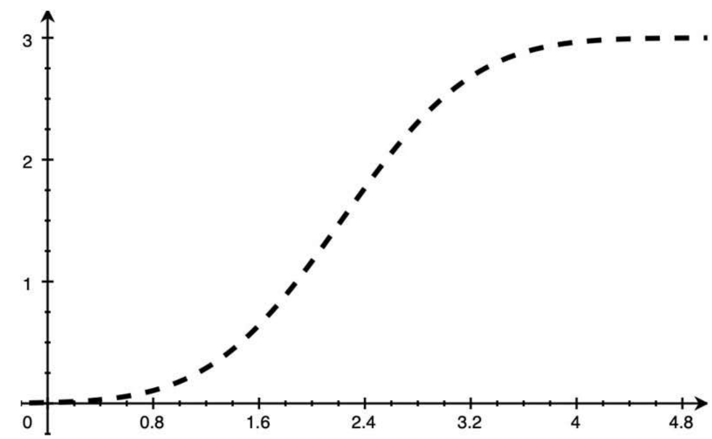
Death rate model (functional form)

- We model the death rate as a sigmoid (ERF):
- Death rate given by

$$D(t, \alpha, \beta, p) = \frac{p}{2}\Psi(\alpha t - \beta) = \frac{p}{2}\int_{-\infty}^{\alpha t - \beta} \frac{1}{2\pi} e^{-\frac{\tau^2}{2}} d\tau$$

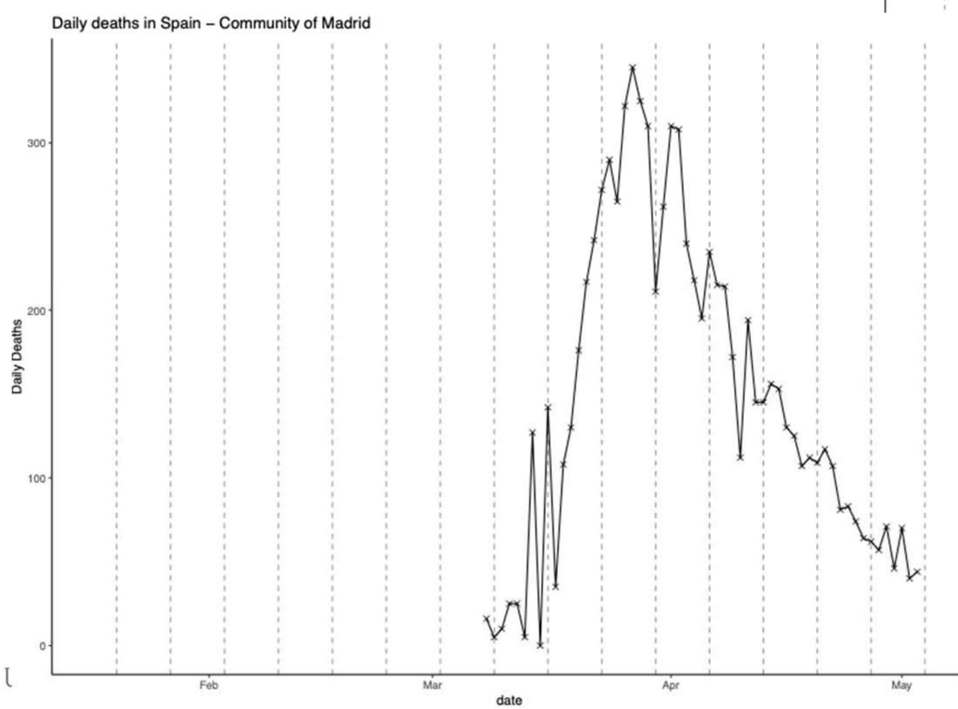


- Independent variable t is ‘time since rate reached 1e-15’
- p captures maximal rate (parameter)
- α controls trajectory (parameter)
- β is time of the daily deaths peak (modeled using social distancing covariate)
- CurveFit tool allows mixed effects structure to borrow strength across locations

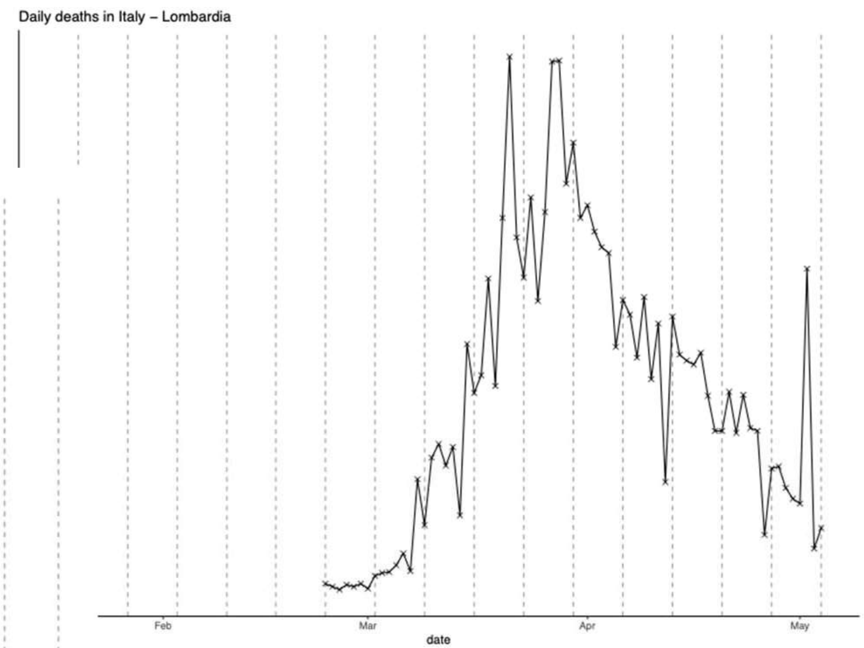
We use locations that have peaked to get peak covariate prior.

