Epidemic models for analysis of policy measures to protect COVID-19 at-risk populations in Los Angeles County

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uscbiostats.github.io/COVID19

USCIMAGE
Integrative Methods of Analysis for Genetic Epidemiology

Overview

We develop epidemic models for analysis of policy measures to protect COVID-19 at-risk populations in Los Angeles County

Motivating research questions:

- How did the epidemic affect different at-risk populations?
- How effective were policies at preventing severe illness in at-risk populations?

Different types of COVID-19 at-risk populations

At higher risk of exposure and infection

- Social and socio-economic factors:
  - Household crowdedness
  - Employment and ability to work from home
  - Income and ability to protect oneself
  - Acces to healthcare

At higher risk of severe illness *given infection*, i.e. of hospitalization and death

- Biological / health-related factors:
  - Age
  - Comorbidities
  - Obesity
  - History of smoking

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Epidemic model + risk model for policy analysis

To analyze policies related to protecting populations at-risk of severe infection, we need two modeling pieces:

1. **Epidemic model** that estimates dyanmics of infections, hospitalizations, and deaths
2. **Risk model** for estimating the probabilities of severe illness in different at-risk populations

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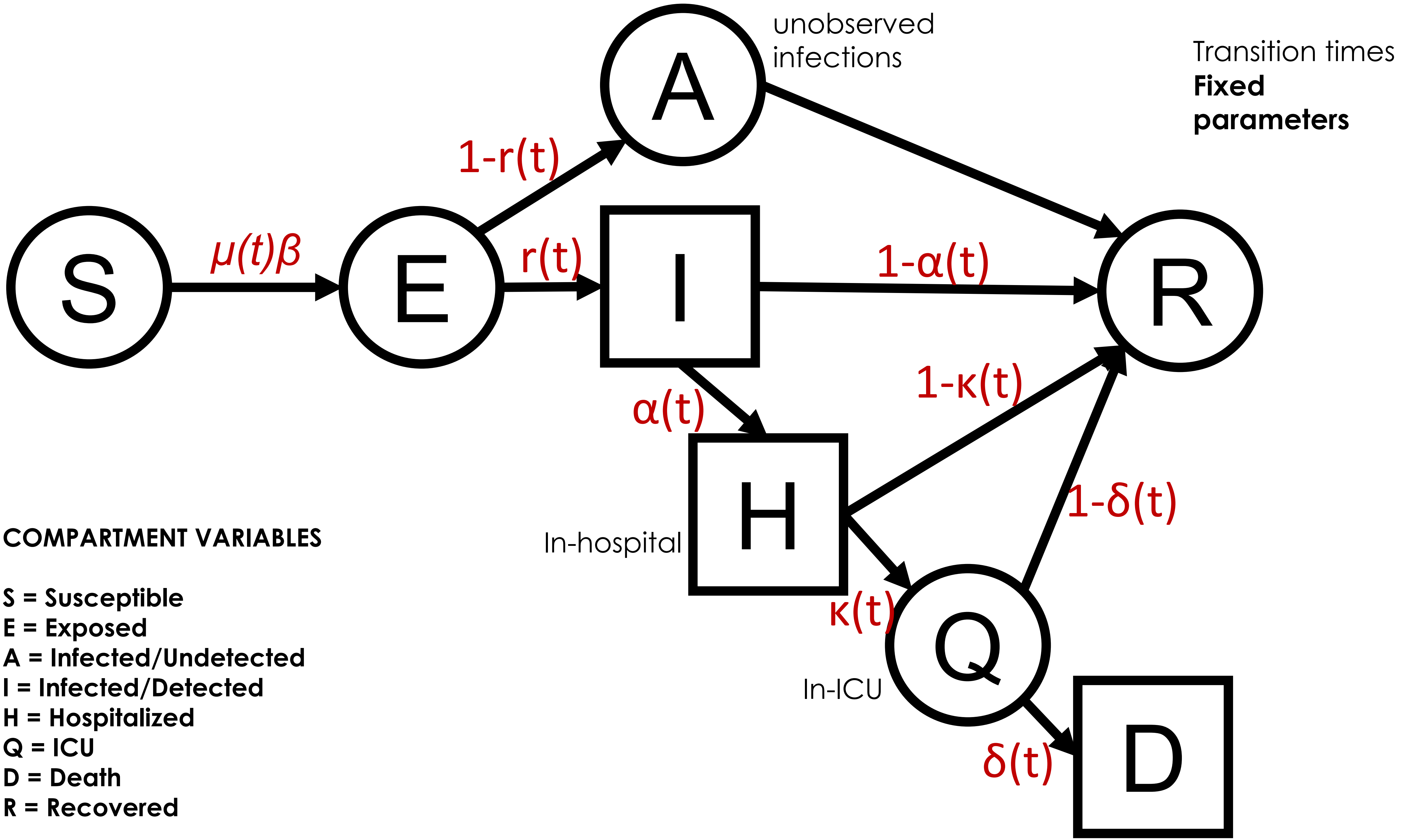
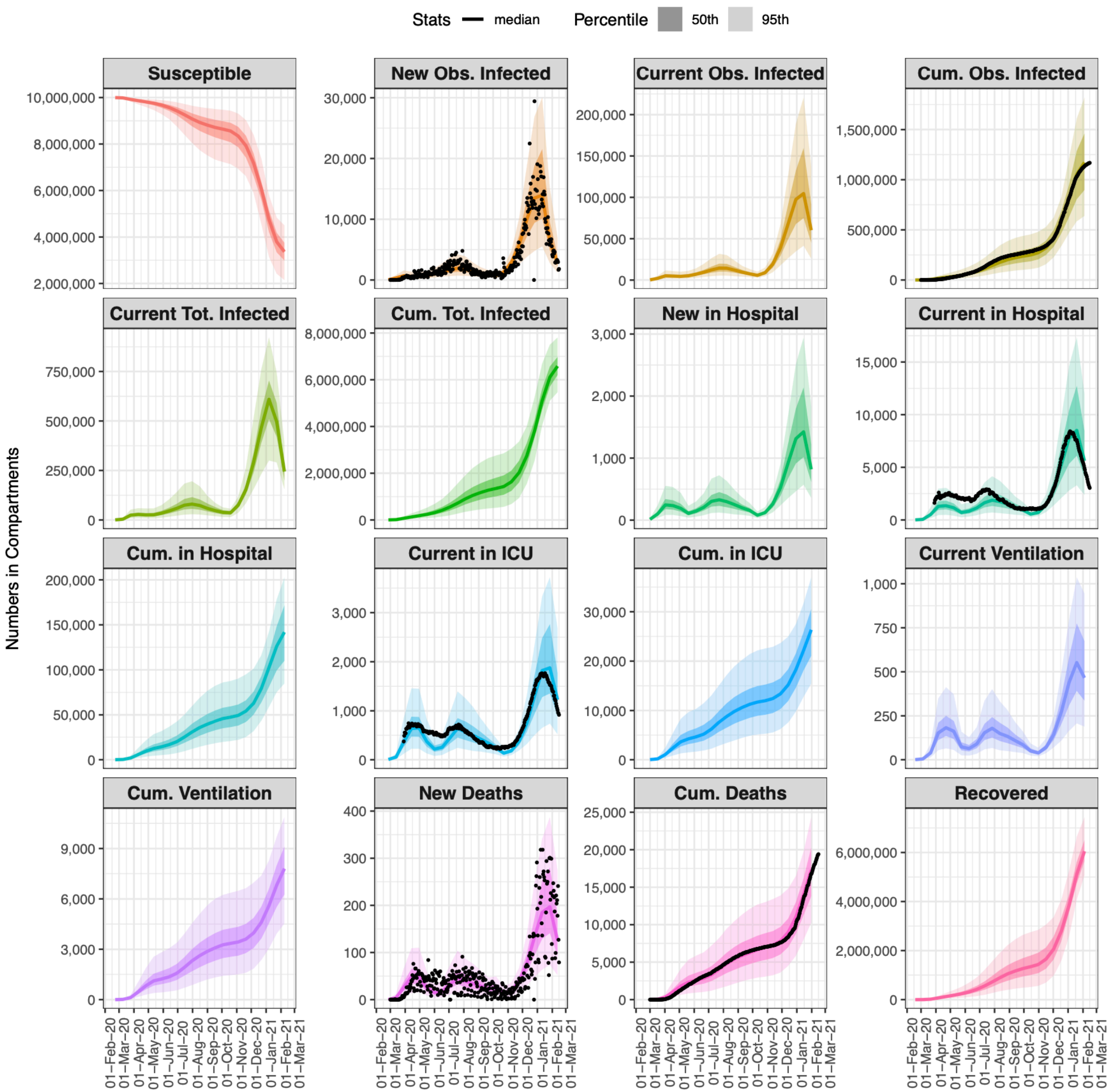
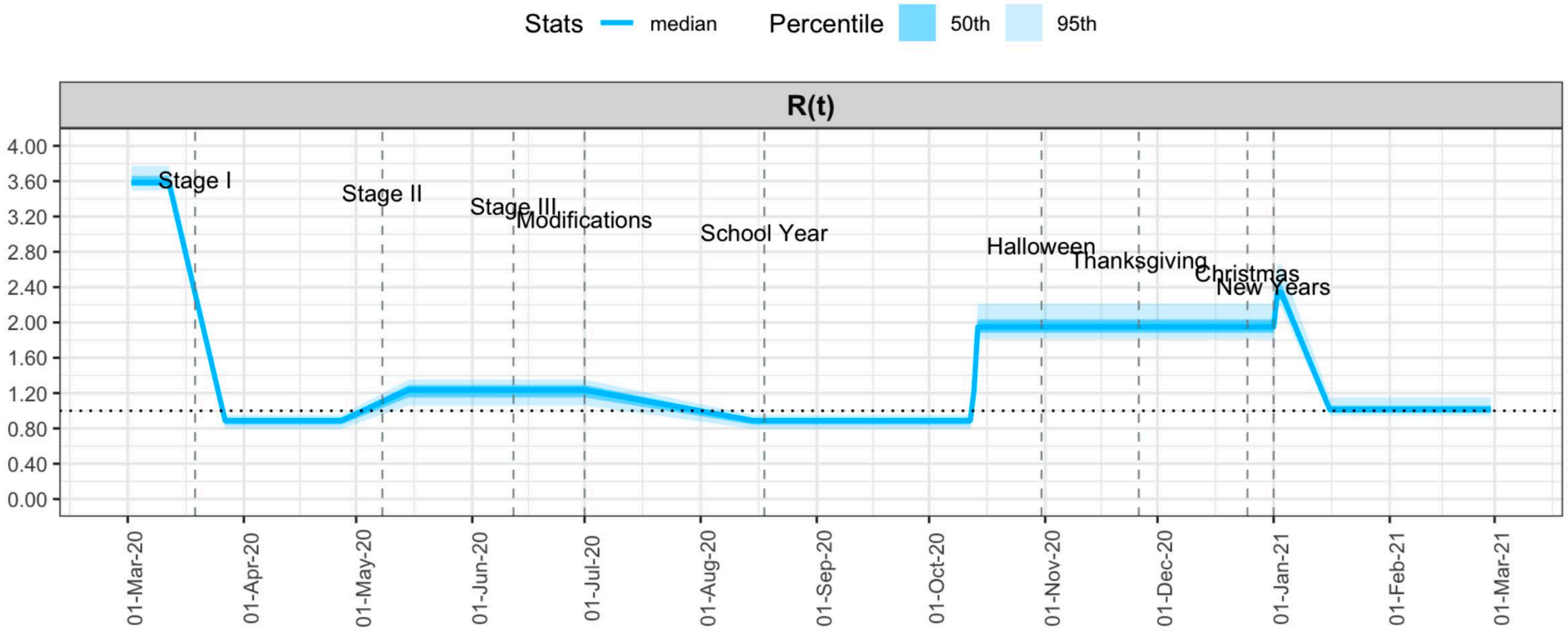

