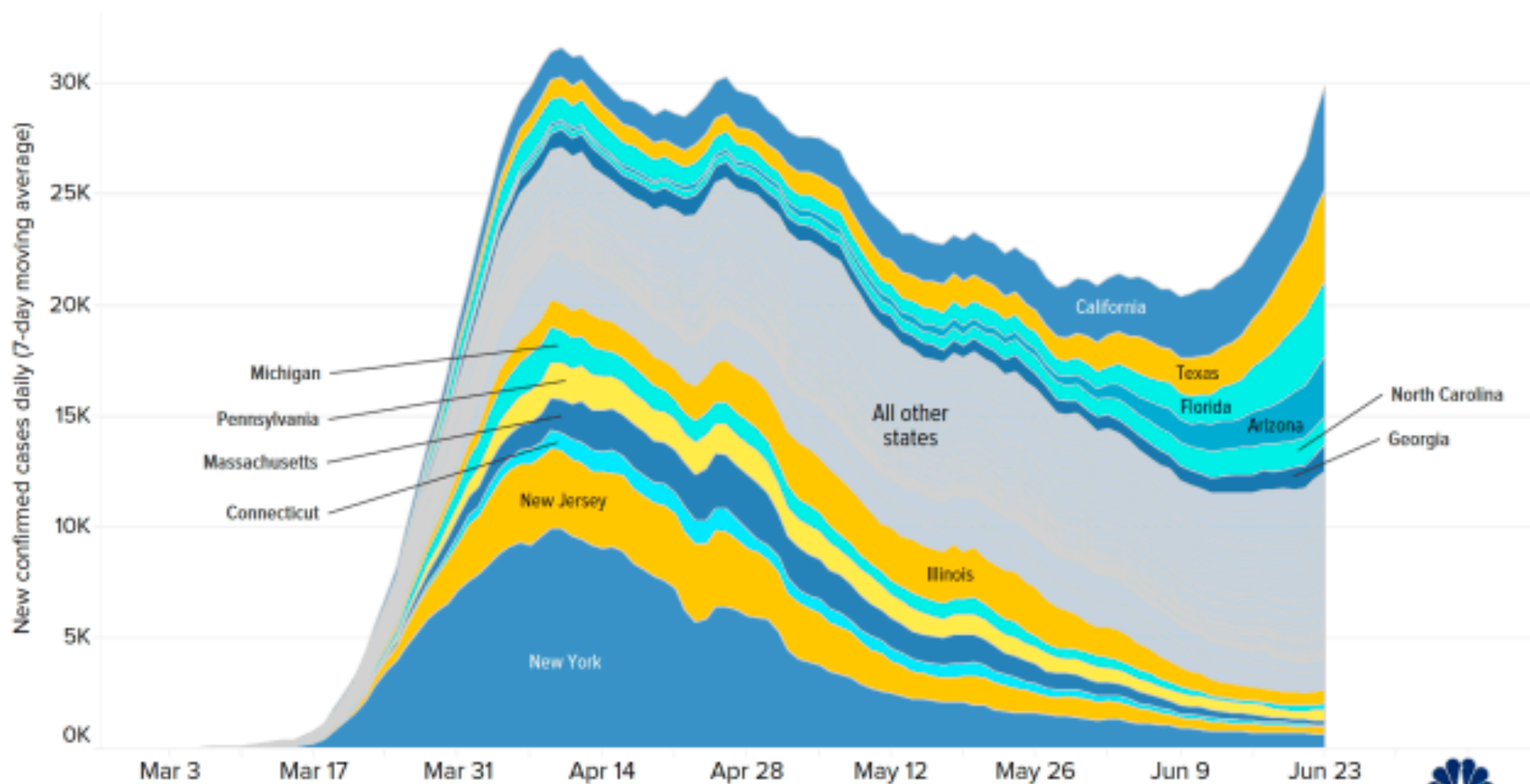


## Coronavirus outbreaks



SOURCE: Johns Hopkins University

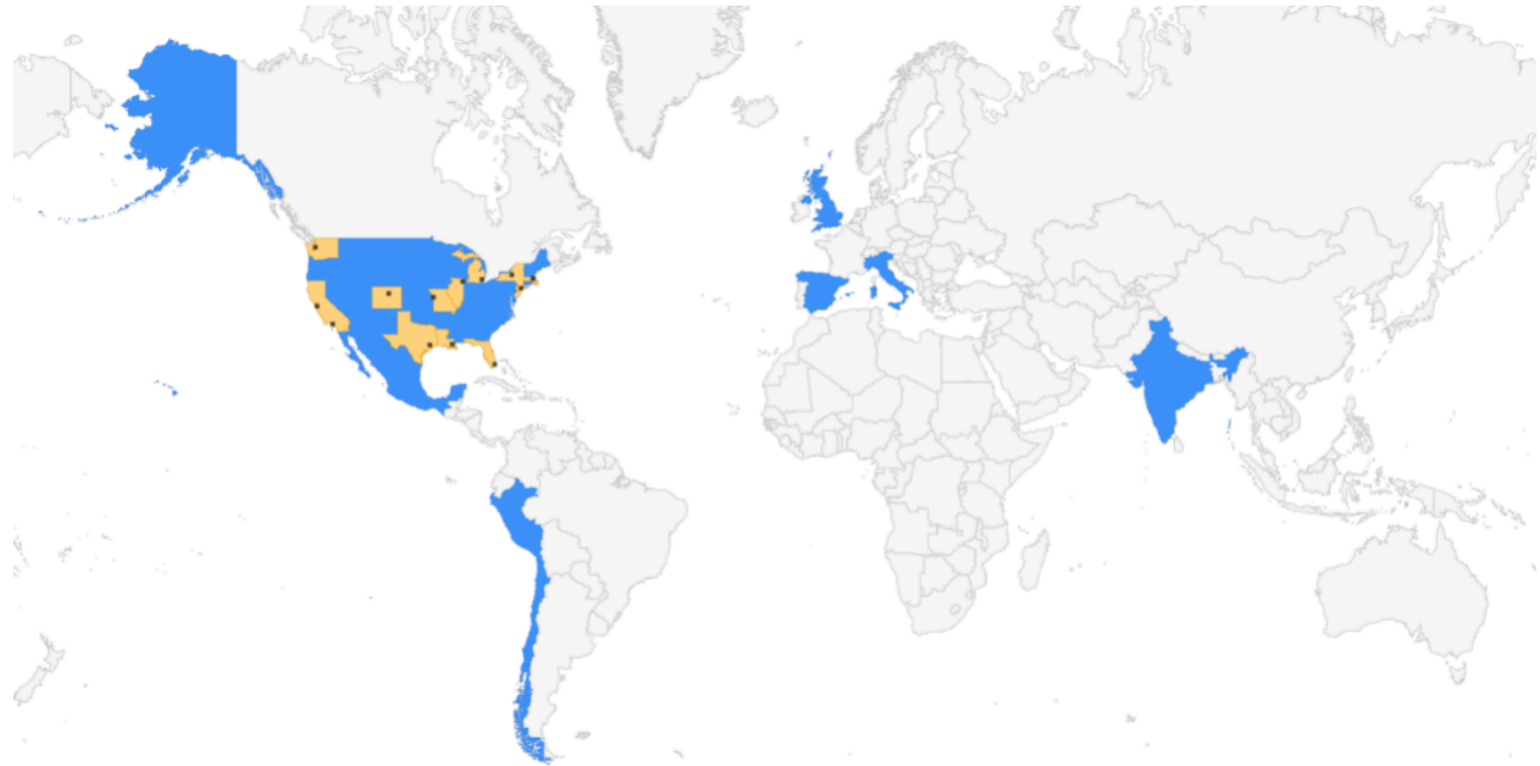


# Outline

- Mobility data: representativeness and meaning
- Testing data: biases in confirmed case reports
- Assessing timing of policies versus epidemiology: accounting for non-linear dynamics