- Peaked locations
- Germany: 15
- Italy: 21
- Spain: 17
- Canada: 1
- USA: 31

Madrid



Lombardia

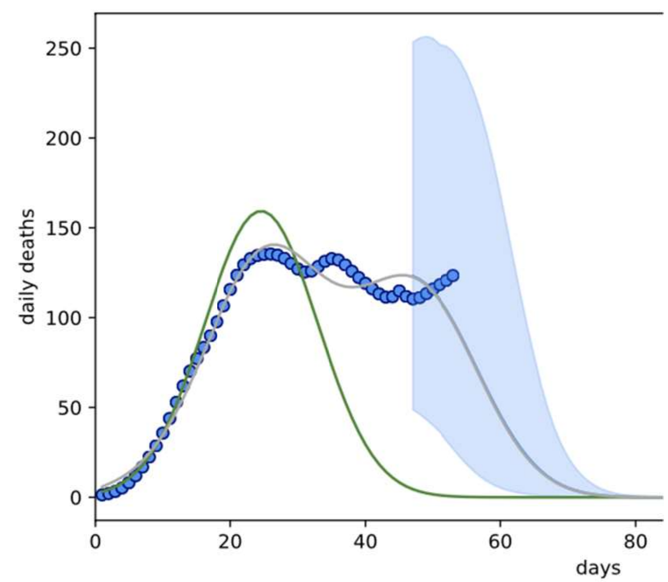


Leading Indicators: Deaths from Cases

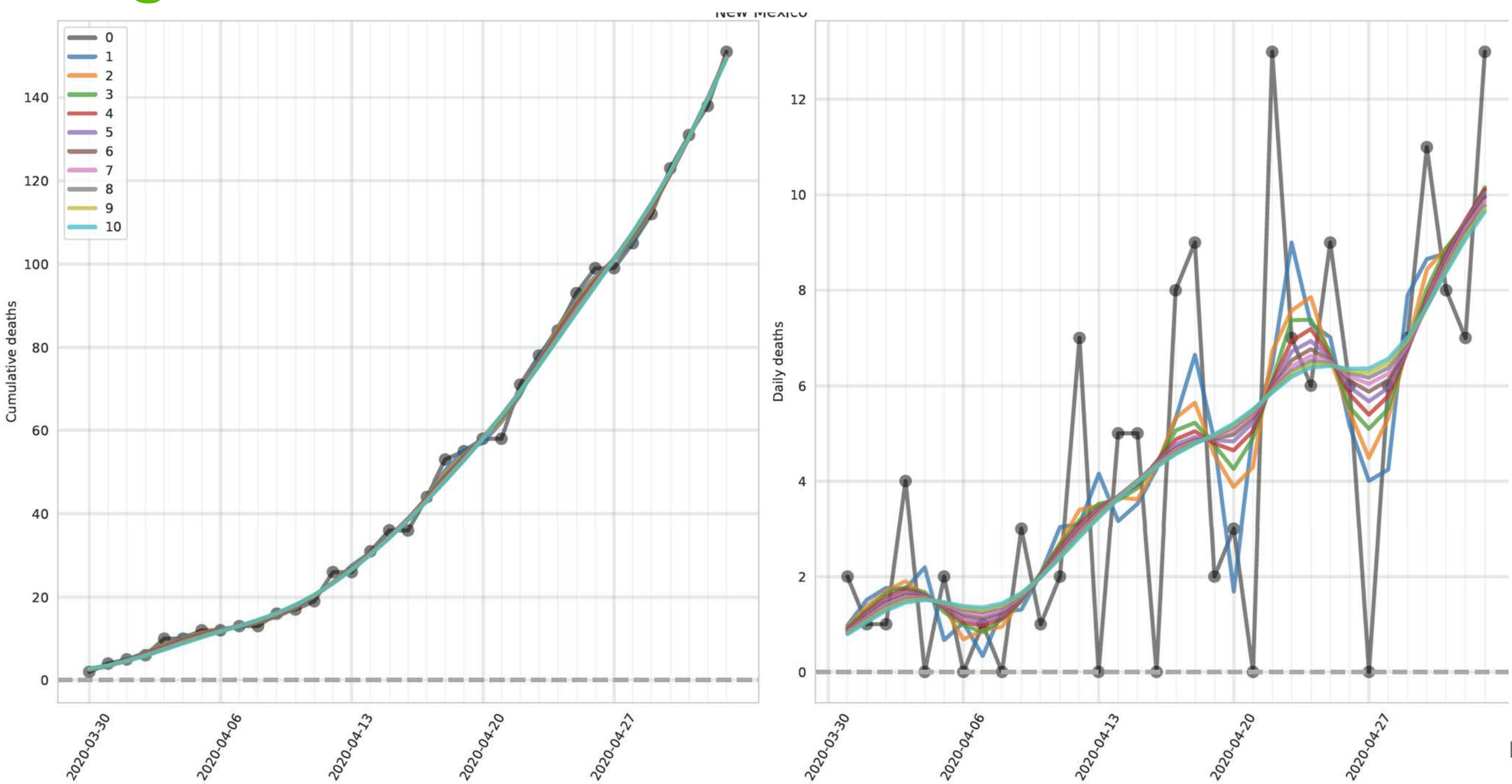
- We compute ratio of deaths on the last day of deaths data to cases 8 days prior

- We use this ratio to predict deaths 8 days out.

- For locations with hospitalizations data, we also use this approach, but with the ratio of deaths to hospitalizations (averaging with deaths predicted from cases).