unobserved infections
Transition times
Fixed parameters
A
S
E
I
R
H
Q
D
μ(t)β
1-r(t)
r(t)
1-α(t)
α(t)
1-κ(t)
κ(t)
1-δ(t)
δ(t)
In-hospital
In-ICU
COMPARTMENT VARIABLES
S = Susceptible
E = Exposed
A = Infected/Undetected
I = Infected/Detected
H = Hospitalized
Q = ICU
D = Death
R = Recovered

Model compartment variable projections

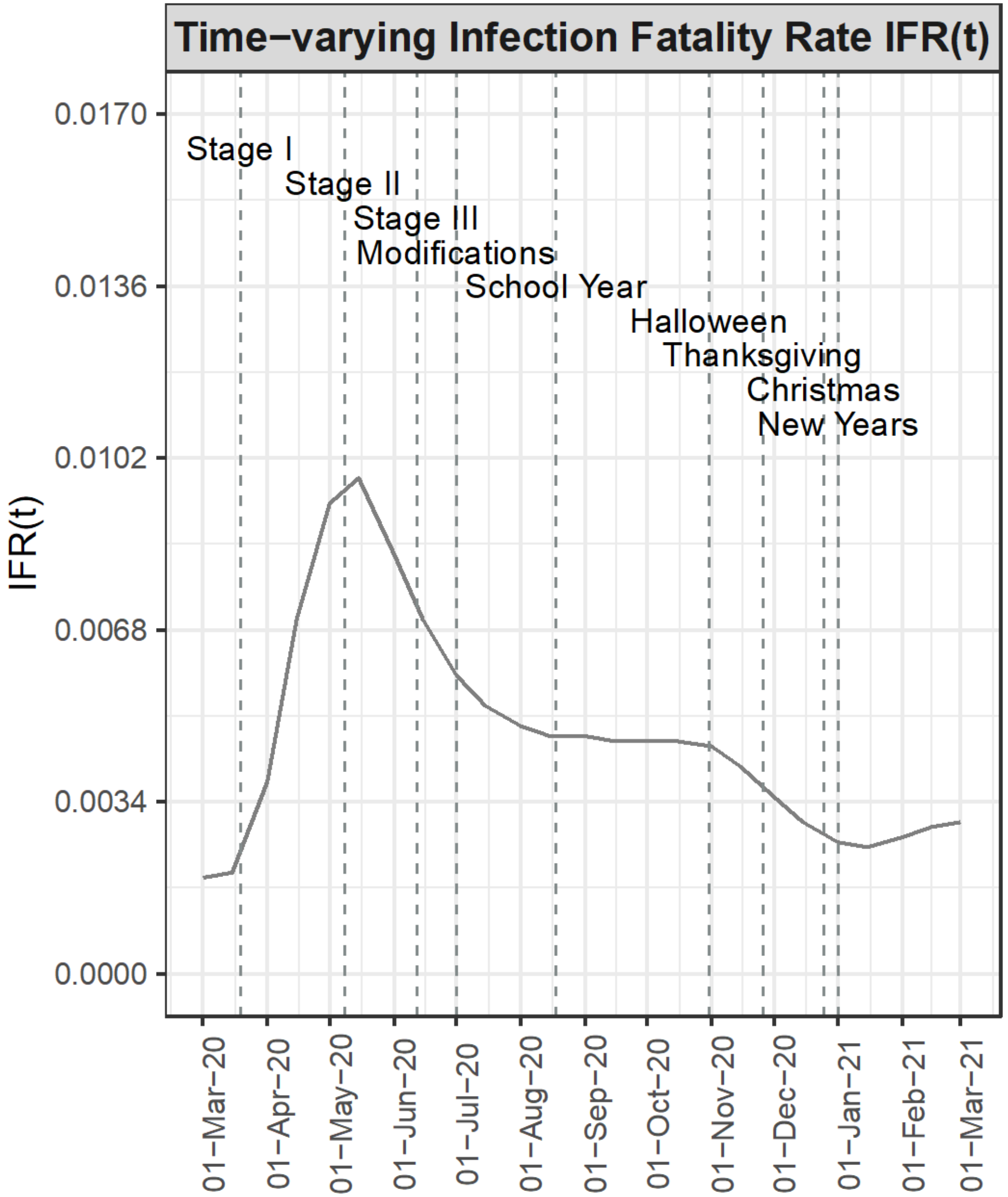


Reproductive Number - R(t)



Reproductive Number - R(t)