## COVID19 Mobility Data Network:

- ~50 researchers internationally
- DUAs with Facebook, Camber Systems (incl unacast etc), Cuebig
- Direct 1:1 connections between network members and local/state policy makers to guide response
- Standardized analyses across locations and data platforms



(Fig. 1 – **Countries** currently receiving support from the COVID-19 Mobility Data Network include: United States, Mexico, Peru, Chile, United Kingdom, Spain, Italy and India. **States** within the US include: New York, Massachusetts, Florida, Illinois, Michigan, Missouri, Louisiana, Texas, Colorado, Washington, and California. **Cities** within the US include: Boston, Cambridge, New York, Syracuse, Miami, Detroit, Chicago, New Orleans, Houston, Denver, Seattle, Santa Clara, San Jose and Los Angeles)

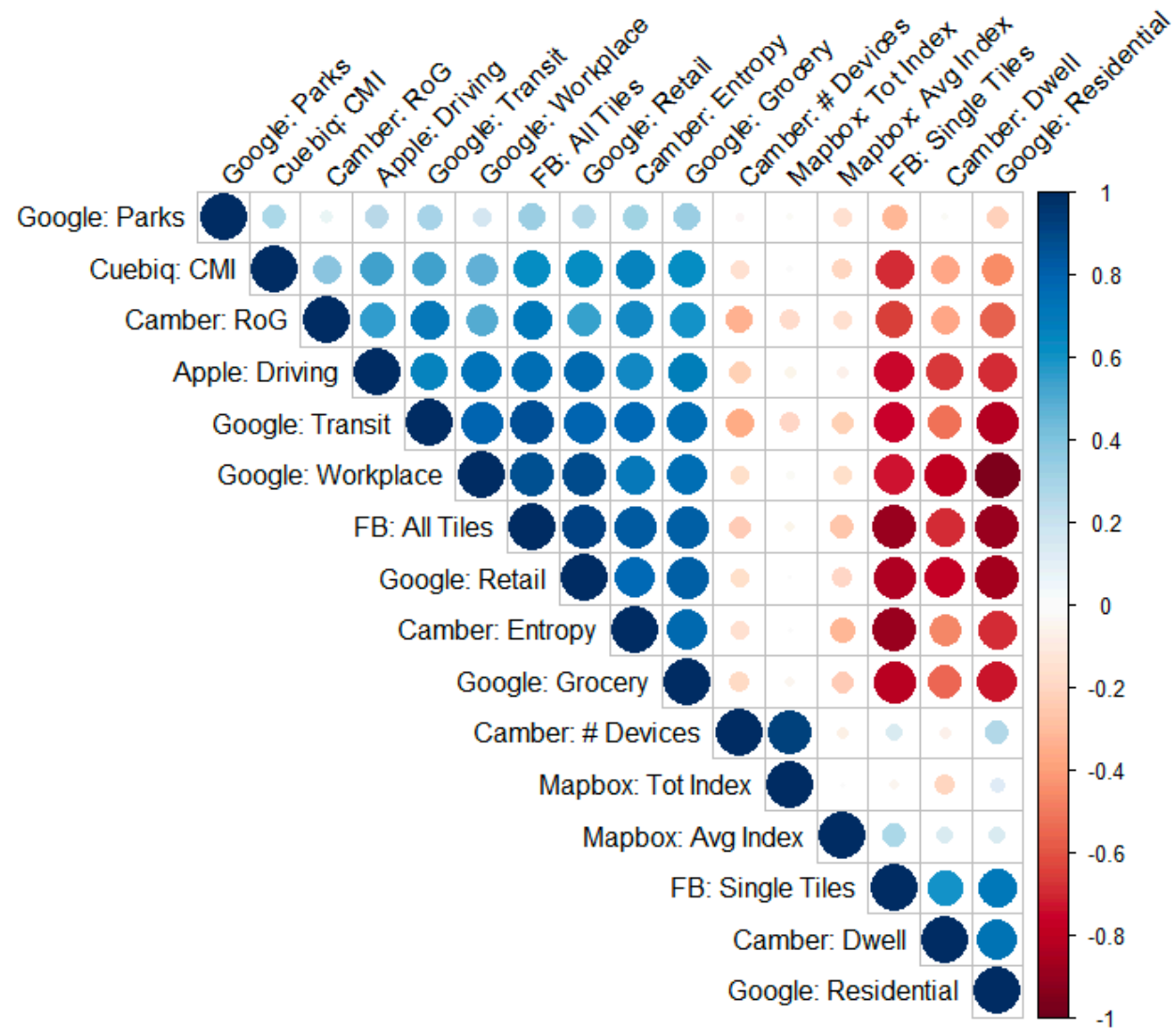
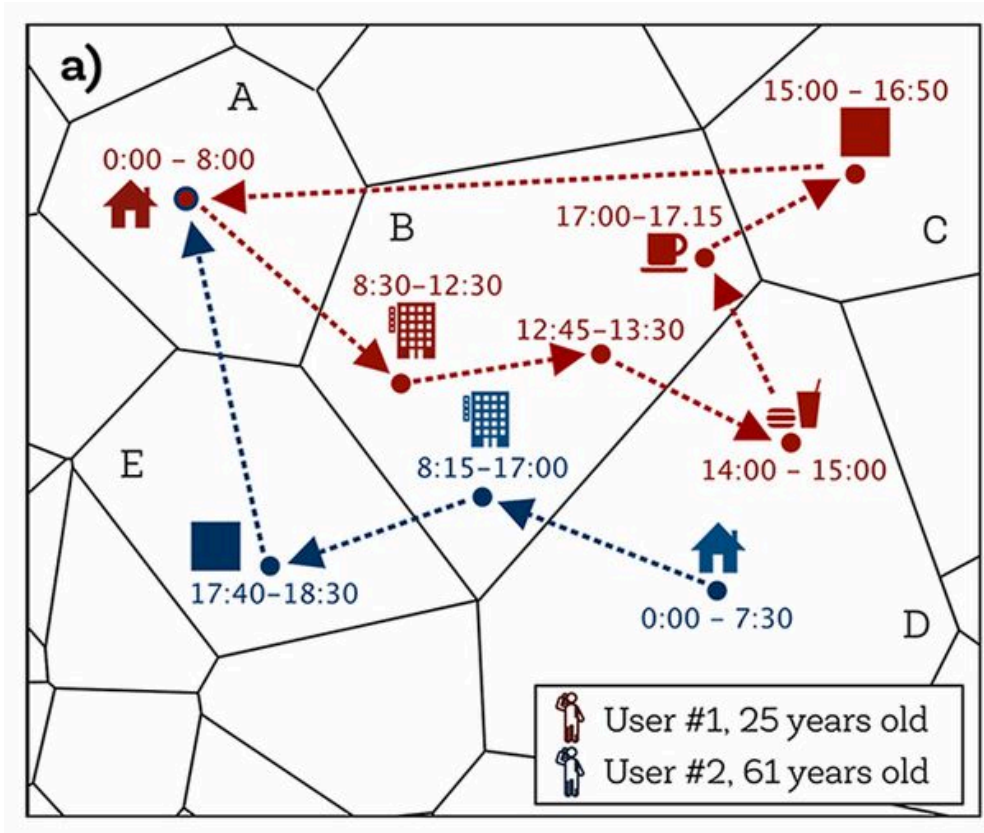
← → ↻ covid19mobility.org

COVID-19 Mobility Data Network Visualization Tools Resources About Partners Contact CCDD Member Login

### COVID-19 Mobility Data Network

We are a network of infectious disease epidemiologists at universities around the world working with technology companies to use aggregated mobility data to support the COVID-19 response. Our goal is to provide daily updates to decision-makers at the state and local levels on how well social distancing interventions are working, using anonymized, aggregated data sets from mobile devices, along with analytic support for interpretation.