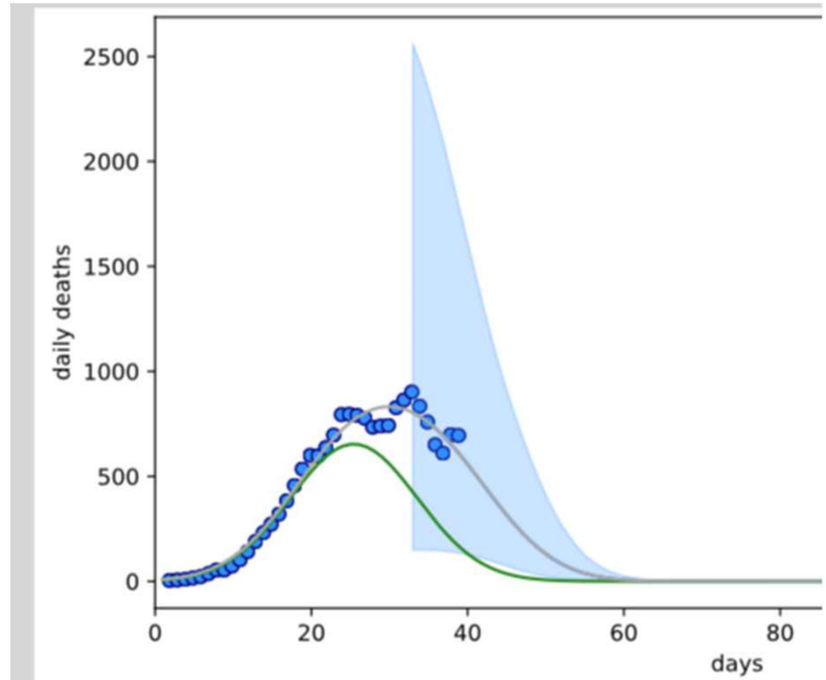


Smoothing deaths data by iterative moving average of log cumulative deaths



Mixture Model

- A single Gaussian may not fit the data well
- We use a mixture of Gaussians models:

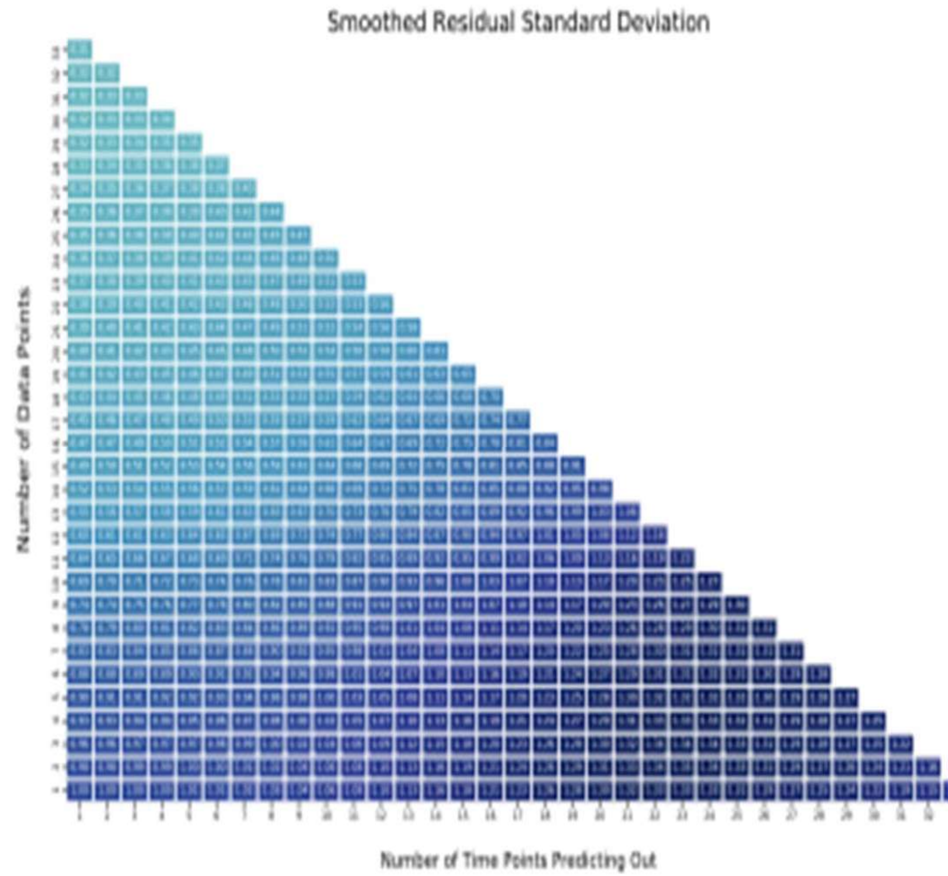


$$\min_{\{0 \leq w_i \leq 1\}} \sum_t \left(y_t - \sum_{i=1}^{13} w_i f_i(t) \right)^2$$

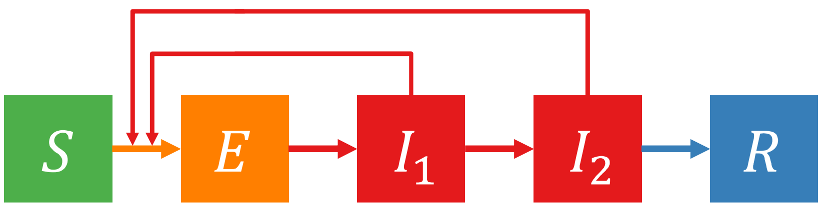
- Each $f_i(t)$ is a Gaussian peak propagated backward/forward in time (13 total)
- Weights w_i are constrained to be between 0 and 1
- Mixture model captures asymmetry and longer peaks (NY above).

Predictive Validity for Deaths Model

- Uncertainty in the deaths model is based on out of sample performance.
- We hold out data to get residuals between predictions and observations.
- Smoothing across locations, we summarize error in two dimensions:
  - Forecast horizon (x-axis, left = more)
  - Number of datapoints (y-axis, up=more)
- Uncertainty is then estimated for future predictions.