Time-varying infection fatality rate (IFR)



$$IFR = \frac{deaths}{observed + unobserved\ infections}$$

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Biological Risk Factors

- **Age** was categorized into five groups:
  - 0-19, 20-44, 45-64, and 65-79, and 80+.
- **Comorbidities**: diabetes, hypertension, chronic obstructive pulmonary disease (COPD), hepatitis B, coronary heart disease, stroke, cancer and chronic kidney disease.
- **Smoking**: Current smoking vs. none.
- **Obesity** was categorized as three groups:
  - BMI$< 30\frac{kg}{m^2}$; $30 \le \mathrm{BMI} \le 40\frac{kg}{m^2}$; BMI$> 40\ kg/m^2$

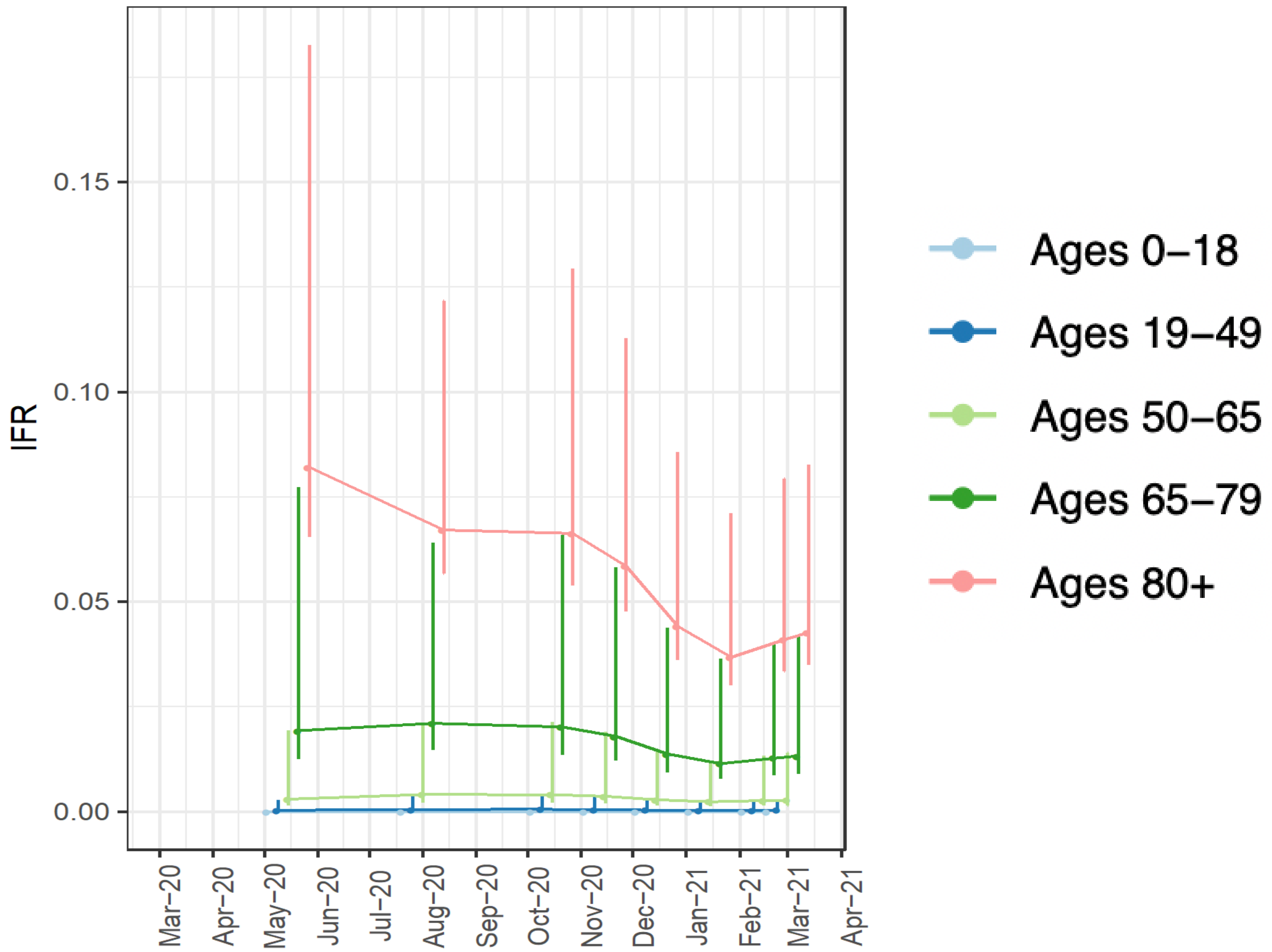
Categorizing the LA population into risk profiles

Group	age	BMI	smoking	comorbidity	Pop.Prev
Risk 2	65+	30<BMI<40	Non Smoker	Comorbidity	0.0110
Risk 3	65+	BMI<30	Non Smoker	Comorbidity	0.0699
Risk 3	45-64	BMI<30	Smoker	Comorbidity	0.0167
Risk 3	65+	BMI<30	Non Smoker	No Comorbidity	0.0254
Risk 3	45-64	30<BMI<40	Non Smoker	Comorbidity	0.0382
Risk 3	45-64	BMI<30	Smoker	No Comorbidity	0.0130
Risk 4	45-64	30<BMI<40	Non Smoker	No Comorbidity	0.0219
Risk 4	45-64	BMI<30	Non Smoker	Comorbidity	0.1510
Risk 4	20-44	BMI<30	Smoker	Comorbidity	0.0206
Risk 4	45-64	BMI<30	Non Smoker	No Comorbidity	0.1045
Risk 4	20-44	BMI<30	Smoker	No Comorbidity	0.0307
Risk 4	20-44	30<BMI<40	Non Smoker	Comorbidity	0.0238
Risk 5	20-44	30<BMI<40	Non Smoker	No Comorbidity	0.0240
Risk 5	20-44	BMI<30	Non Smoker	Comorbidity	0.1055
Risk 5	20-44	BMI<30	Non Smoker	No Comorbidity	0.1401
Risk 5	0-19	BMI<30	Non Smoker	No Comorbidity	0.1463