[Contact Us](#)



## EDITORIAL

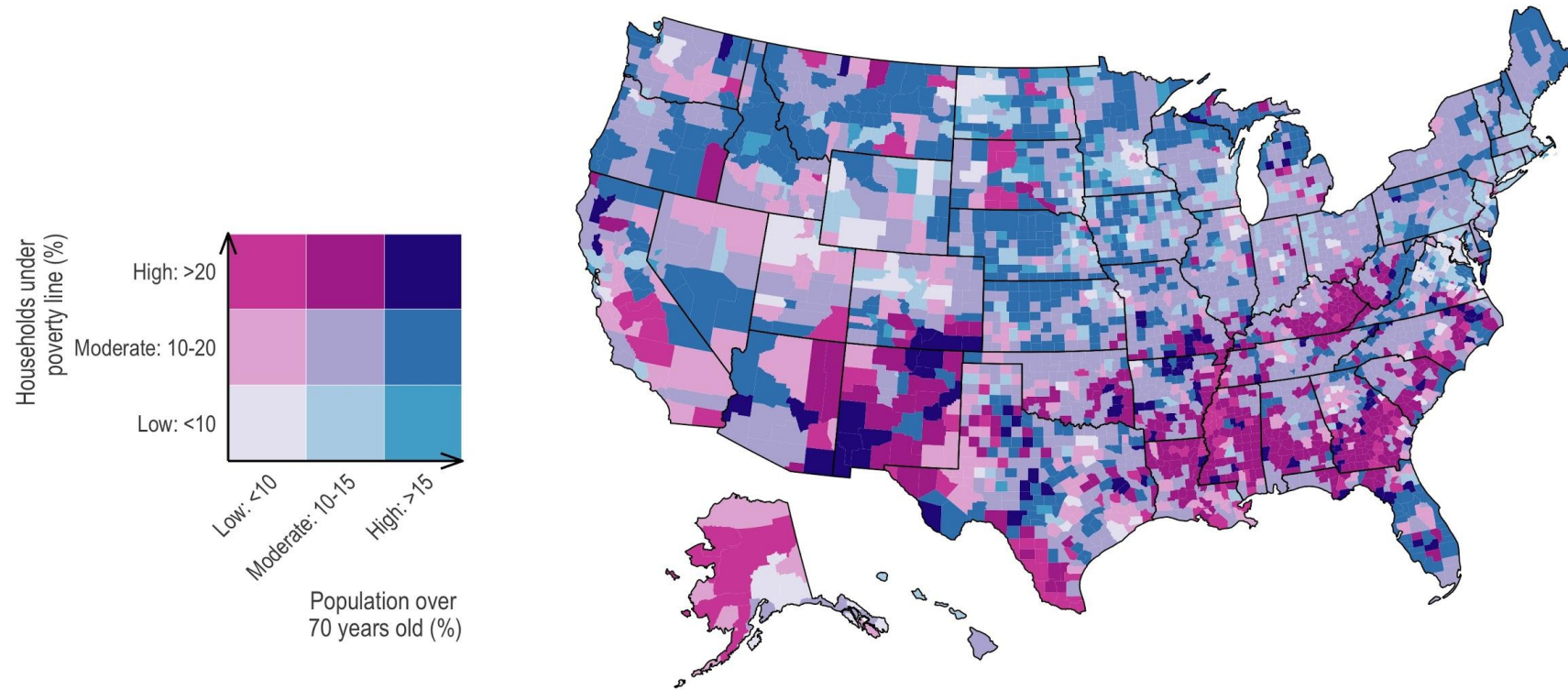
# Mobile phone data for informing public health actions across the COVID-19 pandemic life cycle

Nuria Oliver<sup>1,2</sup>, Bruno Lepri<sup>2,3</sup>, Harald Sterly<sup>4</sup>, Renaud Lambiotte<sup>5,6</sup>, Sébastien Delataille<sup>7</sup>, Marco De Nadai<sup>3</sup>, Emmanuel Leto...








✦ See all authors and affiliations

Science Advances 27 Apr 2020:  
eaac0764  
DOI: 10.1126/sciadv.aac0764

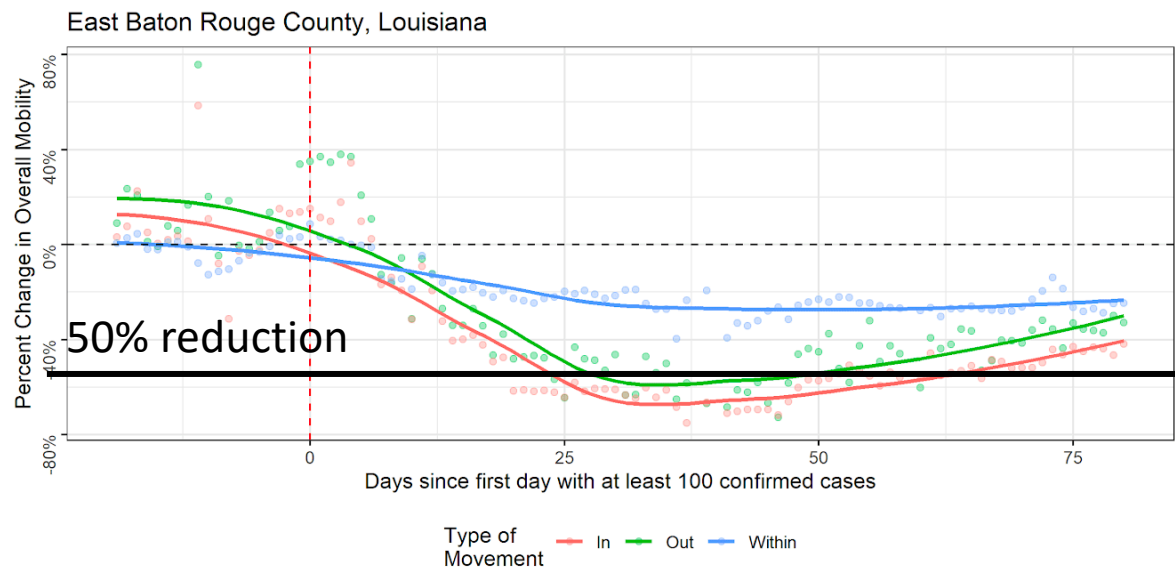
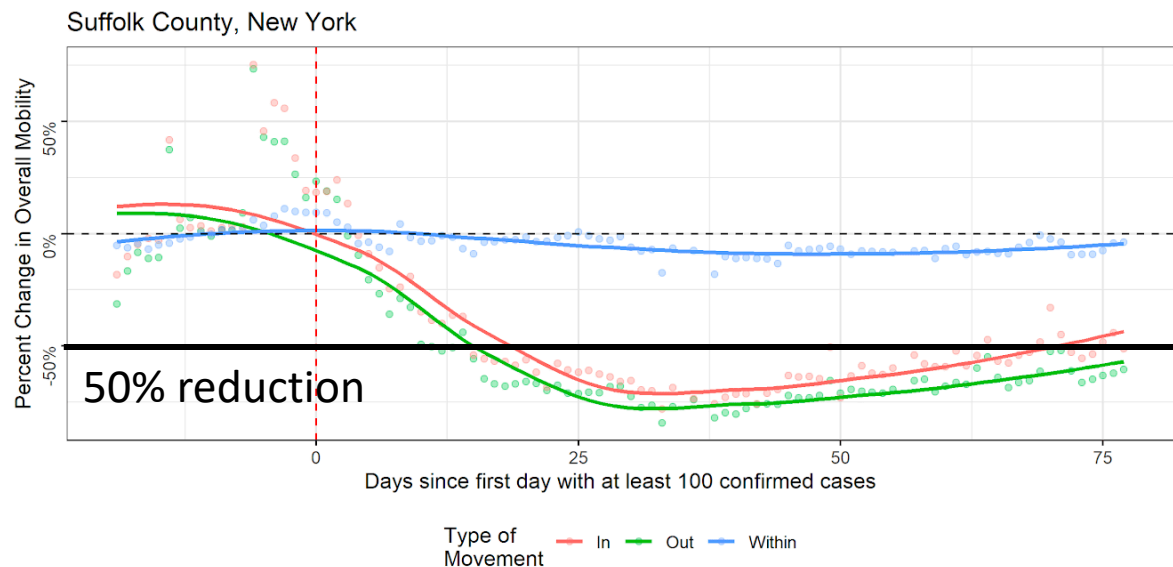
with Nishant Kishore, Mathew Kiang, Navin Vembar