SEIR model fit to death data



$$\frac{dS}{dt} = -\frac{\beta(t)S\,(I_1 + I_2)^\alpha}{N}$$
$$\frac{dE}{dt} = \frac{\beta(t)S\,(I_1 + I_2)^\alpha}{N} - \sigma E$$
$$\frac{dI_1}{dt} = \sigma E - \gamma_1 I_1$$
$$\frac{dI_2}{dt} = \gamma_1 I_1 - \gamma_2 I_2$$
$$\frac{dR}{dt} = \gamma_2 I_2$$

SEIR model steps:

- Fit SEIR model (e.g., fit $\beta(t)$)* to past and recent death model output for all locations.
- Regress $\beta(t)$ on available covariates*
- Forecast time-varying covariates into the future
- Combine regression with forecasts to forecast $\beta(t)$*
- Run forecasted $\beta(t)$ through SEIR model to forecast infections*
- Calculate deaths from infections and IFR*

*** By draw**

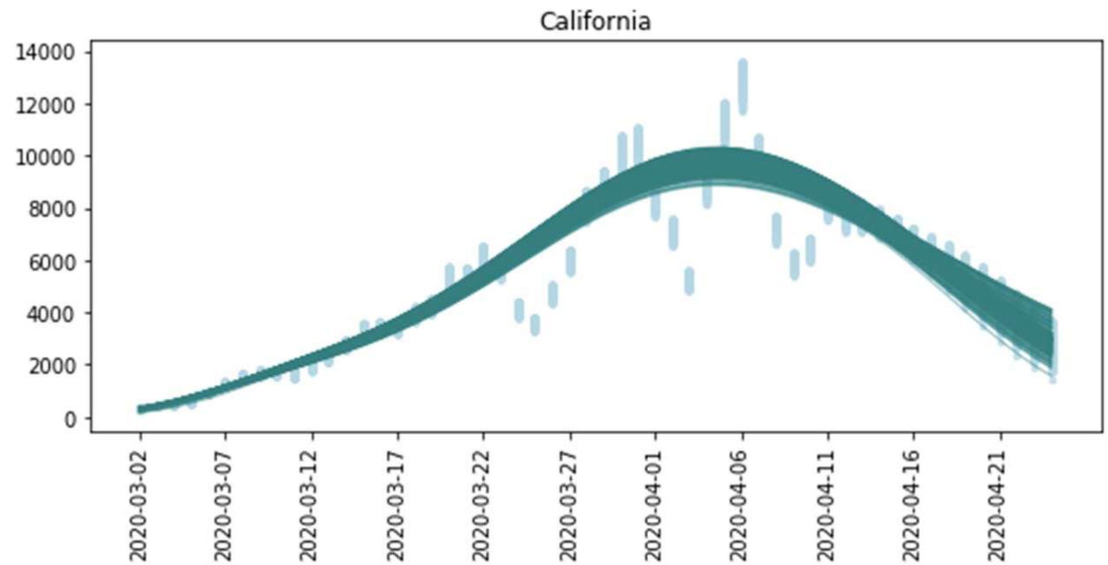
Step 1: Inference for $\beta(t)$: new technique.

- 1a. Fit a spline to new infections:

$$f(t) := \beta(t)\frac{S}{N}(I_1 + I_2)^\alpha$$

- 1b. Solve three ODEs:
  - E(t) using f(t)
  - I_1(t) using E(t)
  - I_2(t) using I_1(t)
  - Integrate to get S(t) and R(t)
- 1c. Compute

$$\beta(t) = \frac{f(t)N}{S(t)(I_1(t) + I_2(t))^\alpha}$$



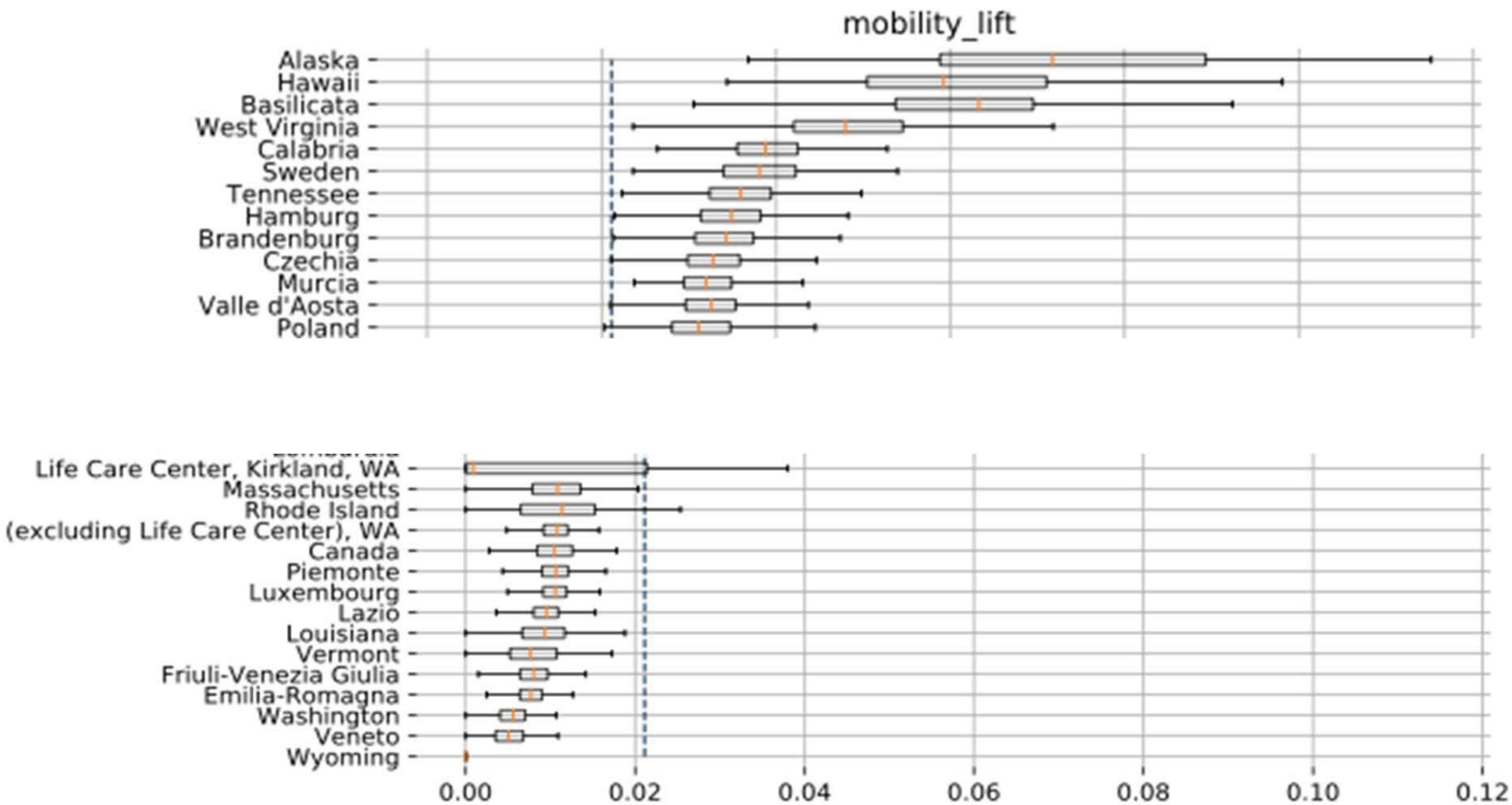
Step 2: Regression of $\beta(t)$ on covariates