Categorizing the LA population into risk profiles

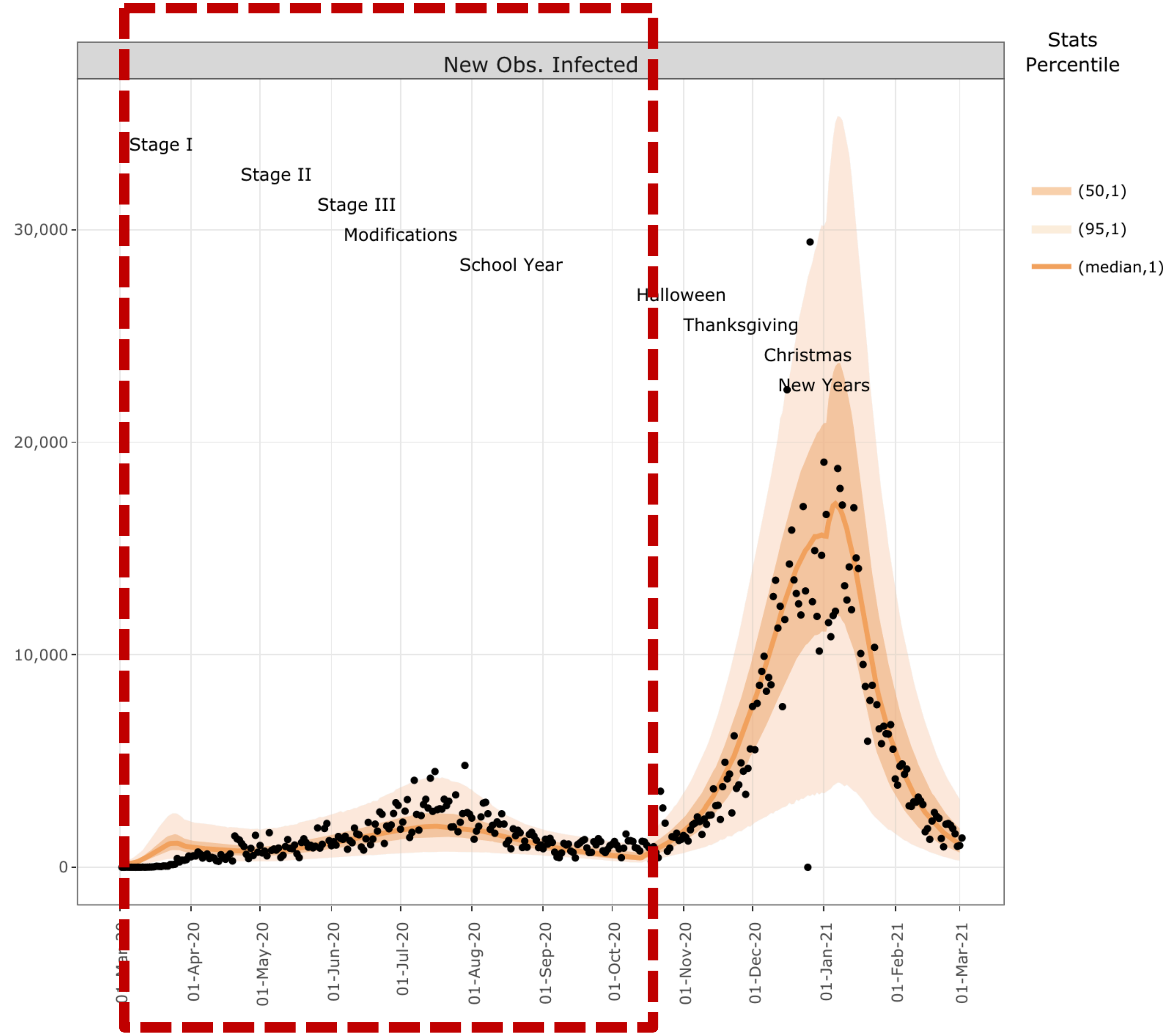
Group	age	BMI	smoking	comorbidity	Pop.Prev	P(H|I).May.15
Risk 2	65+	30<BMI<40	Non Smoker	Comorbidity	0.0110	0.2626
Risk 3	65+	BMI<30	Non Smoker	Comorbidity	0.0699	0.1635
Risk 3	45-64	BMI<30	Smoker	Comorbidity	0.0167	0.1690
Risk 3	65+	BMI<30	Non Smoker	No Comorbidity	0.0254	0.1148
Risk 3	45-64	30<BMI<40	Non Smoker	Comorbidity	0.0382	0.1733
Risk 3	45-64	BMI<30	Smoker	No Comorbidity	0.0130	0.1189
Risk 4	45-64	30<BMI<40	Non Smoker	No Comorbidity	0.0219	0.1221
Risk 4	45-64	BMI<30	Non Smoker	Comorbidity	0.1510	0.1031
Risk 4	20-44	BMI<30	Smoker	Comorbidity	0.0206	0.1069
Risk 4	45-64	BMI<30	Non Smoker	No Comorbidity	0.1045	0.0709
Risk 4	20-44	BMI<30	Smoker	No Comorbidity	0.0307	0.0736
Risk 4	20-44	30<BMI<40	Non Smoker	Comorbidity	0.0238	0.1098
Risk 5	20-44	30<BMI<40	Non Smoker	No Comorbidity	0.0240	0.0757
Risk 5	20-44	BMI<30	Non Smoker	Comorbidity	0.1055	0.0634
Risk 5	20-44	BMI<30	Non Smoker	No Comorbidity	0.1401	0.0430
Risk 5	0-19	BMI<30	Non Smoker	No Comorbidity	0.1463	0.0163

IFR varies widely across risk profiles within age groups

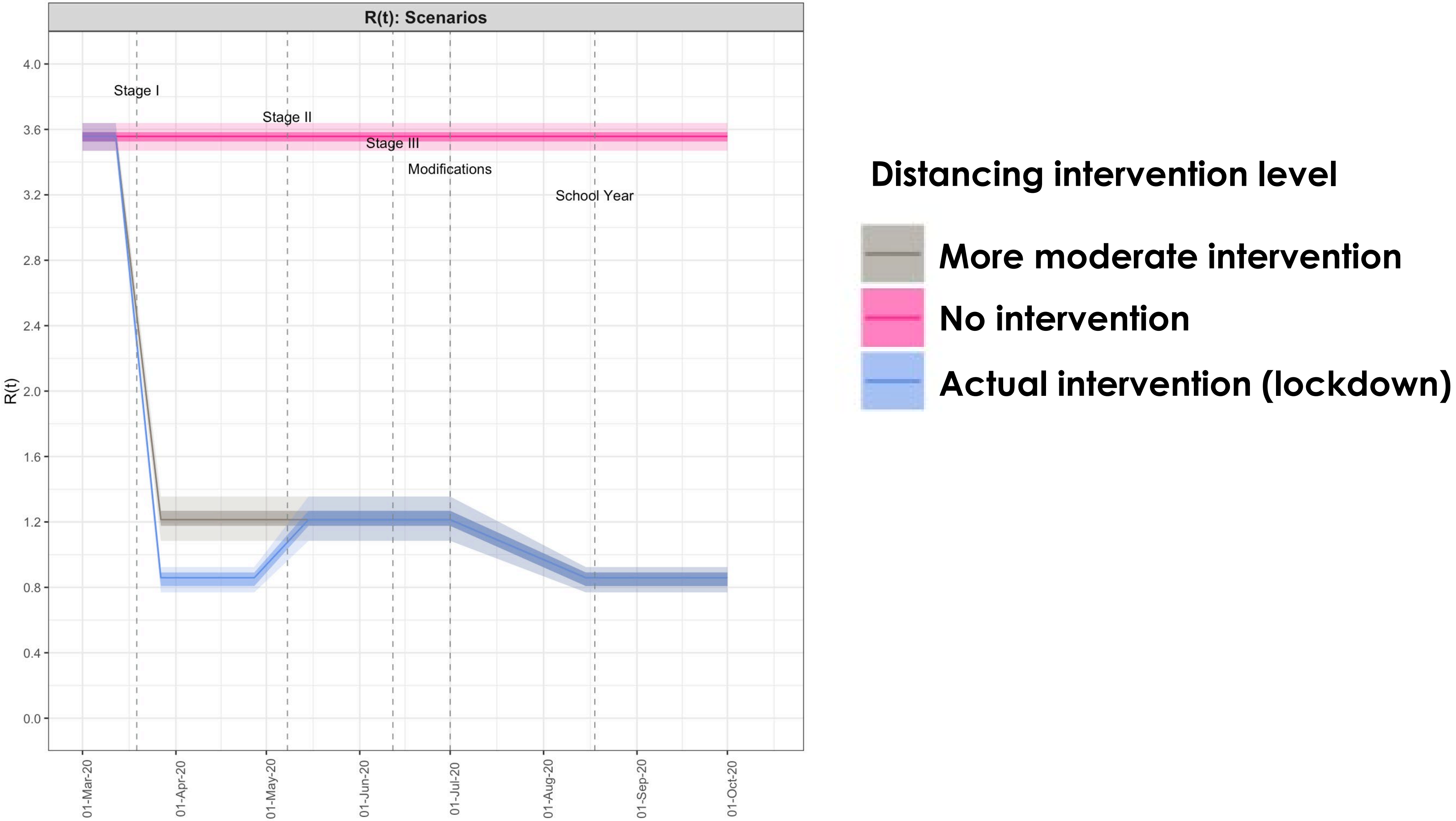


Horn et al. 2021, *PLOS* ONE, to appear.

