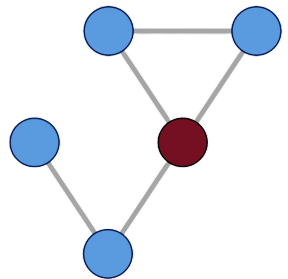


Putting network epidemiology theory to the test

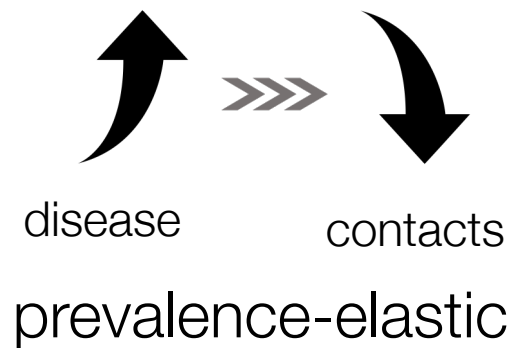
Estimating contact structure across epidemic conditions with implications for control

Juliana Taube

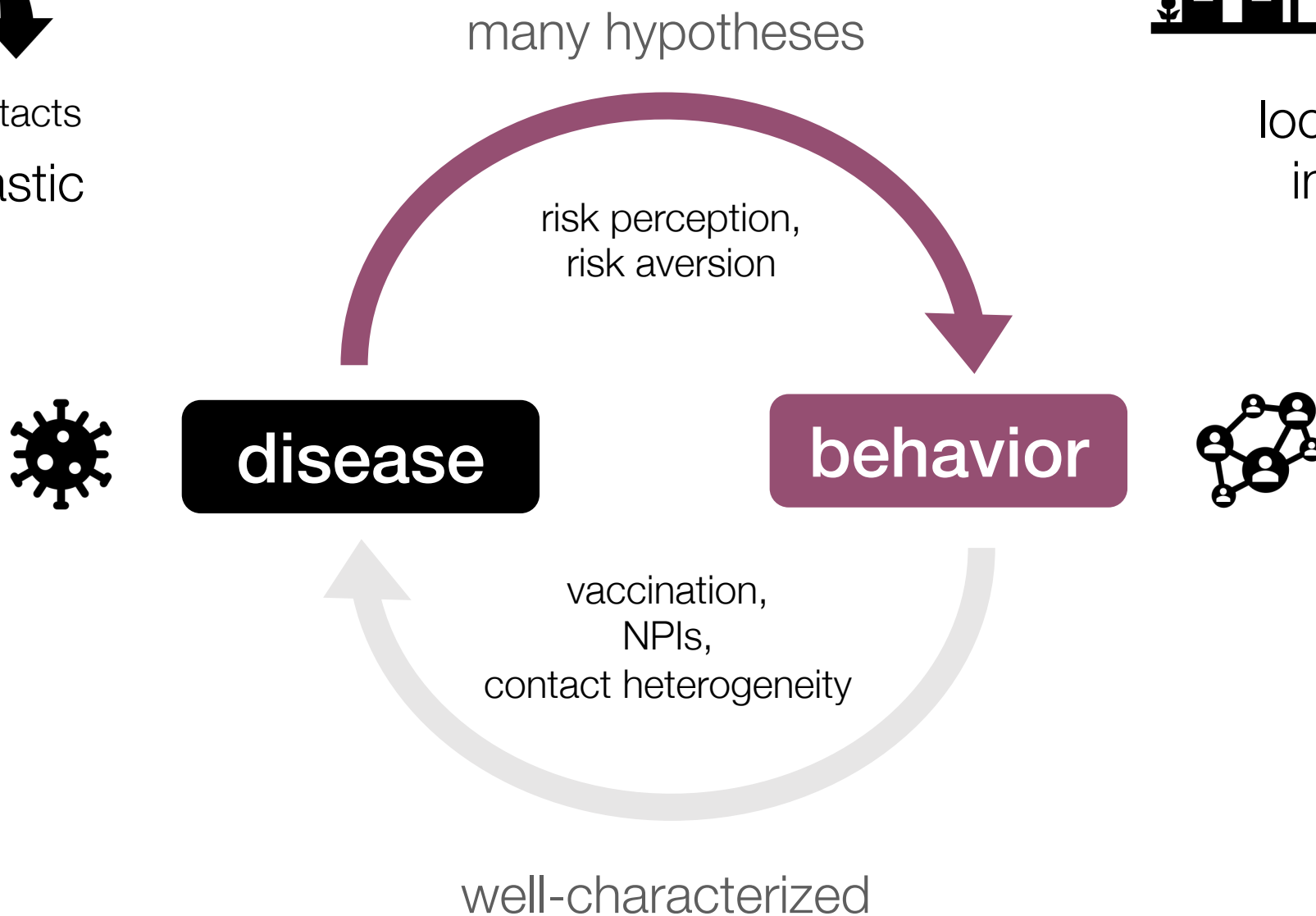
NetSci 2026 Satellite



Bansal Lab



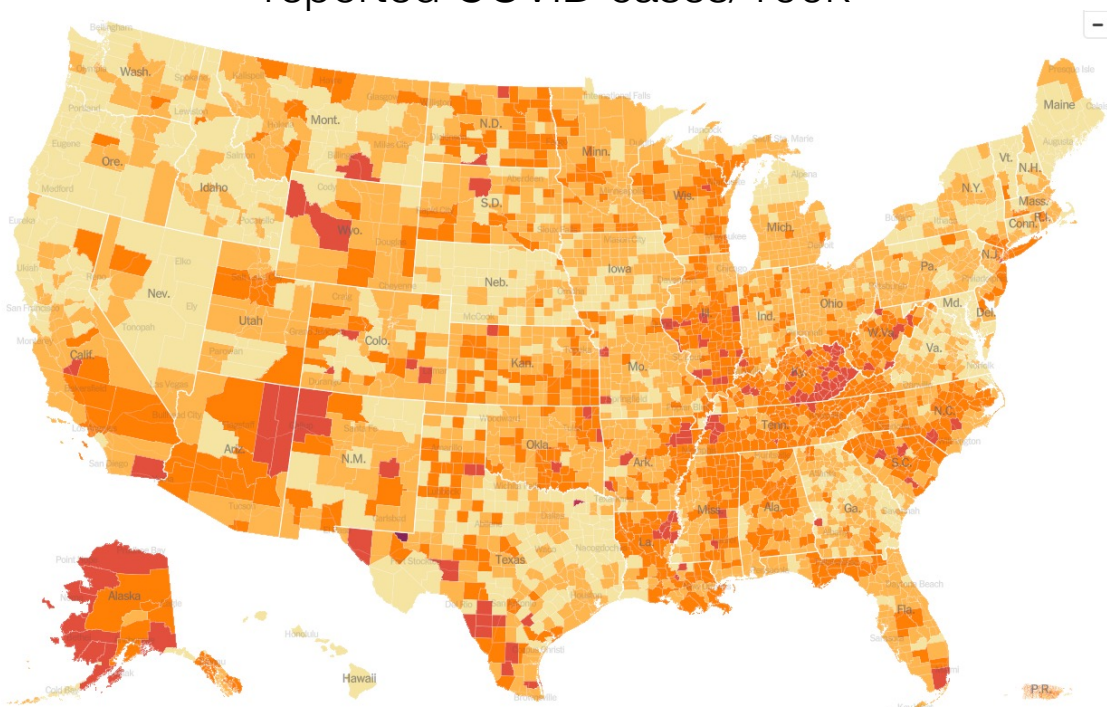
local vs global
information



Heterogeneities in disease across space & time

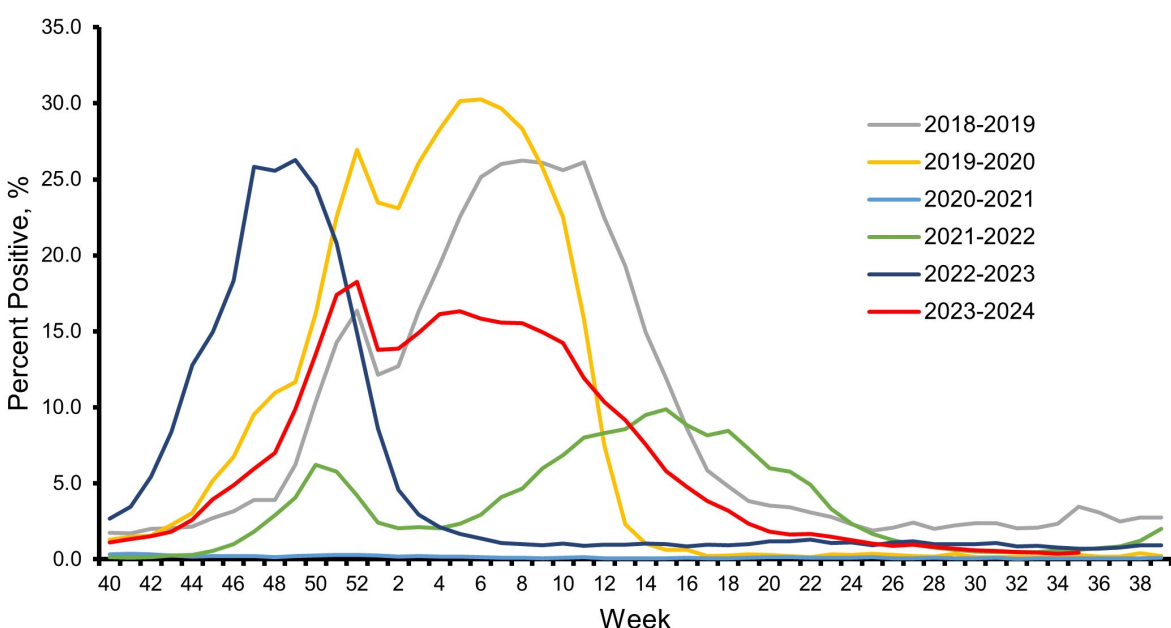