- We have four covariates:
  - mobility, temperature, testing per capita, population density.
- We apply a stage-wise mixed effects regression:
  - Log beta(t) ~ int. + mobility (mobility coef. positive)
  - Log beta(t) ~ int. + [mobility] + density (density coef. positive)
  - Log beta(t) ~ int. + [mobility, density] + temp (temp coef. negative)
  - Log beta(t) ~ int. + [mobility, density, temp] + test/cap (test/cap coef. negative)

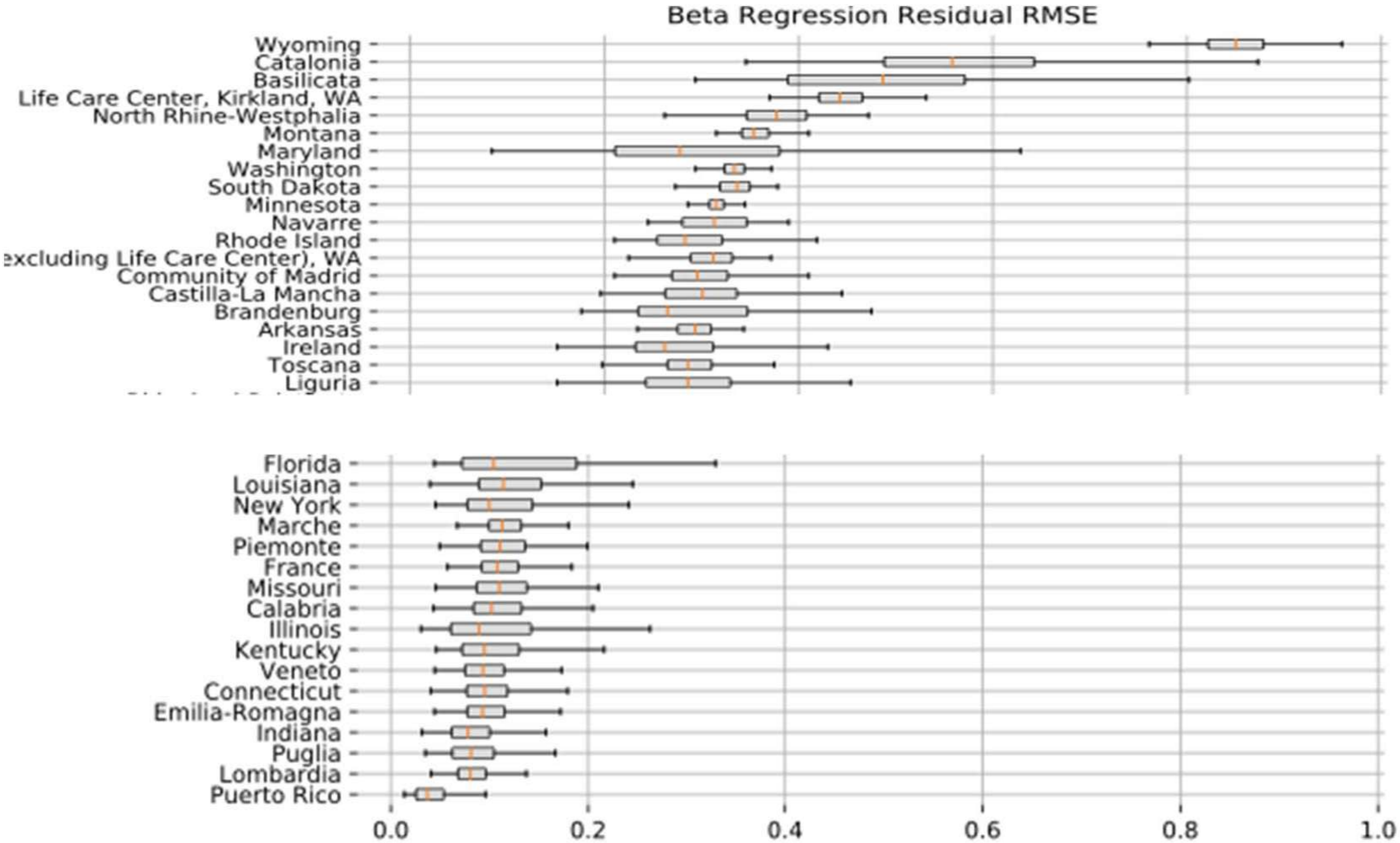
  - Log beta(t) ~ [mobility, density, temp, test/cap] + RE(mobility, intercept)

    (net mobility effect is positive for each location)