Scenario analysis:
1st and 2nd Epidemic Waves, March – October, 2020



Policies evaluated:
More moderate intervention via modifying R(t)



Policies evaluated:
Protection of at-risk populations

No (direct) protection of at-risk groups

- What actually happened

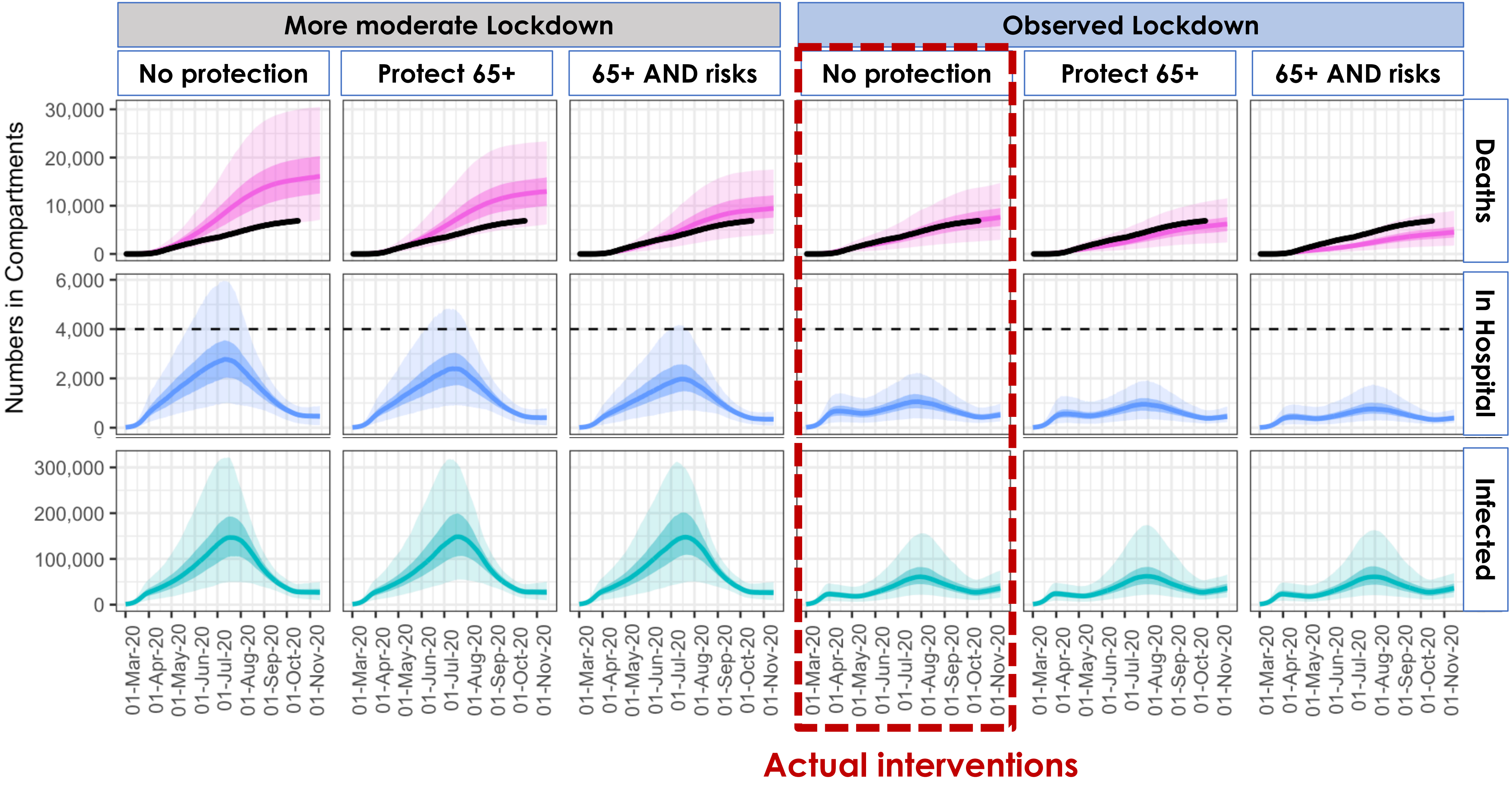
Protect those > 65 years old

- **17%** of the LAC population

Protect those >65 years old AND/OR with highest health risk factors

- **~35%** of the LAC population

Counterfactual Scenario Results

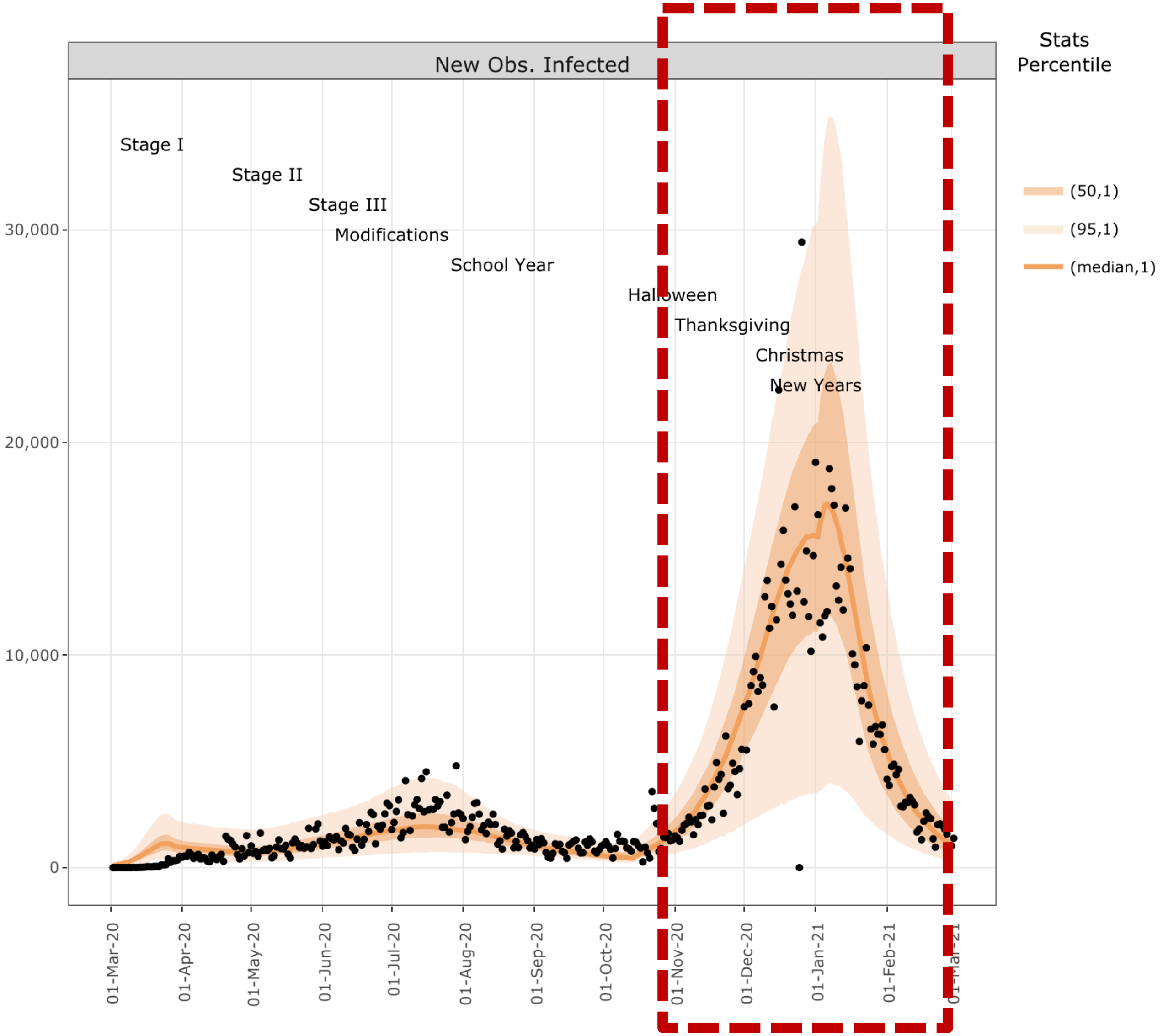


1^{st} and 2^{nd} wave analysis – what went right

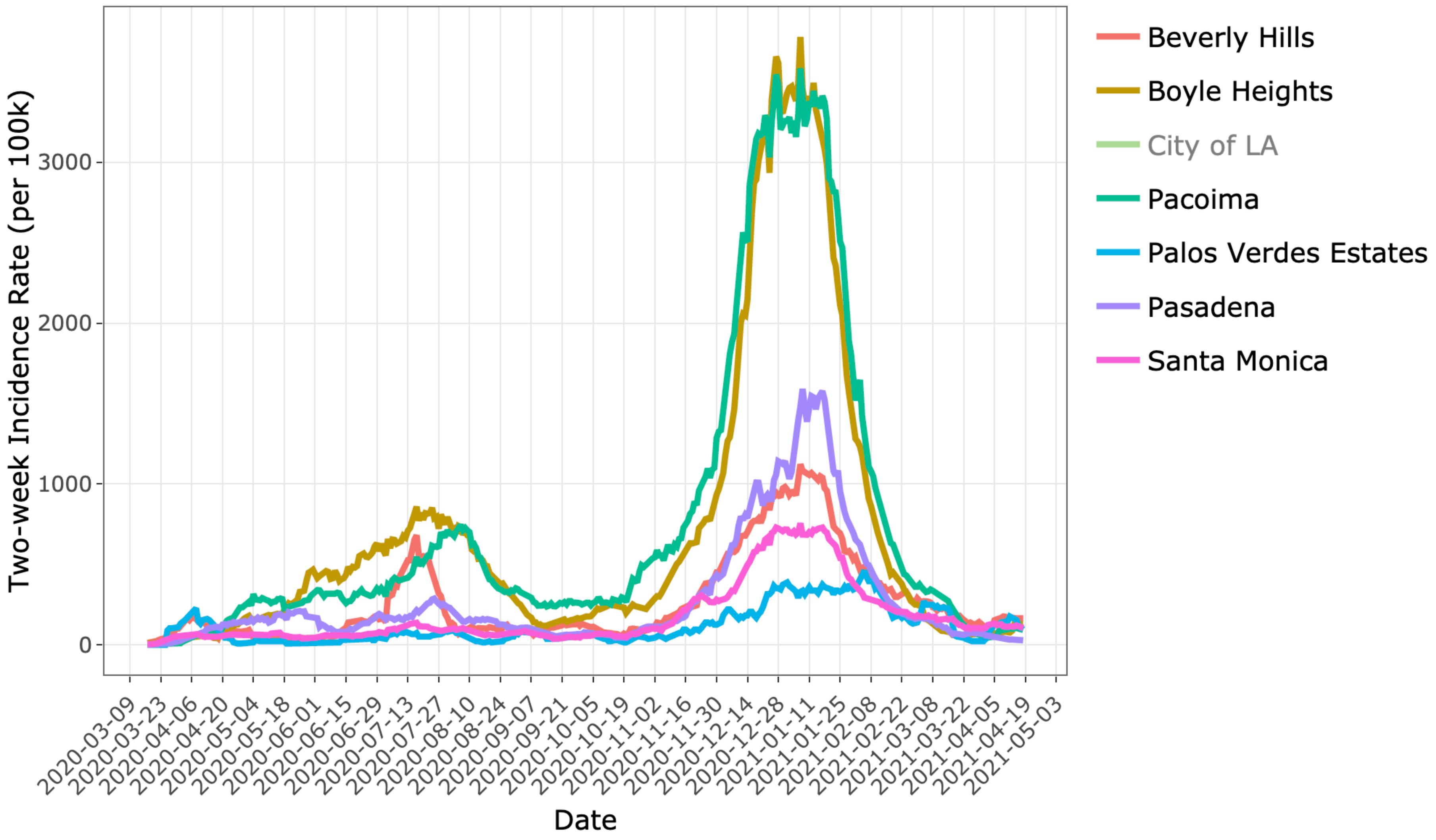
The strict initial lockdown period in LAC was effective because it both **reduced overall transmission** and **protected individuals at greater risk**

Moderate interventions + protection of 65+ alone would have overwhelmed healthcare capacity and doubled the death count

But what about the major 3rd epidemic wave? November 2020 – February 2021



3rd wave dynamics: Driven by major disparities in *risk of infection*



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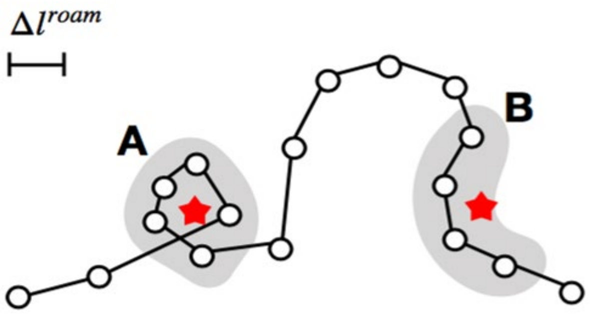