Spatial patterns of disease

reported COVID cases/100k



Seasonality of respiratory viruses

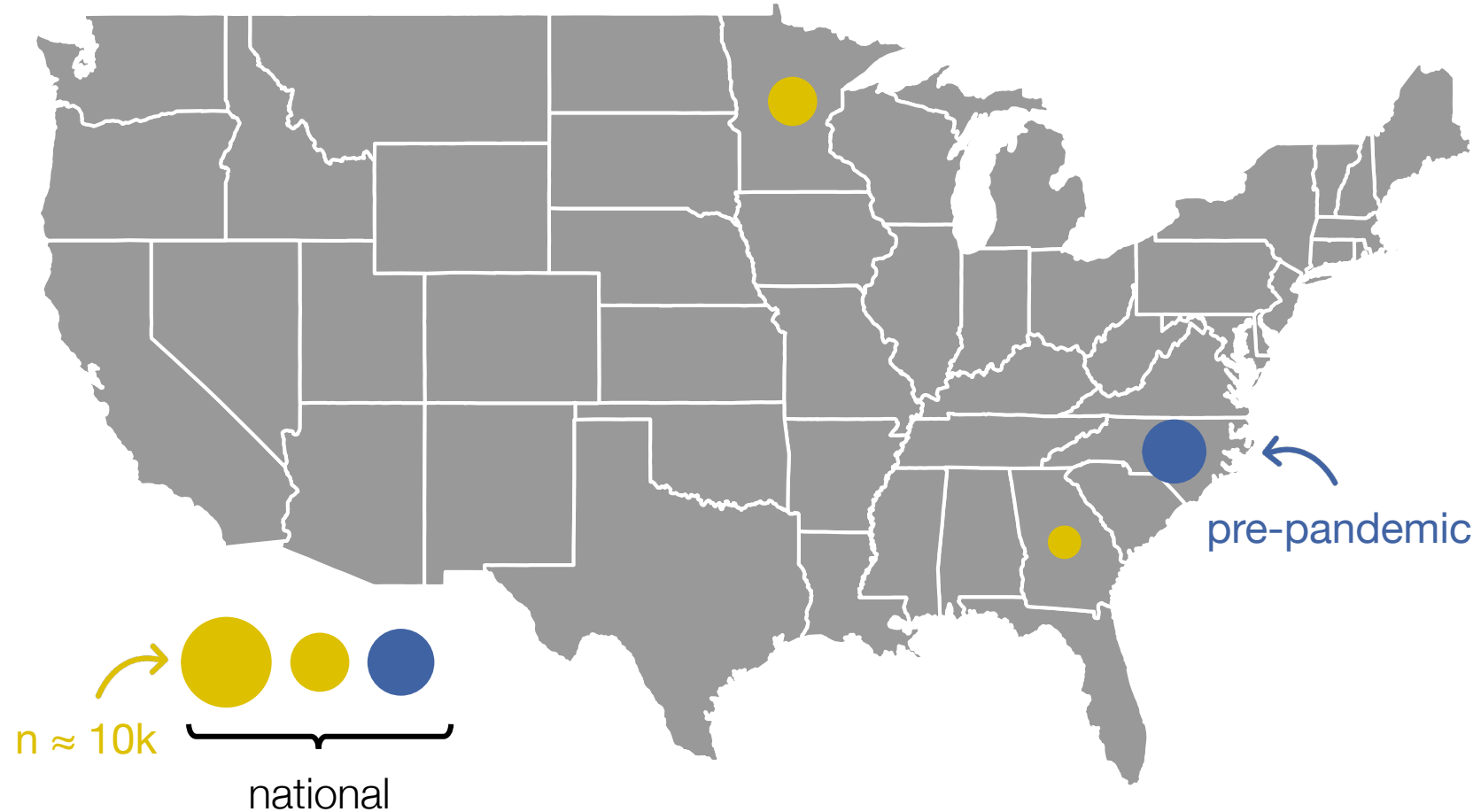
annual influenza activity



Data on contact network structure is limited

Studies that do exist are small and brief...