## U.S. county-level characteristics to inform equitable COVID-19 response

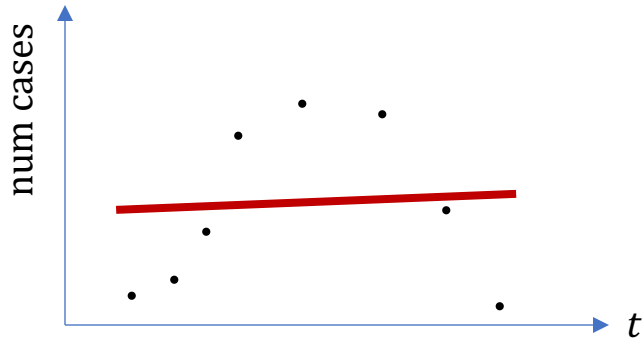
 Taylor Chin,  Rebecca Kahn,  Ruoran Li, Jarvis T. Chen,  
 Nancy Krieger,  Caroline O. Buckee,  Satchit Balsari,  
 Mathew V. Kiang

**doi:** <https://doi.org/10.1101/2020.04.08.20058248>









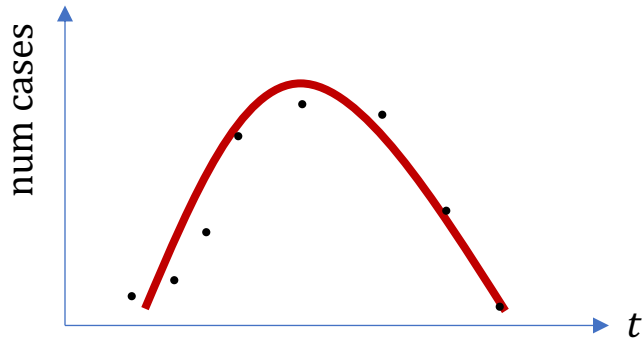
## Linear Regression

$$y = ax + b$$

Advantage: simple interpretation of  $a$

Drawback: does not fit these data

Can we transform the variables?