The Team

- **USC Department of Preventive Medicine**
  - Lai Jiang, MS Biostatistics PhD Candidate
  - Emil Hvitfeldt, MS Research Programmer
  - Wendy Cozen, DO, MPH Professor of Preventive Medicine
  - Kayla de la Haye Assistant Professor of Preventive Medicine
- **USC School of Public Policy**
  - Neeraj Sood, Professor and Vice Dean of Research
- **Los Angeles County Department of Public Health (LACDPH)**
  - Paul Simon, MD, MPH, Chief Science Officer
  - Will Nicholas, PhD, MPH Director, Center for Health Impact Evaluation, LACDPH
  - Faith Washburn, MPH Epidemiology Analyst

BACKUP

Big mobility data:
Informs risk of infection by neighborhood



- Big data from geolocation traces on smartphone devices
- A large and representative population sample (**10% of US population**)
- Spatial measures of:
  - Population able to stay at home
  - Population traveling in to work
- Aggregated individual-level patterns across neighborhoods

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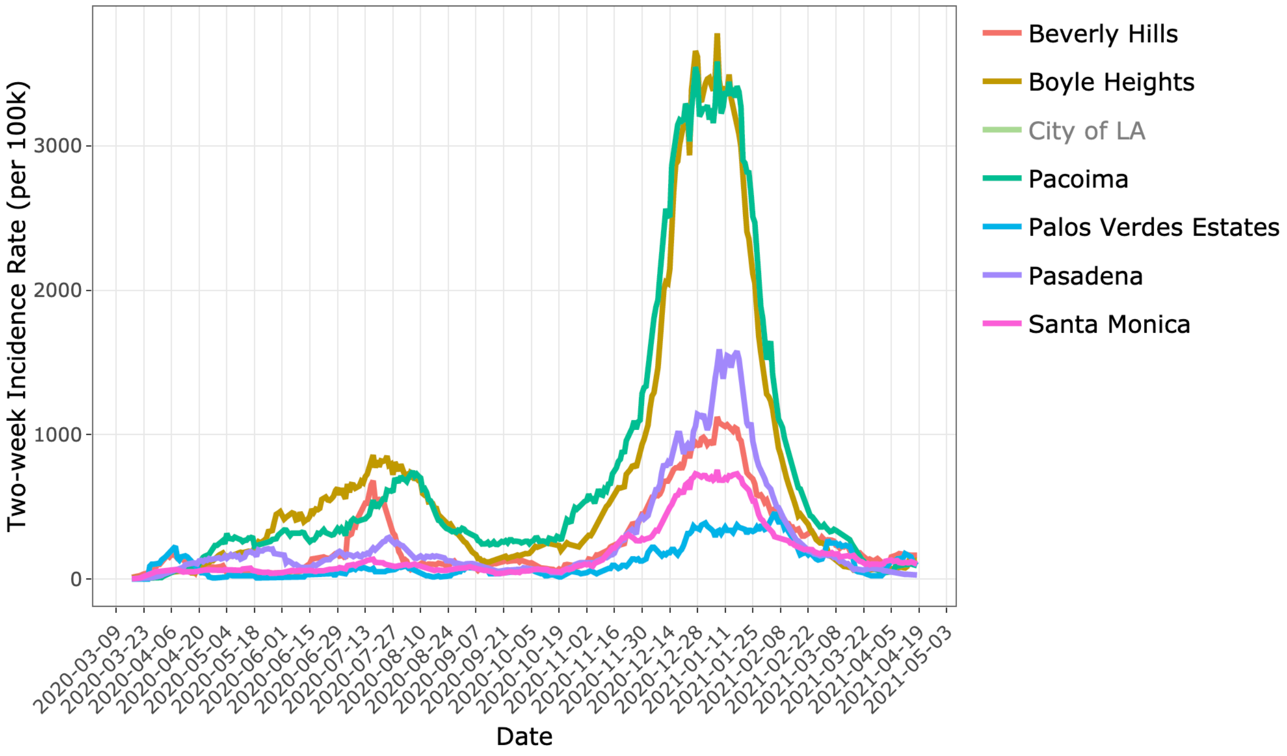
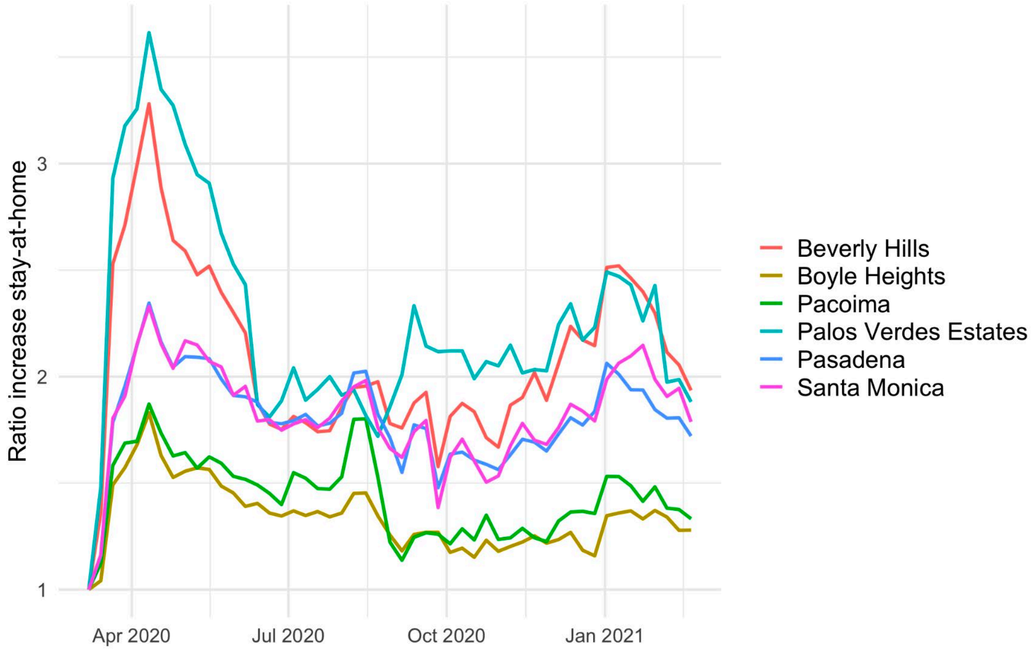
Measures from mobility data: who is able to stay at home