...which prohibits us from analyzing behavior at fine spatial and long temporal scales



each dot is a study & its location

CTIS non-household contact data



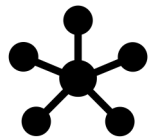
COVID-19 Trends and Impact Survey



Number of direct **non-household** contacts in the last 24 hrs



11.2 million responses (Jun 2020 – Apr 2021)



Estimate **mean degree** & population **degree heterogeneity** at fine spatial & temporal scales

Estimating mean degree across space & time



Zack Susswein



We want fine spatial & temporal estimates of contact rates

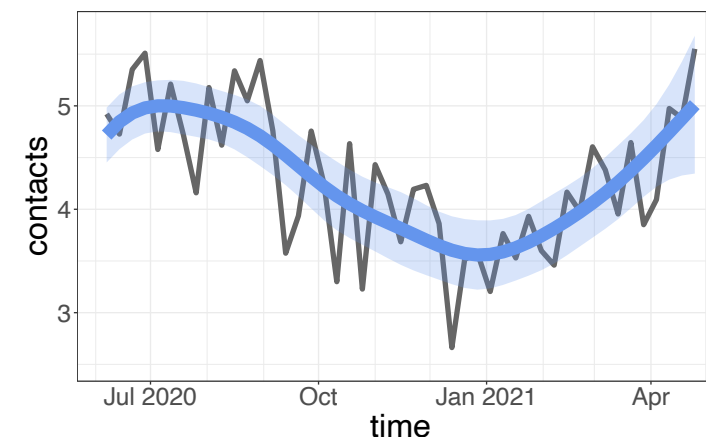


But low sample sizes in some locations + temporal noise make this hard

We use [Generalized Additive Models](#) (GAMs)