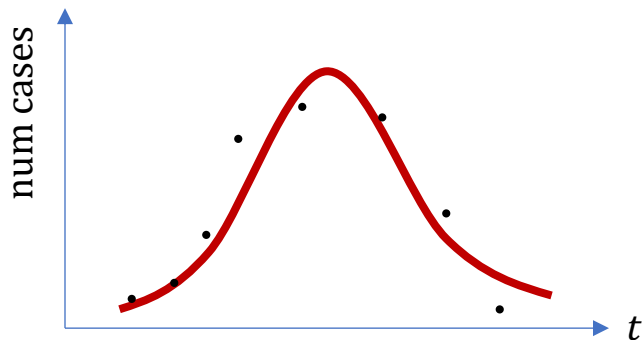


## Quadratic Regression

$$y = ax^2 + bx + c$$

Advantage: fits the data better

Drawback: cannot interpret  $a$  and  $b$



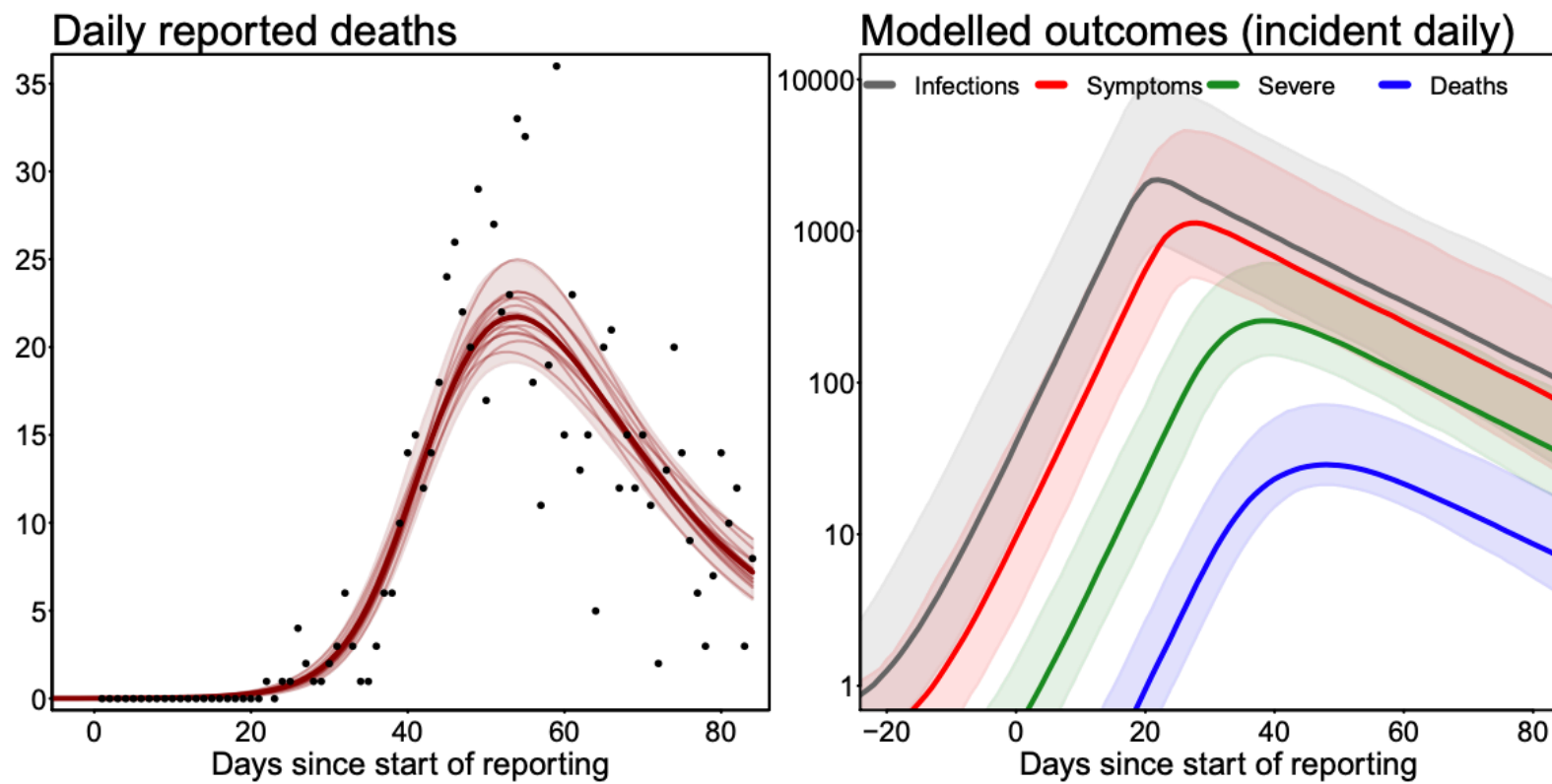
## “SIR” Regression

$$y = f(\beta, \nu)$$

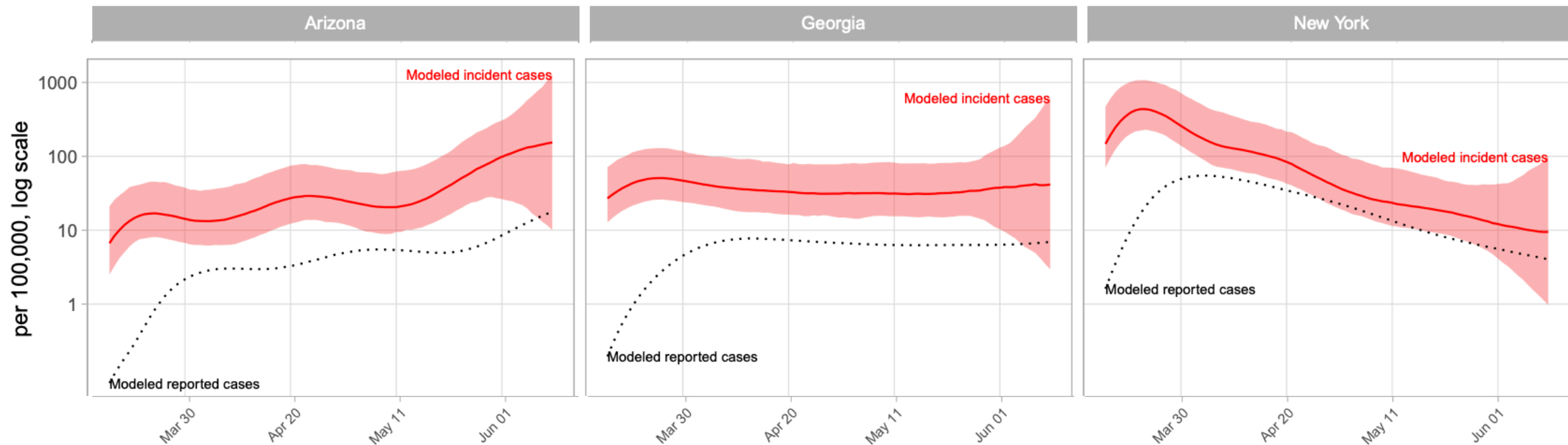
Advantage: fits the data well

Advantage: can interpret  $\beta$  and  $\nu$





Collaboration with Nishant Kishore (HSPH), Nick Menzies (HSPH), Ted Cohen (Yale), Aimee Taylor (HSPH), Pierre Jacob (Harvard)



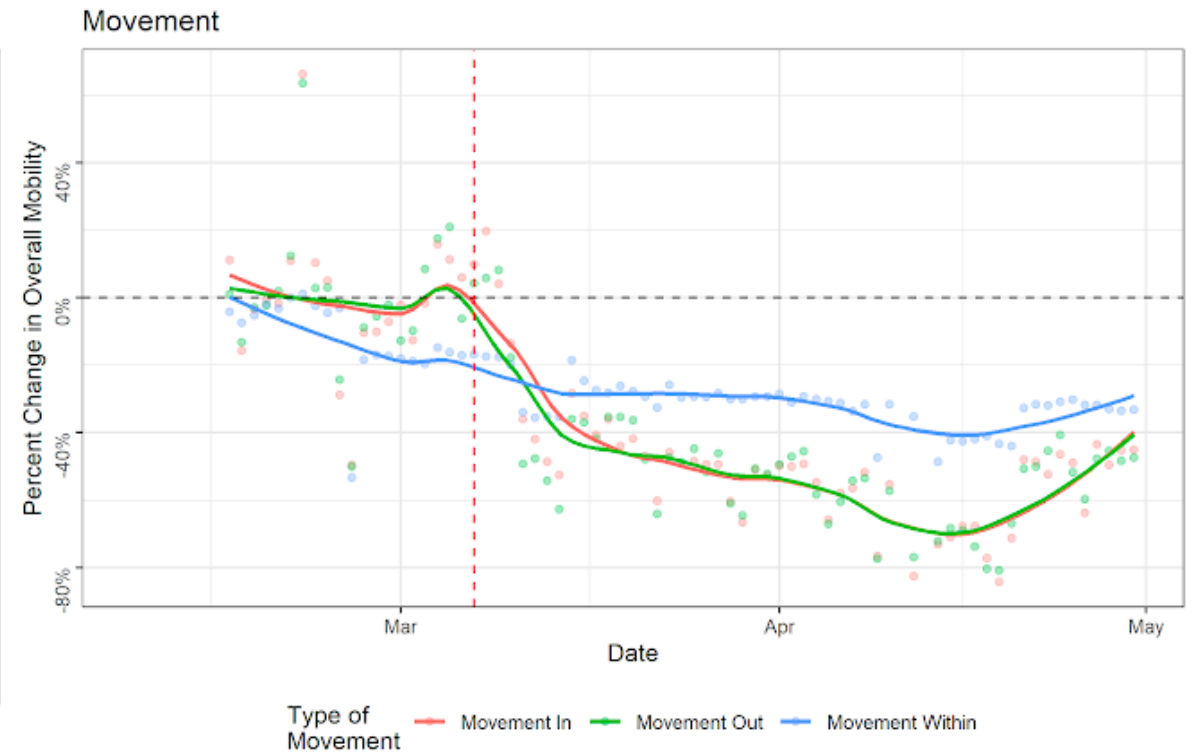
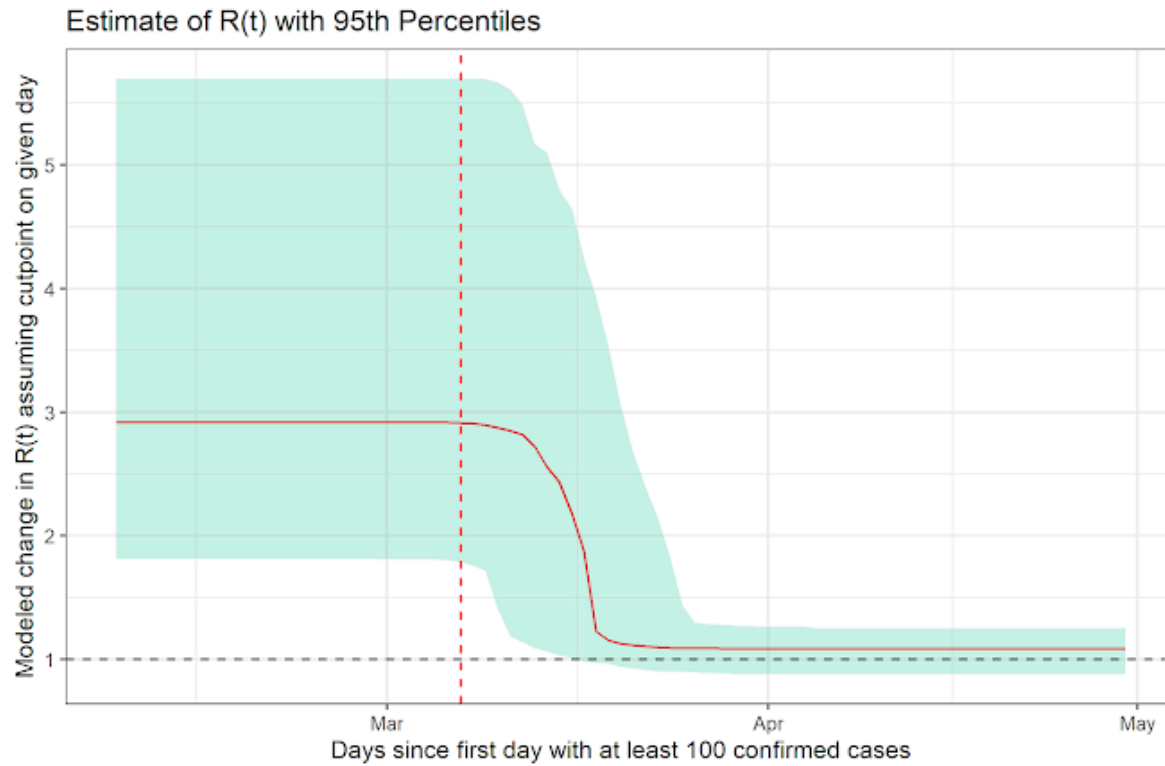
Bayesian nowcasting with adjustment for delayed and incomplete reporting to estimate COVID-19 infections in the United States