COVID-19 Incidence Rate



Population staying at home (ratio difference from pre-pandemic)



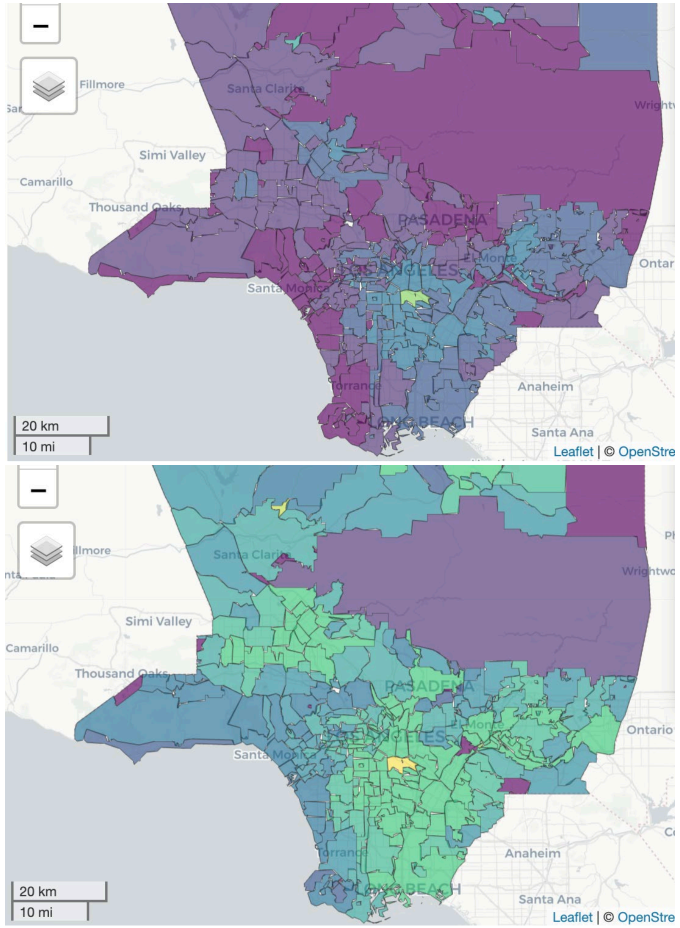
Measures from mobility data – by neighborhood

COVID-19 7-day Crude Incidence Rate

Population able to stay at home

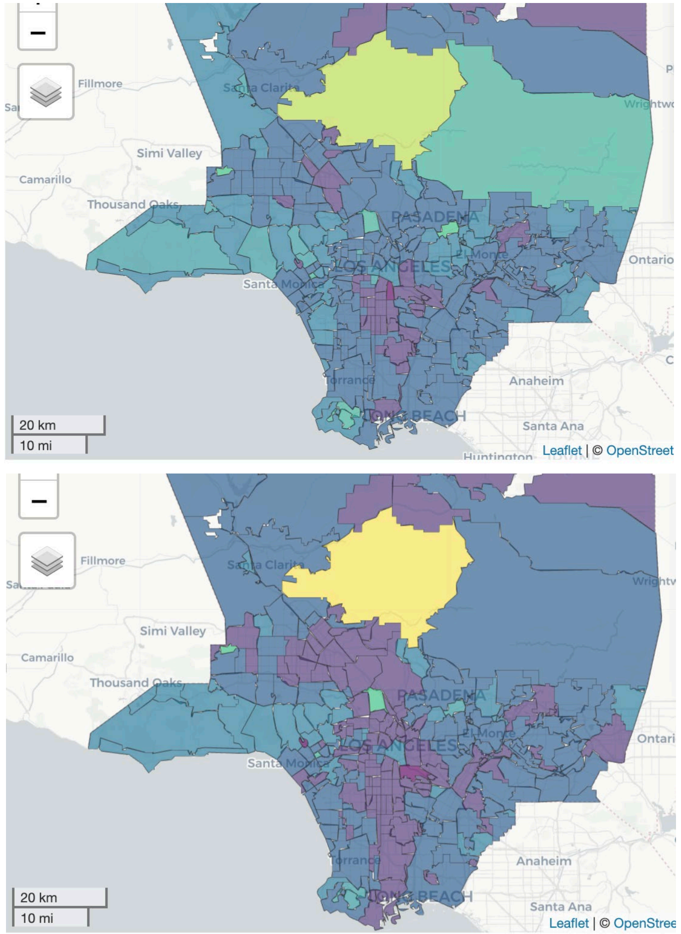
June 2020

December 2020



Crude Incidence Rate per 100,000

- 0 – 50
- 50 – 100
- 100 – 200
- 200 – 400
- 400 – 600
- 600 – 800
- 800 – 1,000
- 1,000 – 2,000
- 2,000 – 4,000
- 4,000 – 8,000
- 8,000 – 10,000



Ratio increase in stay-at-home proportion

- 0.0 – 1.0
- 1.0 – 1.5
- 1.5 – 2.0
- 2.0 – 2.5
- 2.5 – 3.0
- 3.0 – 3.5
- 3.5 – 4.0
- 4.0 – 4.5
- 4.5 – 5.0
- 5.0 – 10.0

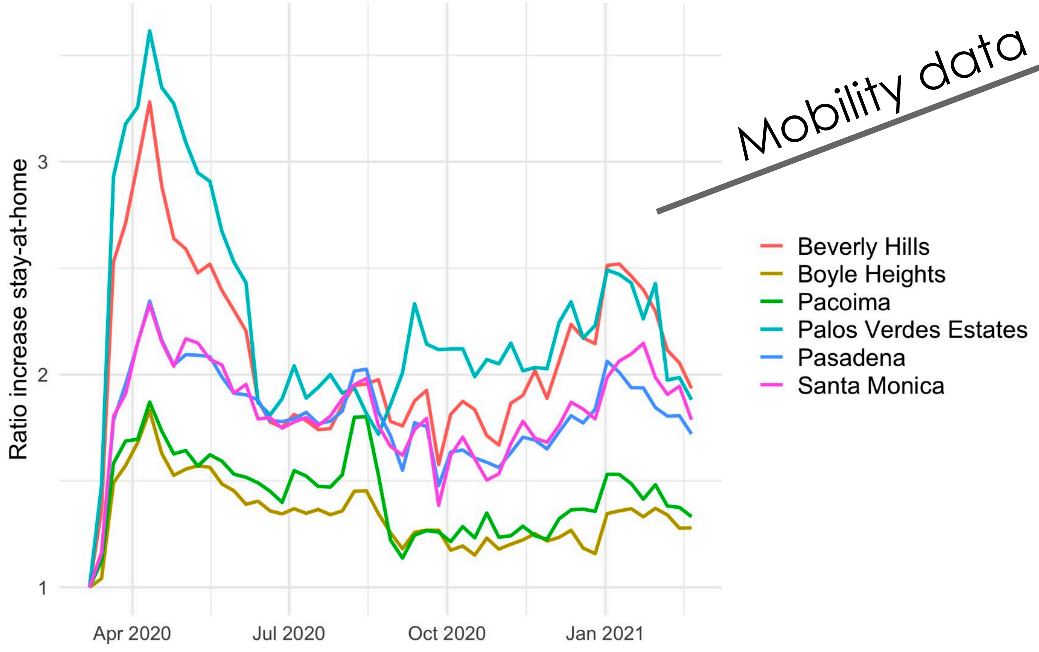
Next steps: Investigating 3rd wave with neighborhood model