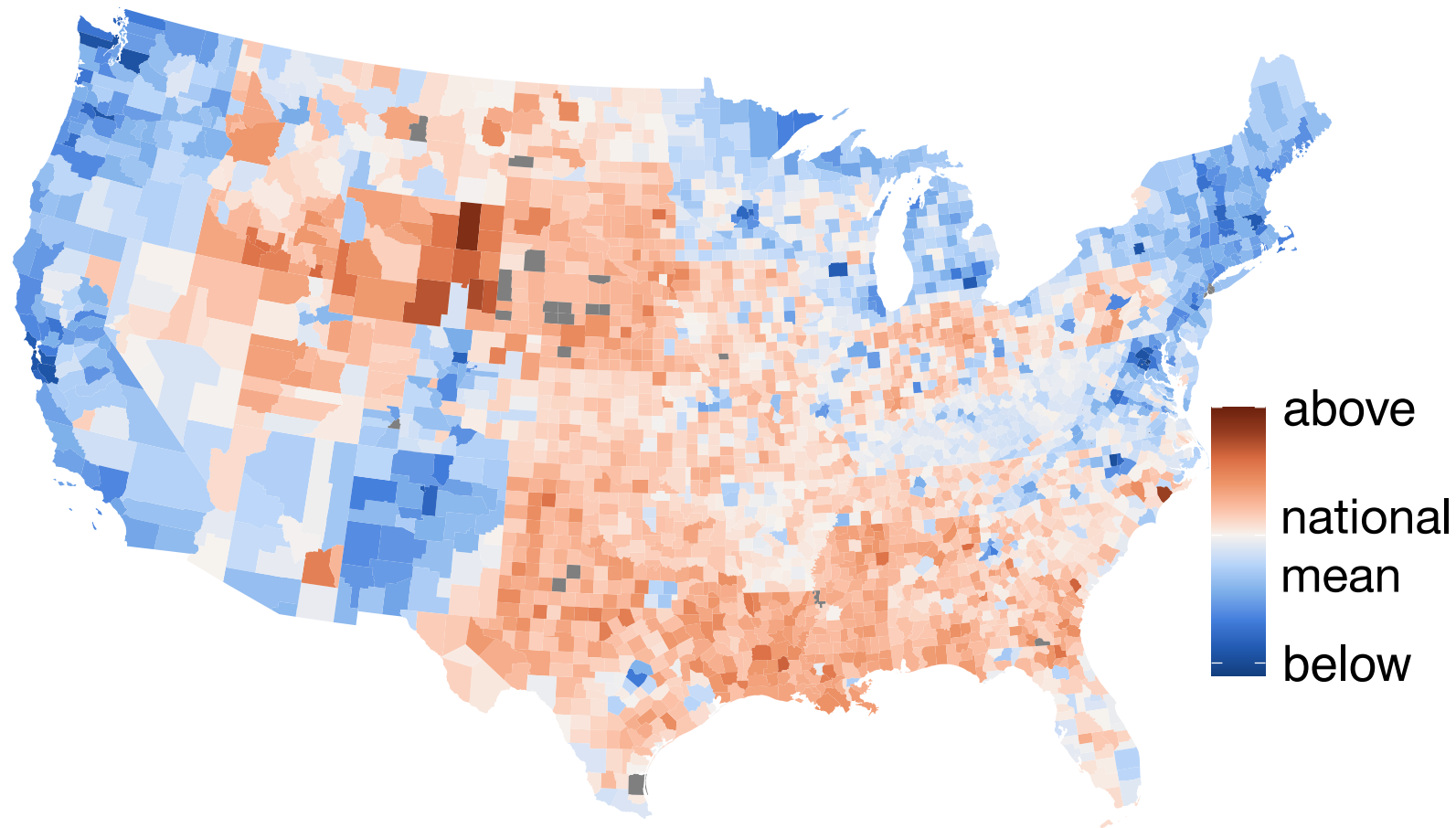


- Create smooth temporal trend
- Allow counties within a state to share information (hierarchical)

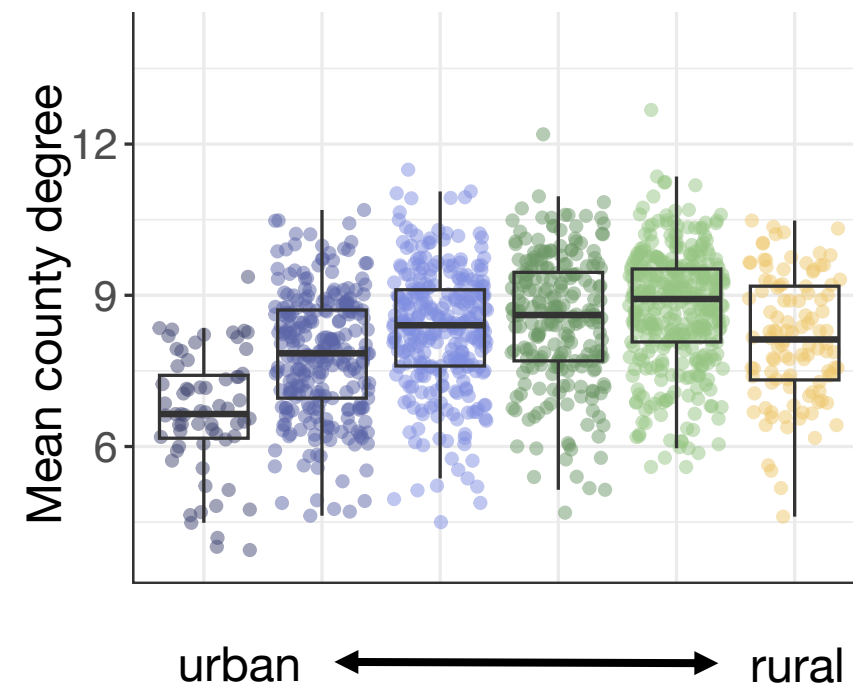