Melanie H Chitwood, Marcus Russi, Kenneth Gunasekera, Joshua Havumaki, Virginia

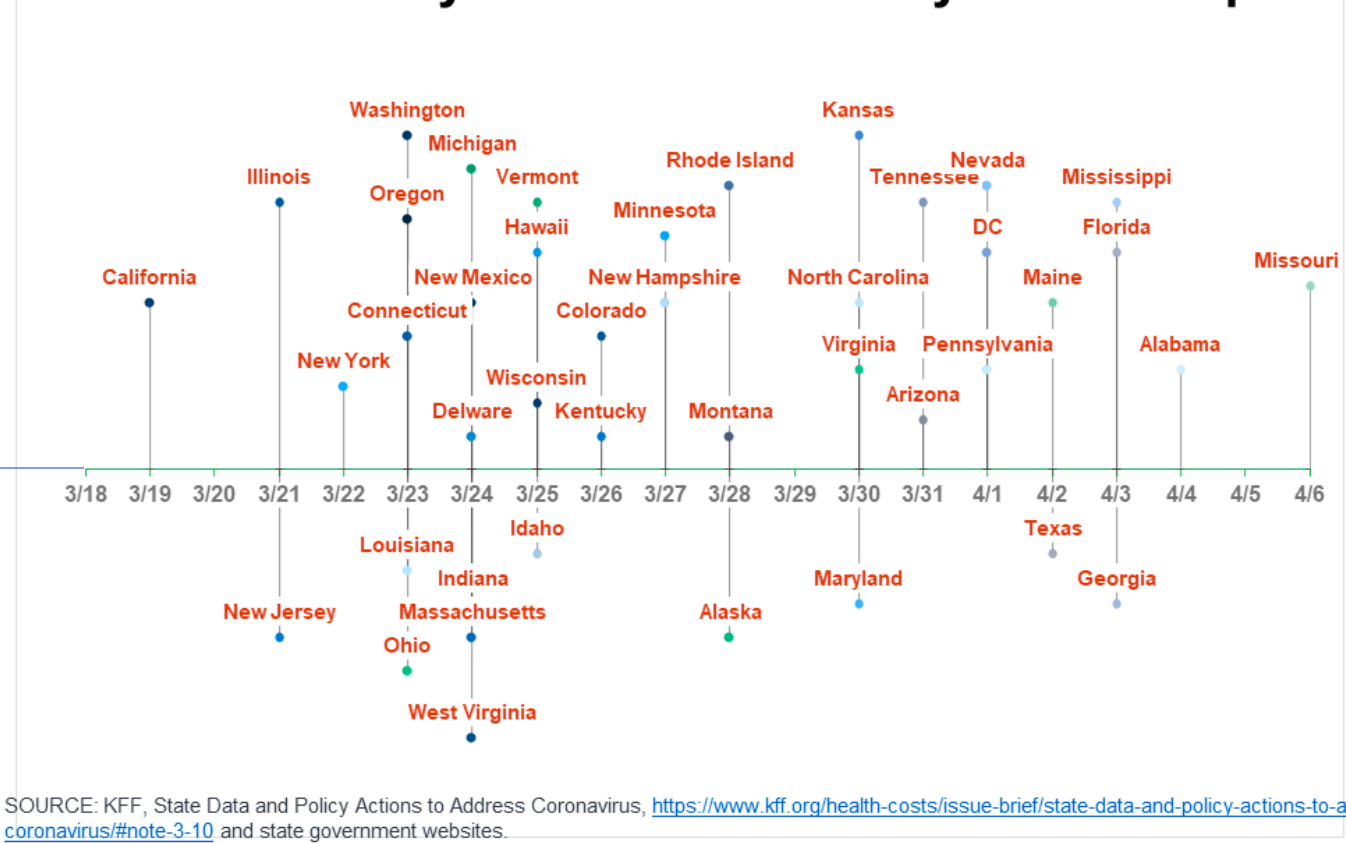
E. Pitzer, Joshua L Warren, Daniel Weinberger, Ted Cohen, Nicolas A Menzies