Use the neighborhood model to do scenario analysis on the 3rd wave to investigate:

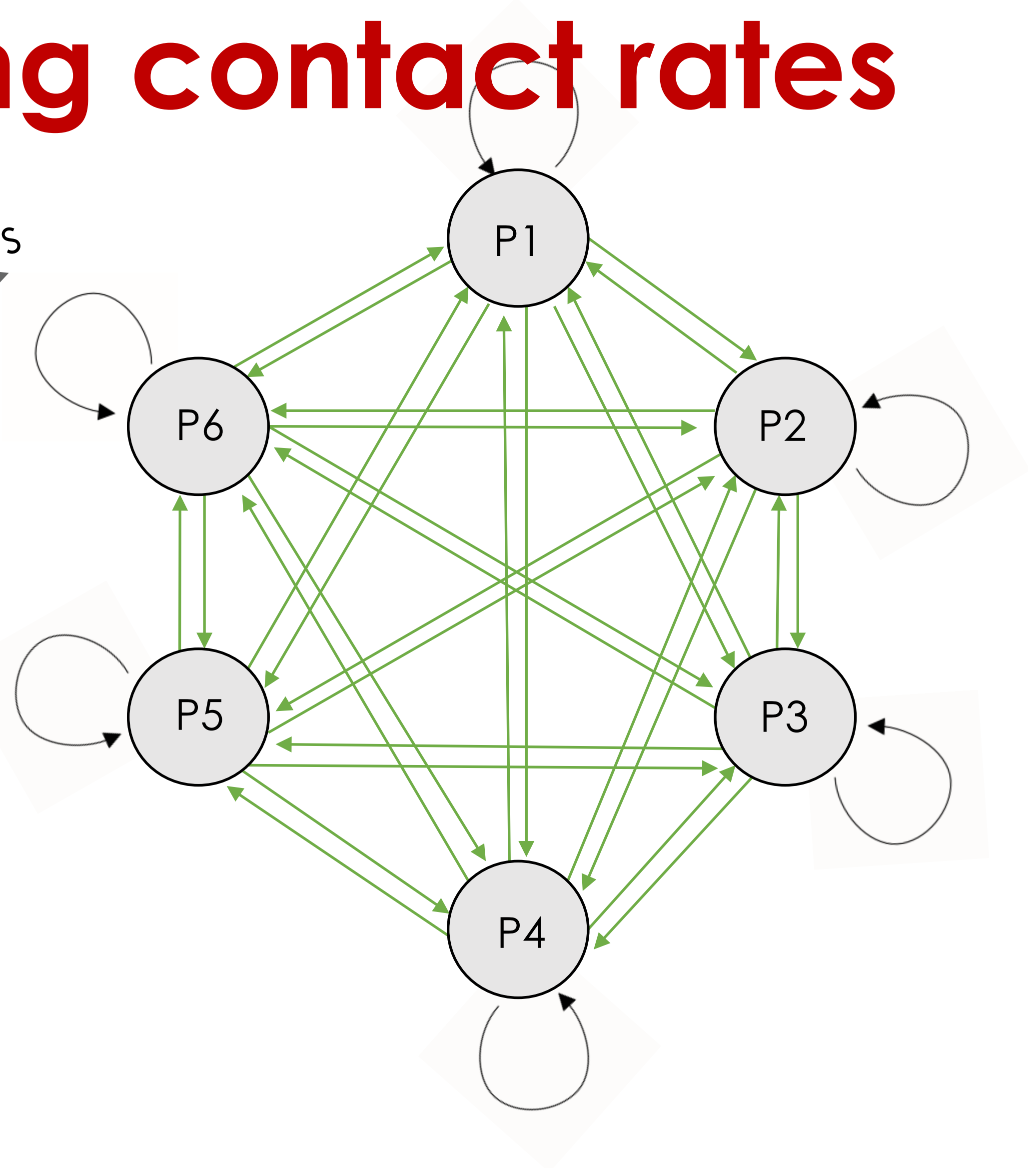
- How effective were policy measures to protect different populations from infection, hospitalization, and death?
- What would things have looked like if we had done a greater job to help more people stay at home or not go to work if sick?

Mobility data informing contact rates

- Incorporate mobility data. Ongoing.

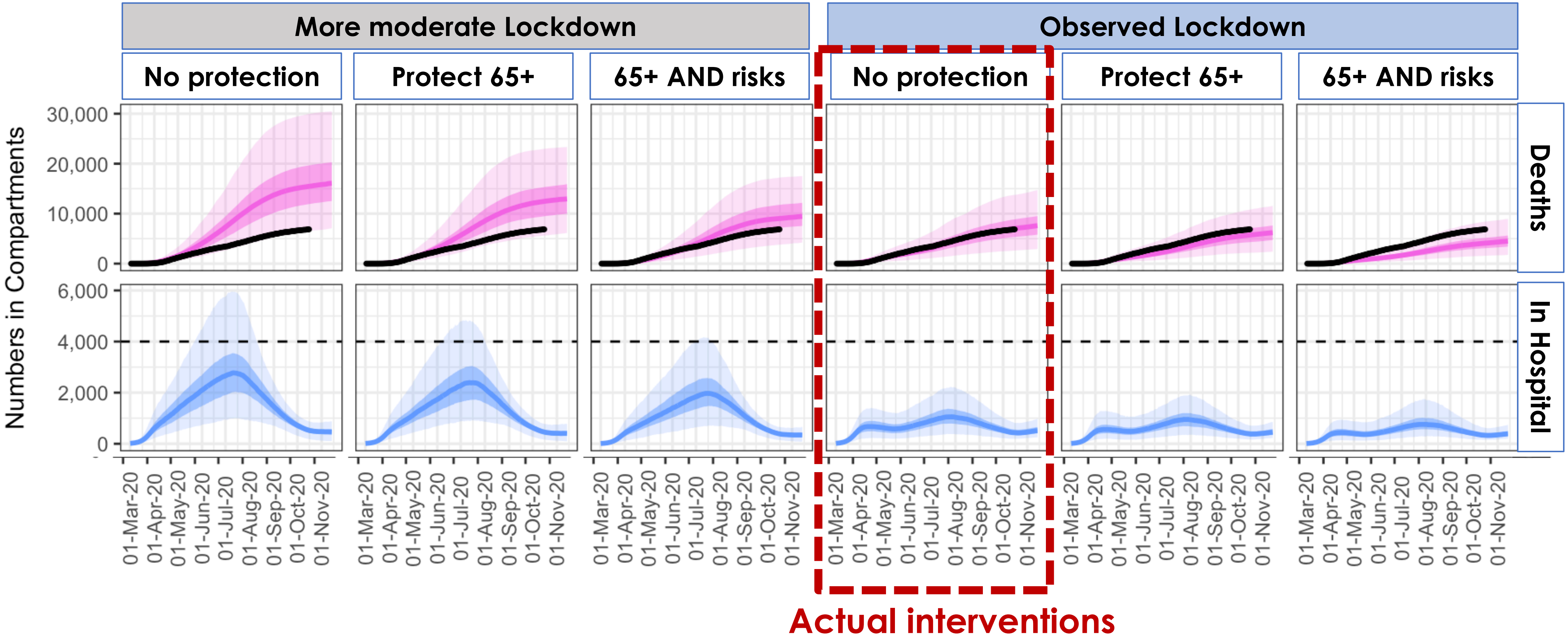


Mobility data defines priors



(Ratio increase in staying at home, relative to pre-pandemic baseline)

Counterfactual Scenario Results



Horn et al. 2021, *MedarXiv*.