Output: county-week estimates of mean non-household degree

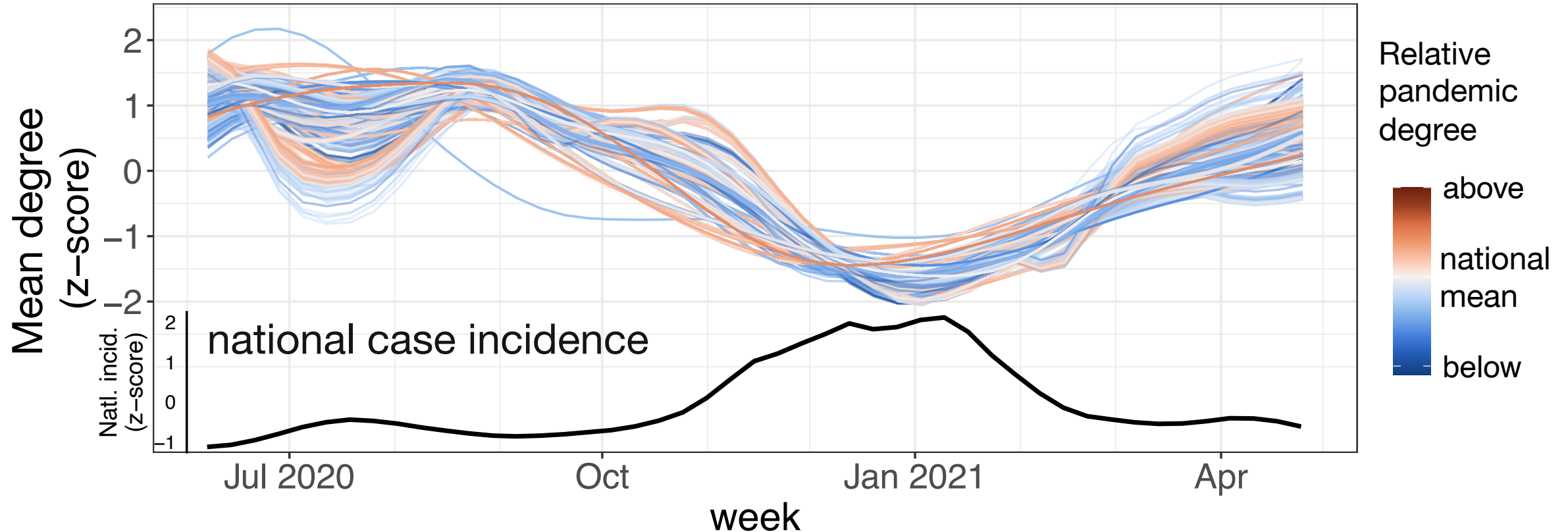
Degree varied spatially during the pandemic