medRxiv 2020.06.17.20133983; doi: <https://doi.org/10.1101/2020.06.17.20133983>

Fresno County, California - Day 0: Mar 07, 2020

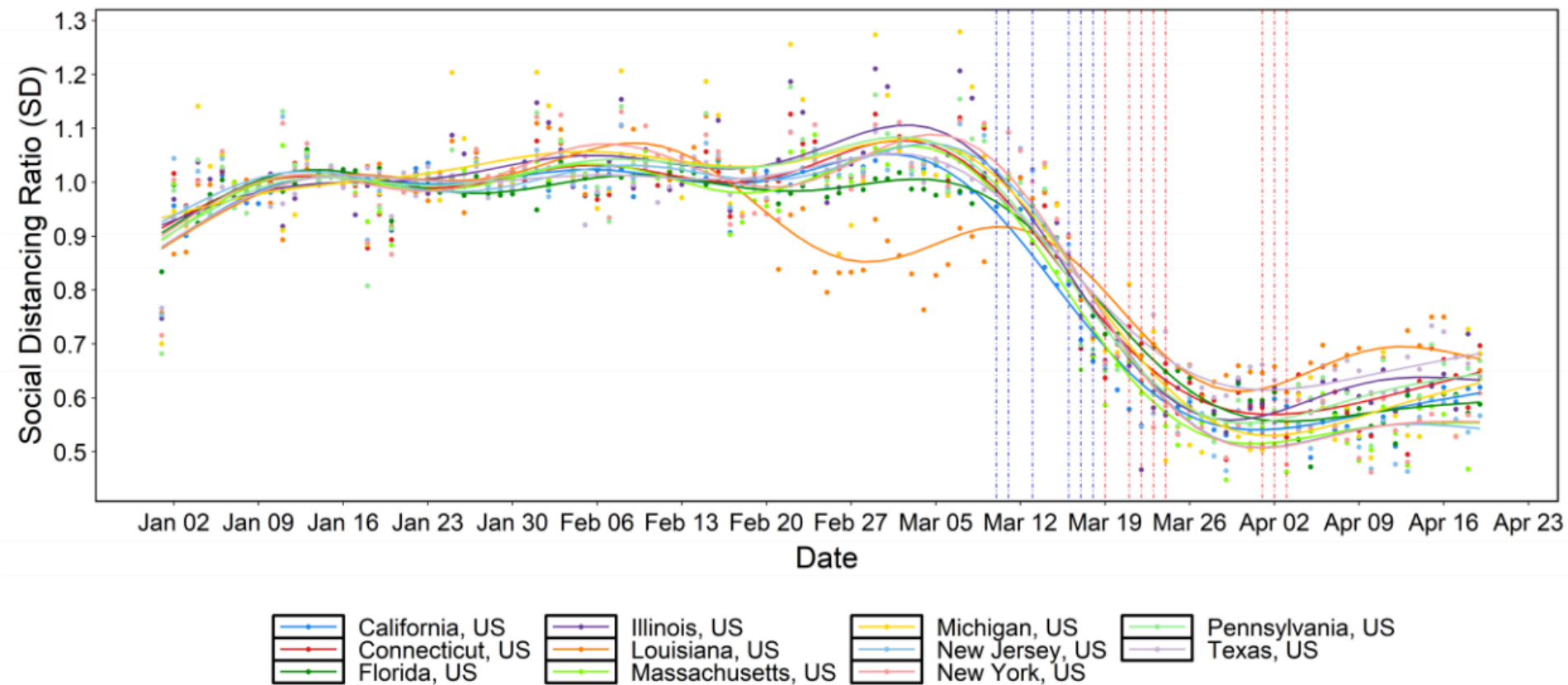


## State Mandated Stay-At-Home Orders by Date of Implementation



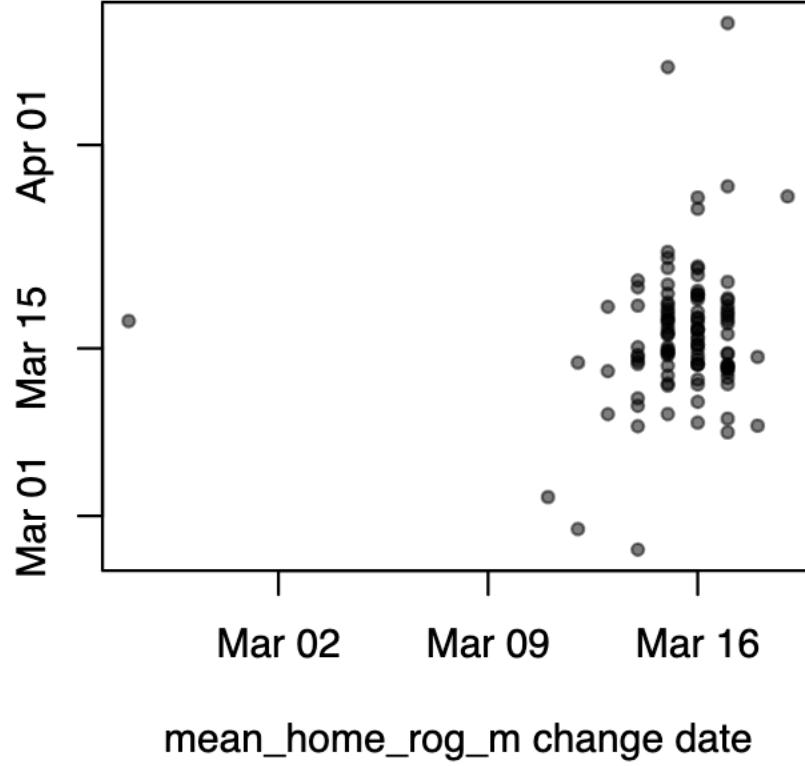
State of emergency declared, March 13

NBA cancels season, March 11

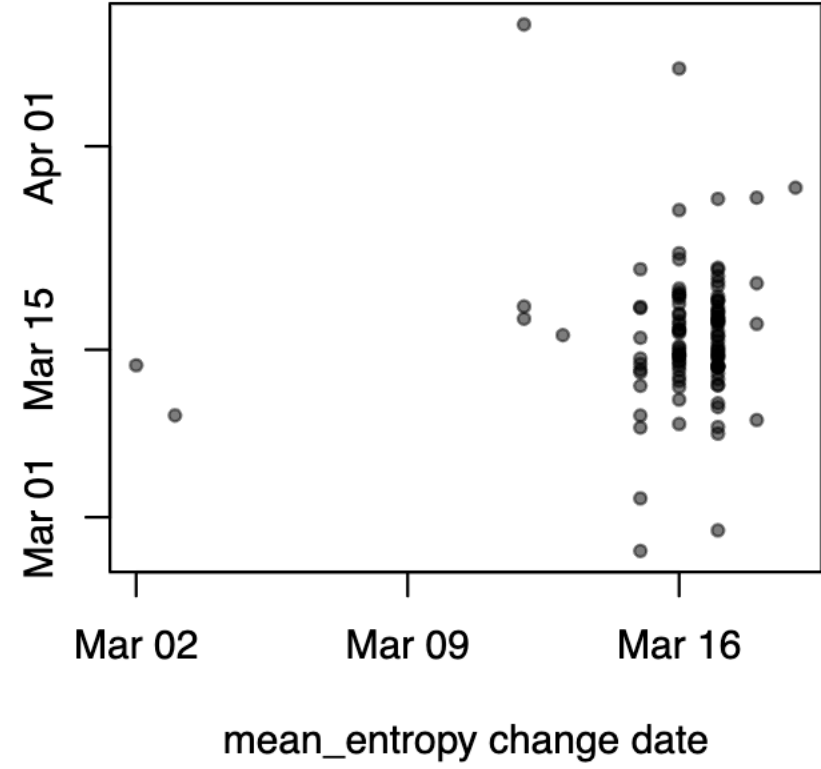


Social Distancing is Effective at Mitigating COVID-19 Transmission in the United States  
 Hamada Badr, Hongru Du, Max Marshall, Ensheng Dong, Marietta Squire, Lauren Marie Gardner  
 medRxiv 2020.05.07.20092353; doi: <https://doi.org/10.1101/2020.05.07.20092353>