Regression results: Mobility Coefficients

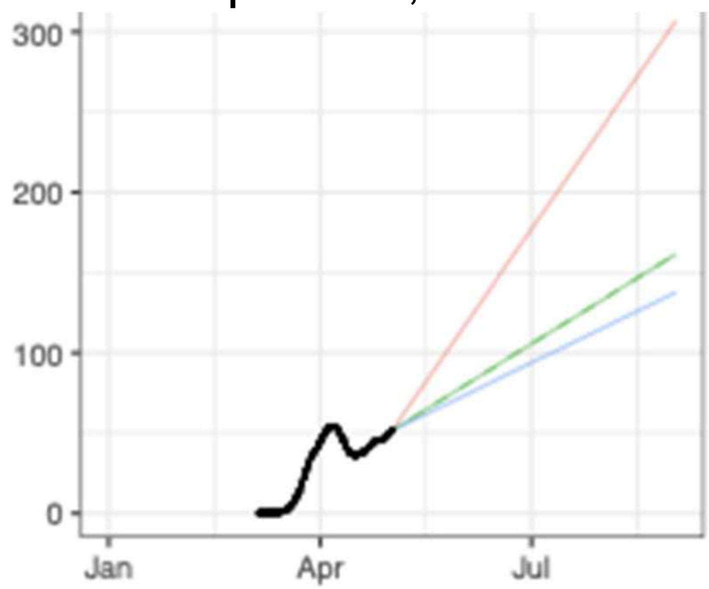


Regression results: In-Sample RMSE

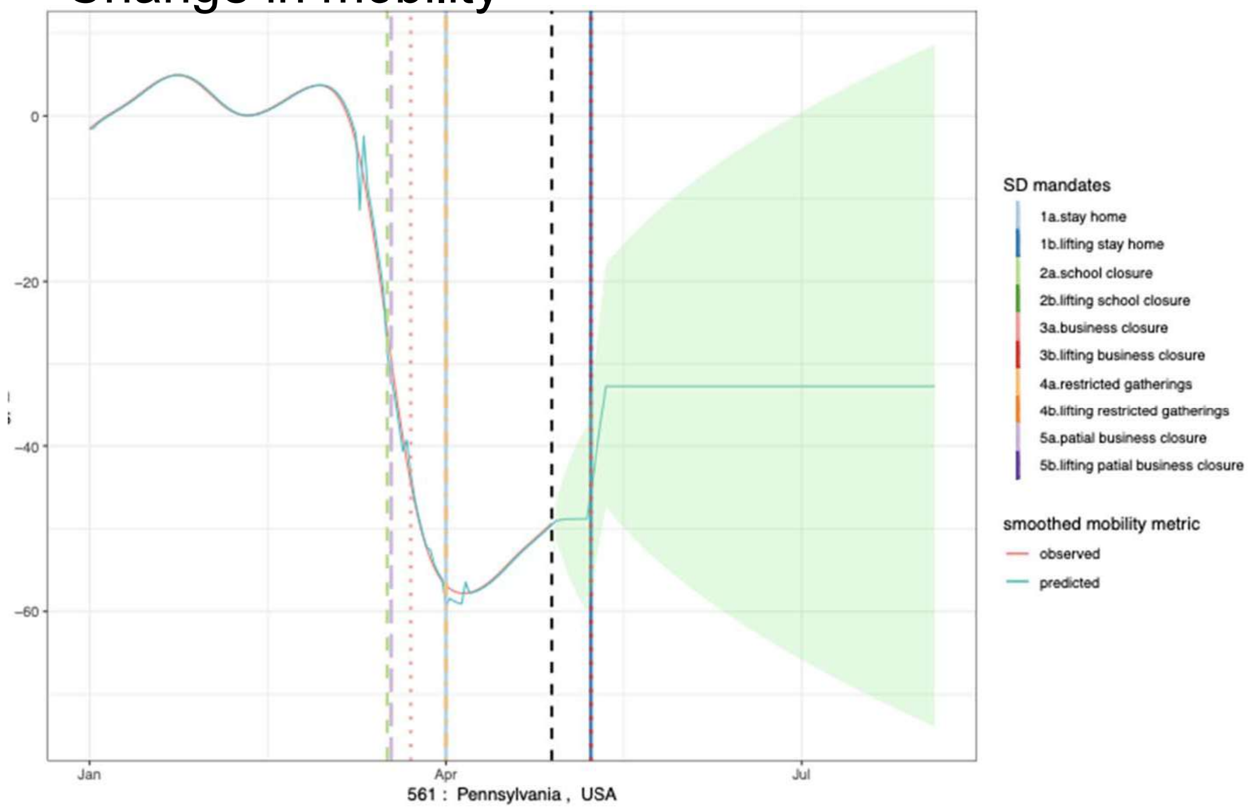


Step 3: Forecast Covariates

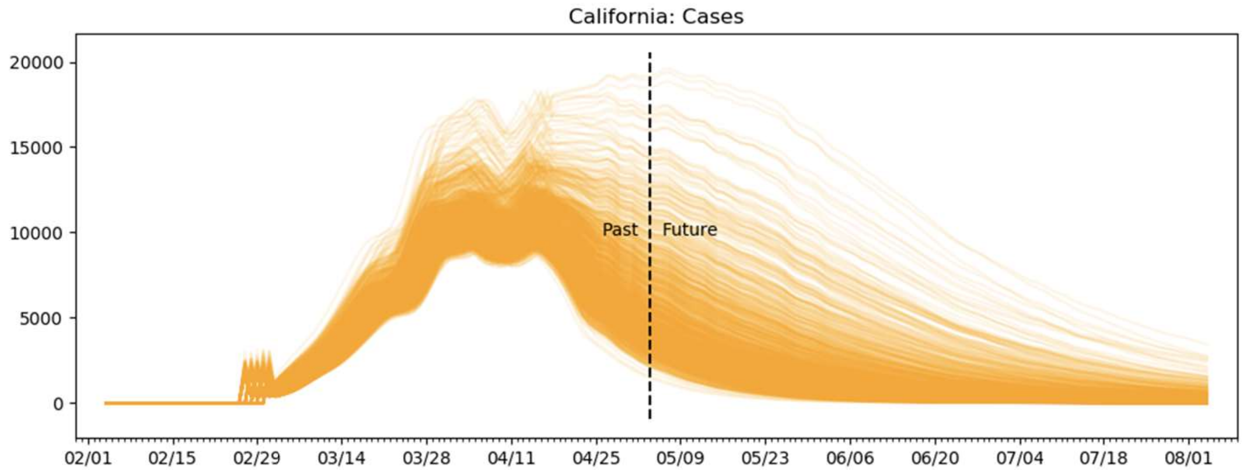
Tests per 100,000

