the reductions in total visits
  - Finally, one that incorporates both

- To give a simple explanation of our model, I would say that it fits two quadratic forms for each county: a pre and a post intervention polynomial and these two adjacent pieces meet at the time of the intervention plus an intervention lag of 12 days. The intervention in the figures is depicted by the blue vertical lines and the intervention lag by the blue dotted lines
- This piece-wise property of our fit allows us to move the intervention time sideways and produce hypothetical scenarios had the policy or mobility interventions been enacted 10 days before or 10 days after the observed date. The late posterior predictions are in red, the early posterior prediction are in green.
- The Figure in the middle of the slide shows the counterfactual trajectories of daily deaths for New York Kings County using stay-home as intervention on the left and mobility decrease on the righe. In this case, the observed reduction total visits lagged the stayhome by 3 days and we can see diverging coutnefactuals.
- With this images I would also like to underline that if we measured the reduction of deaths after a given date we would not necessarily be capturing whether an intervention induced a bend in a death trajectory or not, because death drops is not necessarily the same thing as death trajectory shift .
- For example, Washington King's adoption of a stay-home order does not appear to have an impact on the post-intervention trajectory, so our model suggests that its curve had already flattened by the time the policy enacted. Probably as a result of awareness brought by national attention to this case.

- Another quality of our model is that it captures associations from death curves of different counties and it expresses a death curve as a sum of components: average trends extracted from all curves, and random effects that are specific to a single county.
- This is why even if the policy and mobility interventions occurred on the same date in a given county, after pulling information from the bends induced by these two interventions in all other counties, the posterior predictions of late policy-intervention are different from the ones associated with late mobility-intervention.
- These quality is exemplified by the posterior predictions of Lousiana Jefferson's County where interventions that originally occurred on the same day have diverging counterfactuals.
- So what can we say from the average trends?
- We see that counties in the more rural areas in groups 4,5,6, it is hard to estimate the timing effect of mobility reductions with our method because these happened significantly early
- But when we look at the peaks of the average counterfactuals, our model suggests that mobility reduction timing more heavily influenced the bending of death curves relative to timing of stay-home orders

- This last result is also corroborated by the two intervention model whose outcomes depicted in this last image
- **Open questions**: Total visits is mostly comprised of schools, colleges, restaurants and bars visits, its reductions are a direct consequence of school and business closures? Other drivers?
- Stay-home orders increased the actual time people spent at home state level(Abouk 2020) and might have a larger role in maintaining low activity for longer periods
- **Limitations**: measure relative effectiveness of intervention timing, not the overall effectiveness nor the absolute lack of them. Rely on quadratic forms and not in epi engines