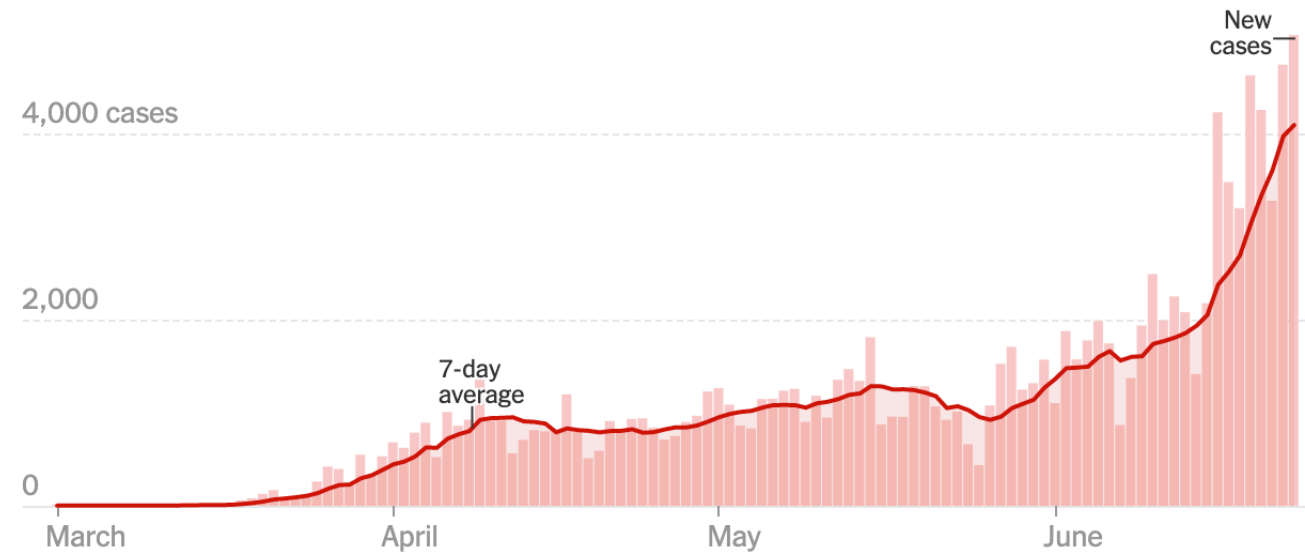
Posterior  $R_t$  mean change date



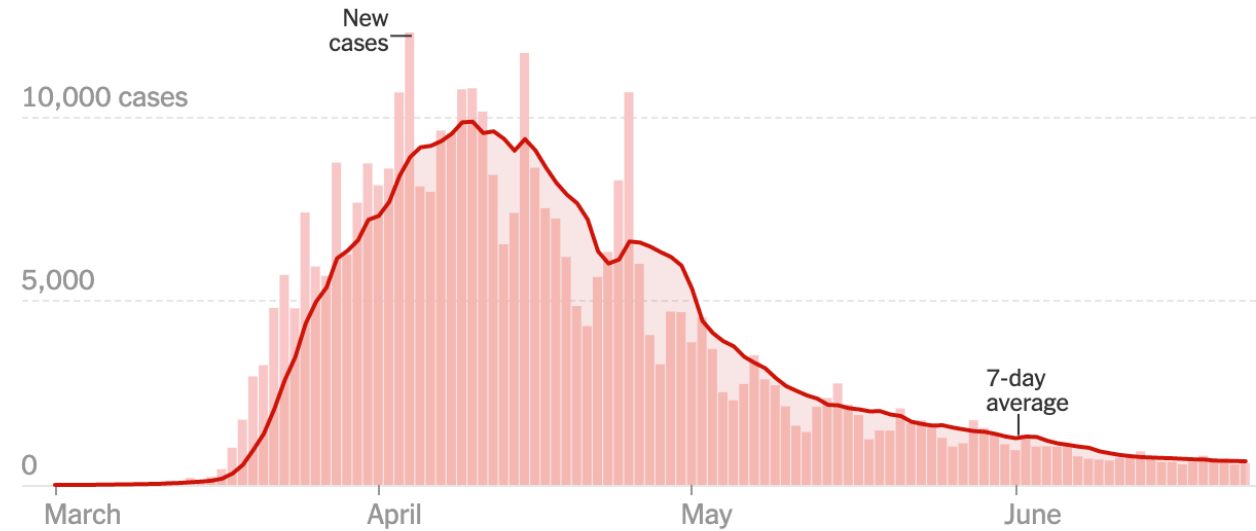
Posterior  $R_t$  mean change date



**New reported cases by day in Texas**

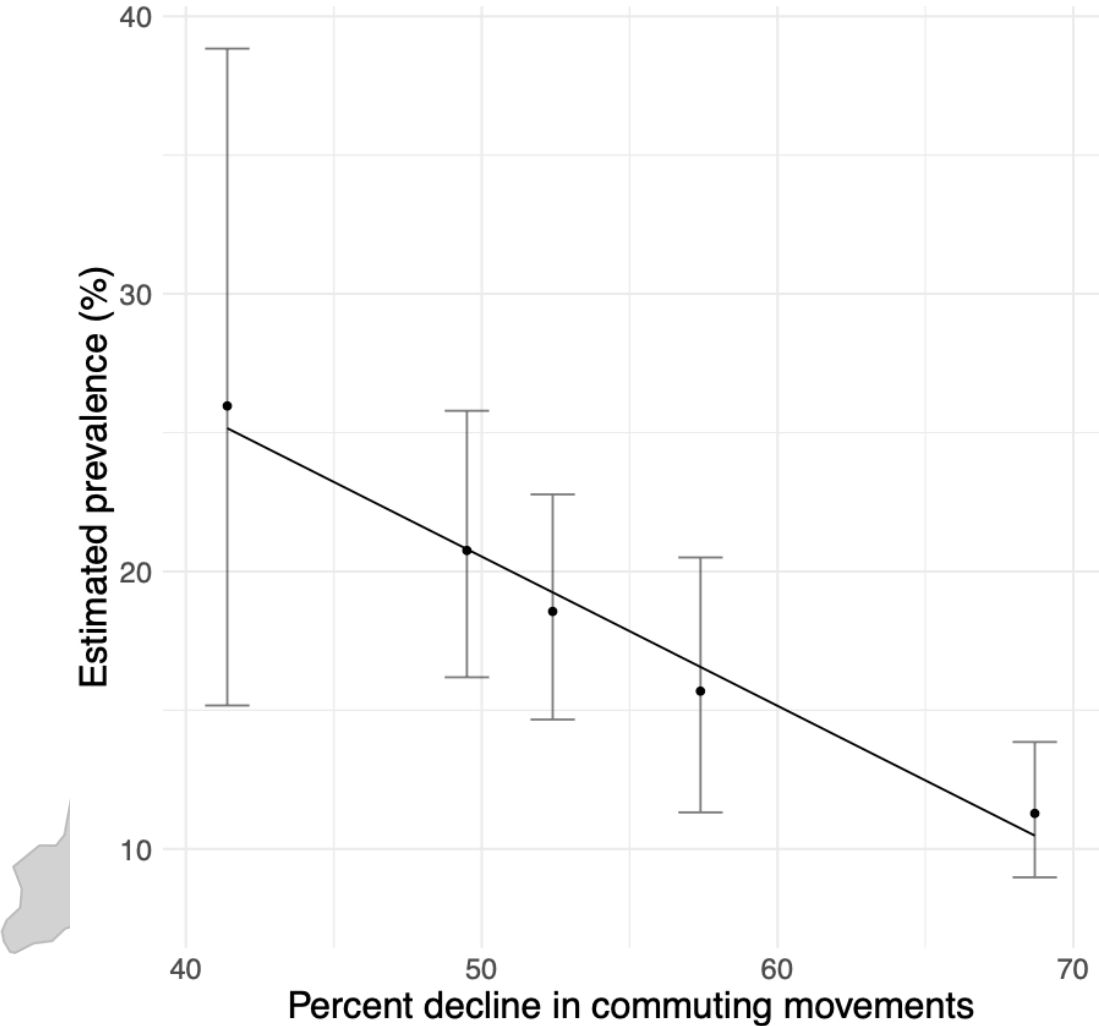
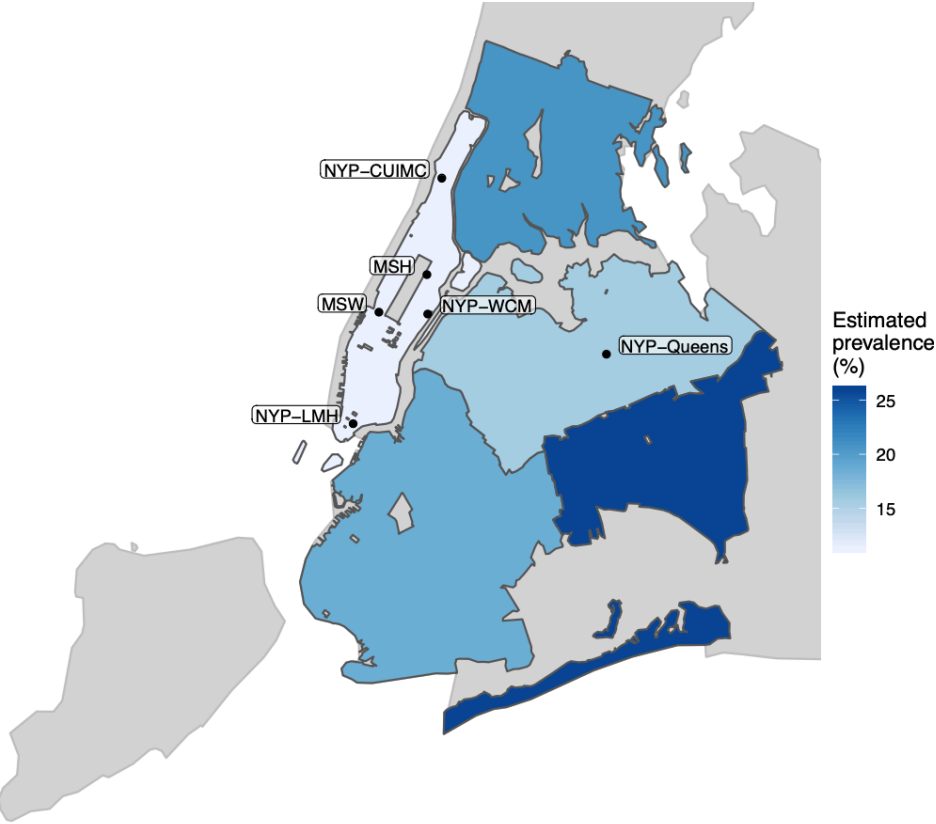


**New reported cases by day in New York**





# Cumulative incidence measured by serosurveillance



Reductions in commuting mobility predict geographic differences in SARS-CoV-2 prevalence in New York City

Stephen M. Kissler<sup>1\*</sup>, Nishant Kishore<sup>2\*</sup>, Malavika Prabhu<sup>4\*</sup>, Dena Goffman<sup>5\*</sup>, Yaakov Beilin<sup>8,9\*</sup>, Ruth Landau<sup>6</sup>, Cynthia Gyamfi-Bannerman<sup>5</sup>, Brian T. Bateman<sup>7</sup>, Daniel Katz<sup>8,9</sup>, Jonathan Gal<sup>8</sup>, Angela Bianco<sup>9</sup>, Joanne Stone<sup>9</sup>, Daniel Larremore<sup>3</sup>, Caroline O. Buckee<sup>2</sup>, Yonatan H. Grad<sup>1</sup>

# Conclusions

- Consistency in finding that messaging and orders unlikely to have been driving factor in behavior change
- Lockdowns *were* highly effective at reducing growth rate of epidemics
- Nonlinearities and variable timing intrinsic to epidemic dynamics important
- Testing and mobility data both have limitations, not necessarily appropriate to use them quantitatively as indicators
- We are very far from herd immunity. This is going to be a long haul.