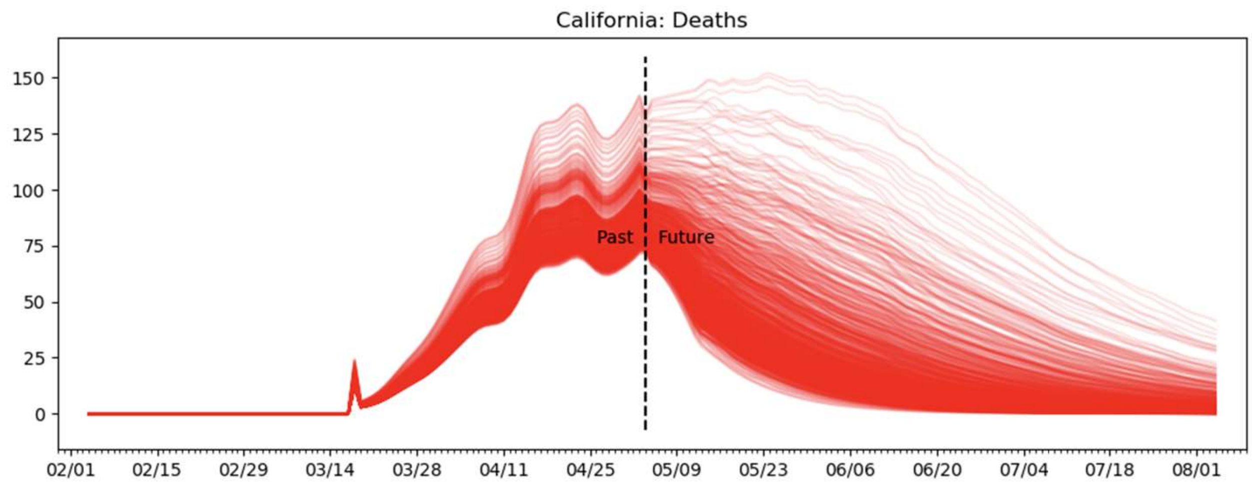


Change in mobility



Step 4: Forecast beta(t), cases, deaths, …





Computational load:

- SEIR fits: 123 locs x1000
- Regressions: 1000
- Forecasts: 123 locs x 1000

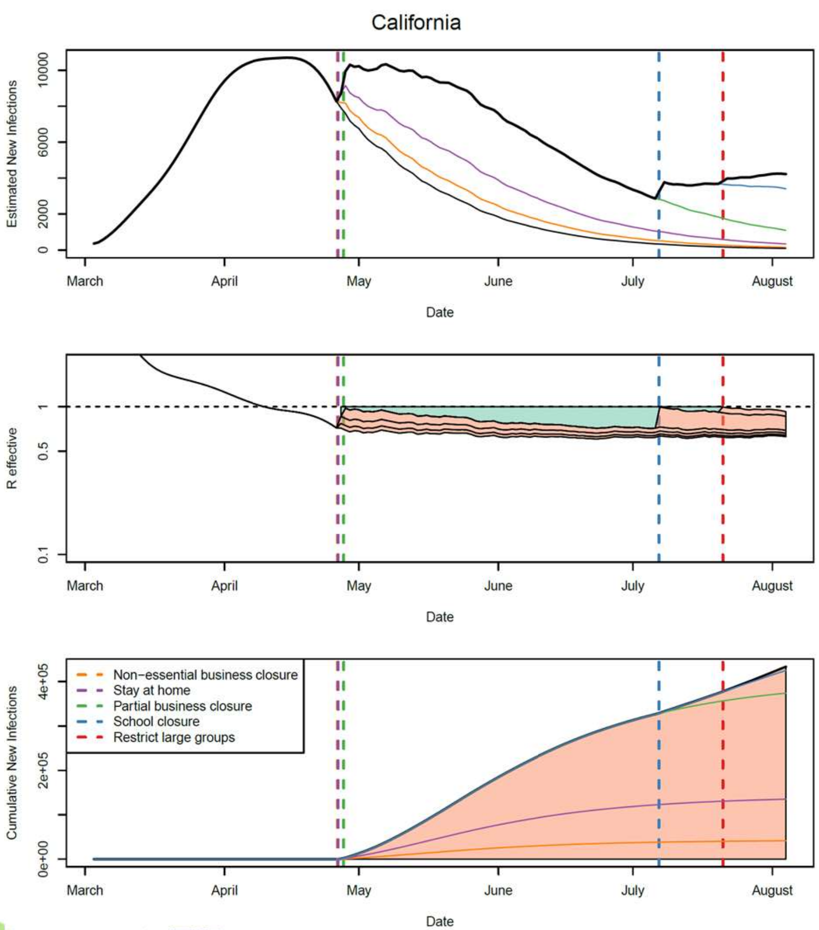
Parallelized on cluster:

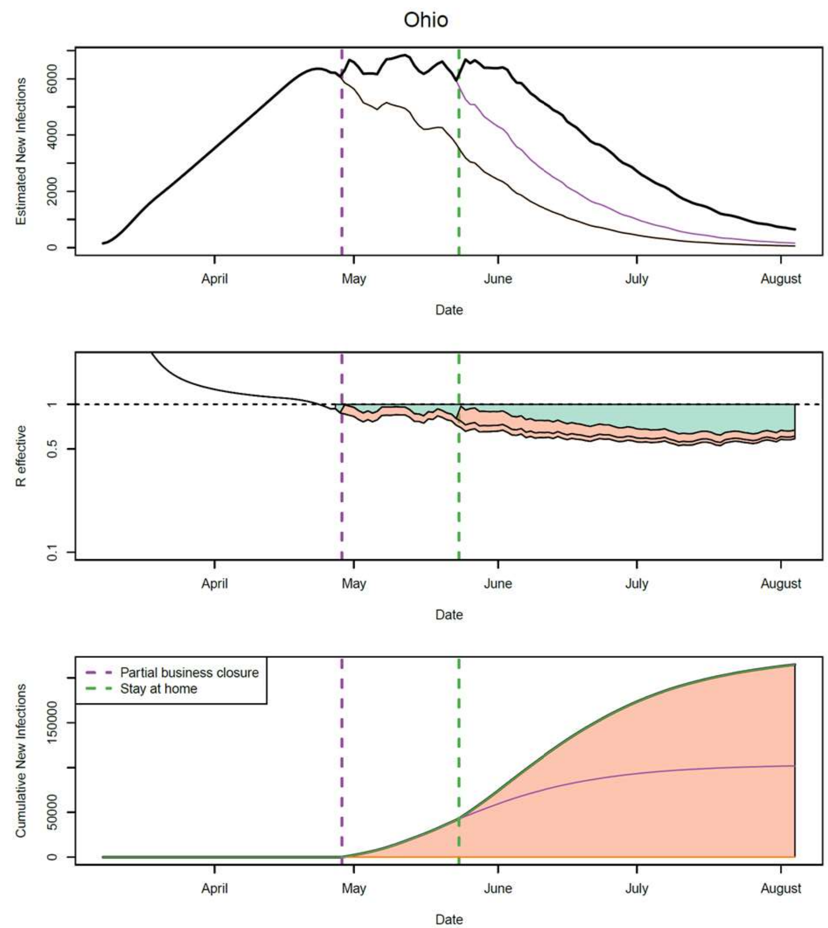
- 10 min total time.

Agenda

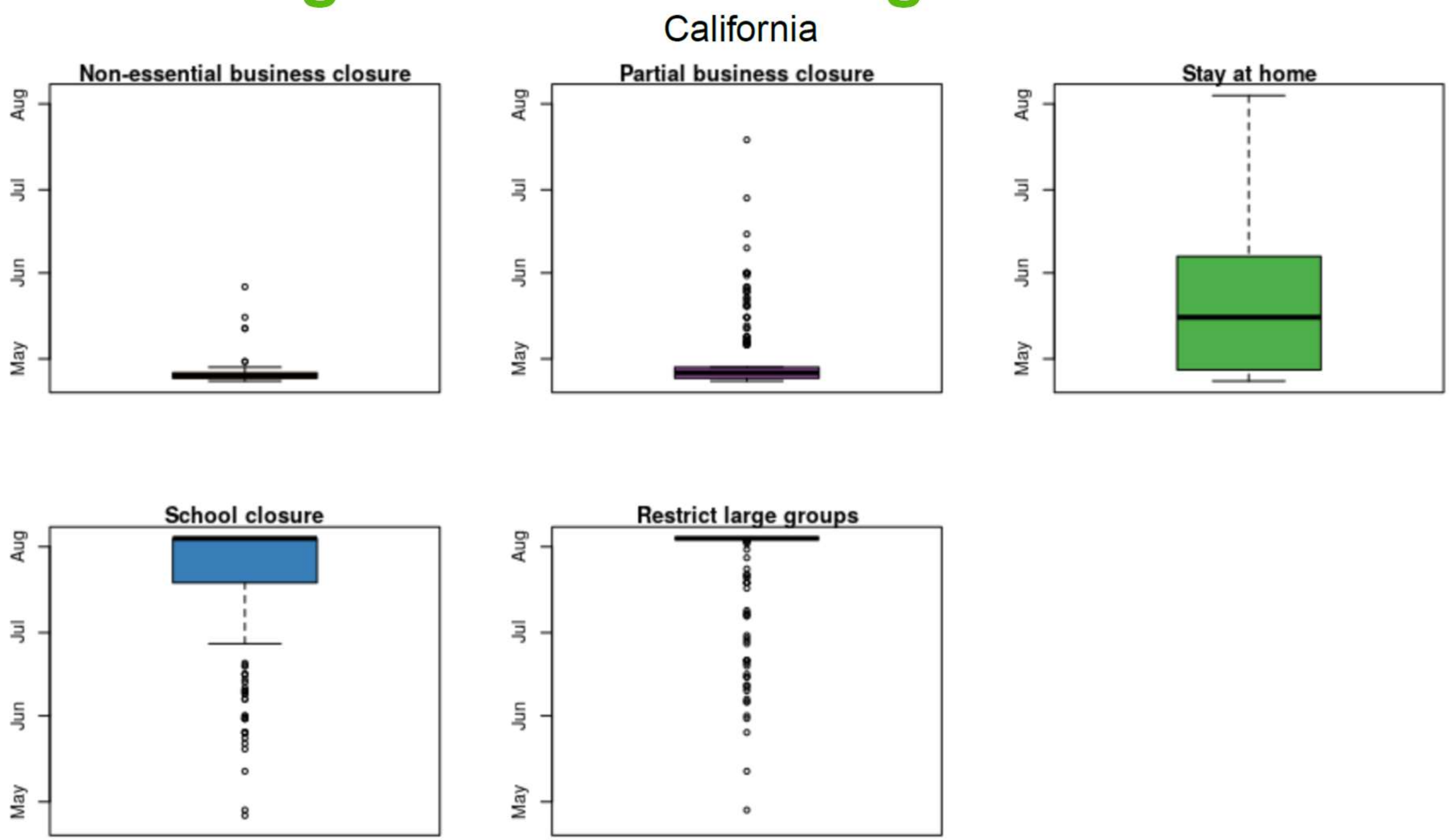
- COVID-19 projections
  - Update on the model
  - Death projection model
  - **Transmission and hospital utilization model (Chris)**
  - Excess mortality
  - Future directions
- Plan for incorporating COVID-19 into GBD
- Release strategy for GBD 2019 results

Effect of lifting social distancing mandates





Effect of lifting social distancing mandates



Estimating health utilization from deaths

- Individual simulation model:

1. Age-specific deaths using age pattern of mortality
2. Median time from admission to death
3. Hospital admissions discharged alive based on ratio of admissions per death
4. ICU admissions based on % of admissions
5. Invasive ventilation based on % of ICU patients
6. Apply median LOS to determine beds, ICU, ventilation use by day

- Input parameters based on meta-analysis of available data

Hospitalization – Out of sample fits