Mean county degree



Degree varied temporally during the pandemic



What is driving these spatial & temporal heterogeneities? Disease?

What factors are driving pandemic behavior change?



measured risk

policy



perceived risk



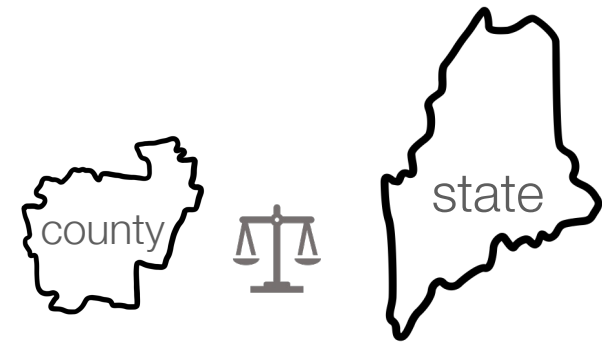
disease

behavior



disease
prevalence-elastic

contacts



local vs global
information

What factors are driving pandemic behavior change?



behavior $\sim$ measured risk + perceived risk + policy + control variables



weather



popn. density



demography



essential workers



education



income



We use Integrated Nested Laplace Approximation (INLA) models

- Can handle spatial and temporal autocorrelation



Output: estimated effects of each factor on county mean degree



Casey Woika

Measured risk



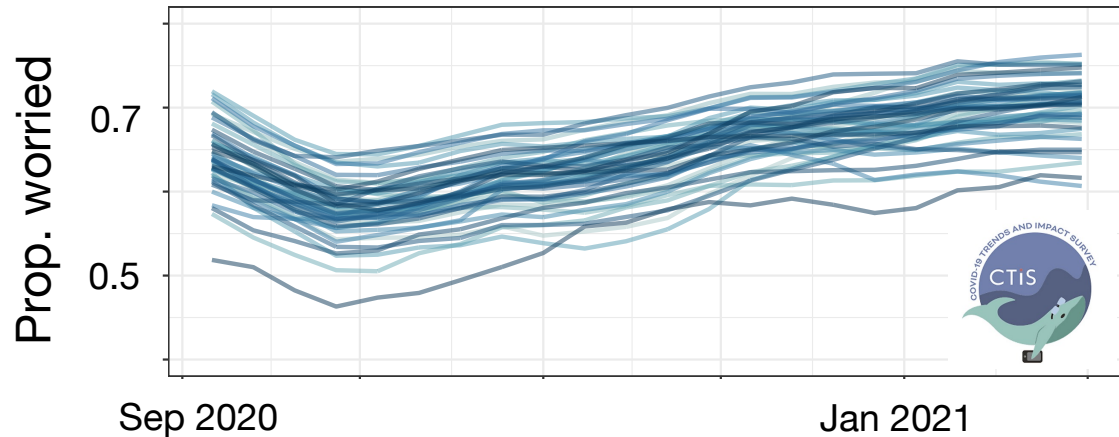
COVID-19 case incidence



Perceived risk



Prop. of respondents concerned about becoming seriously ill



Policy

nonessential



food & drink



entertainment



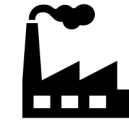
outdoor recreation



worship



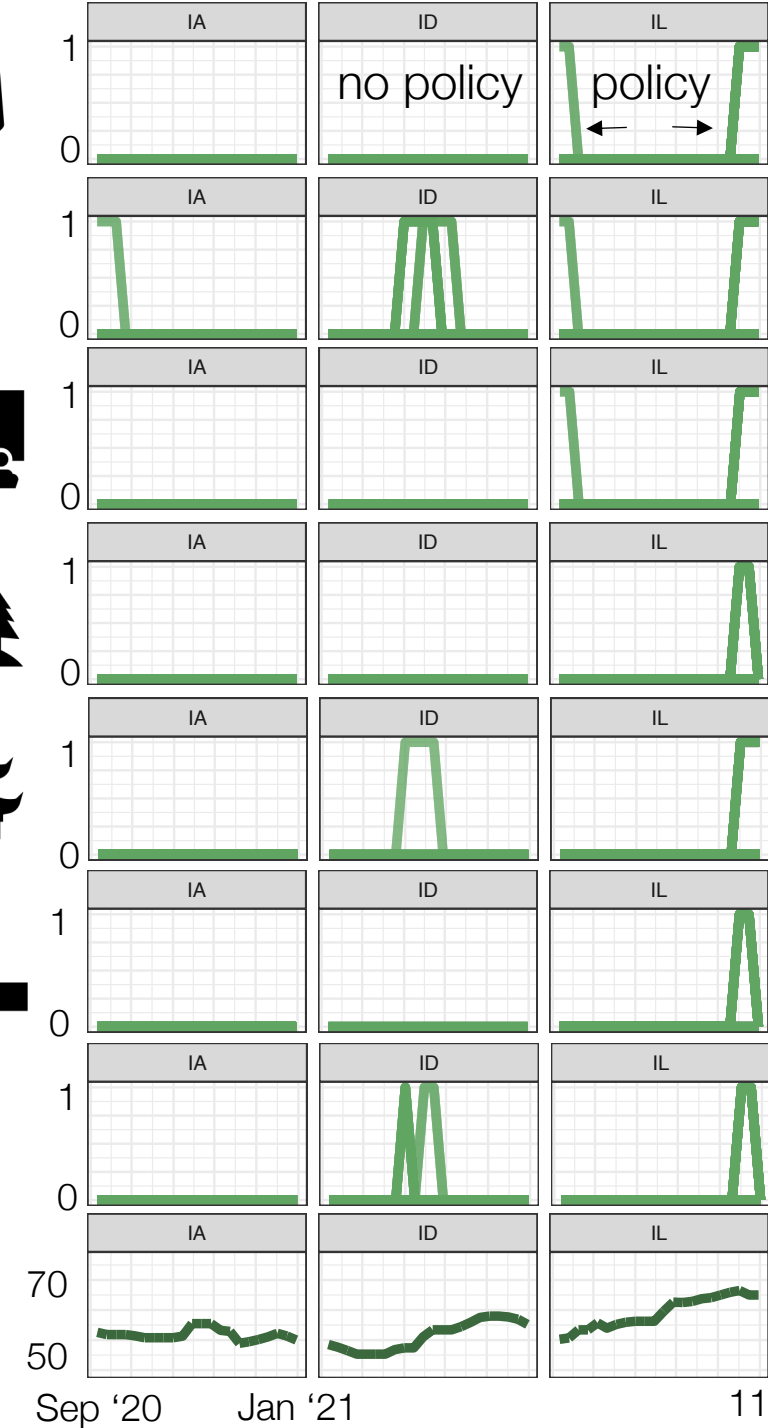
manufacturing



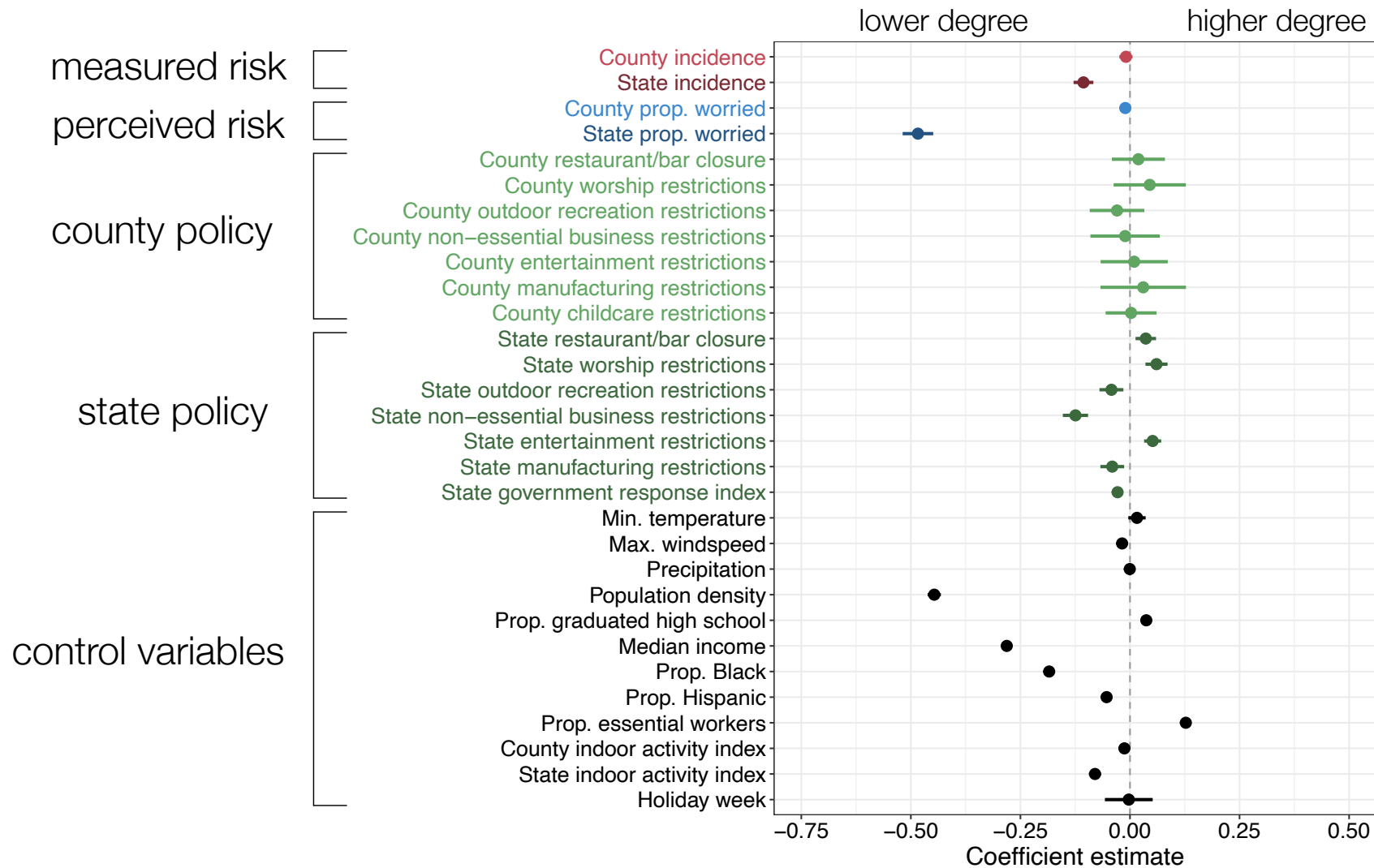
childcare
(county-level only)



Oxford Stringency Index
(state-level only)



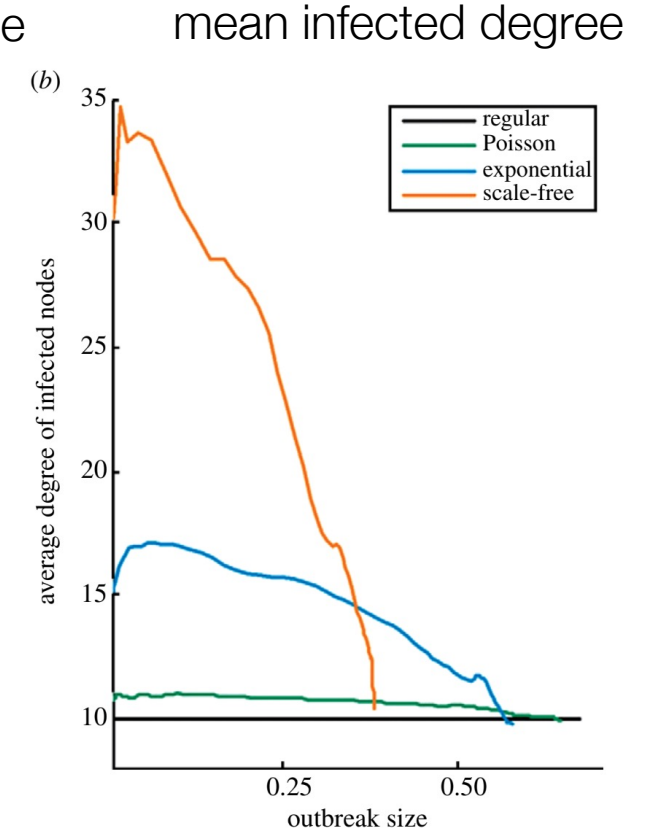
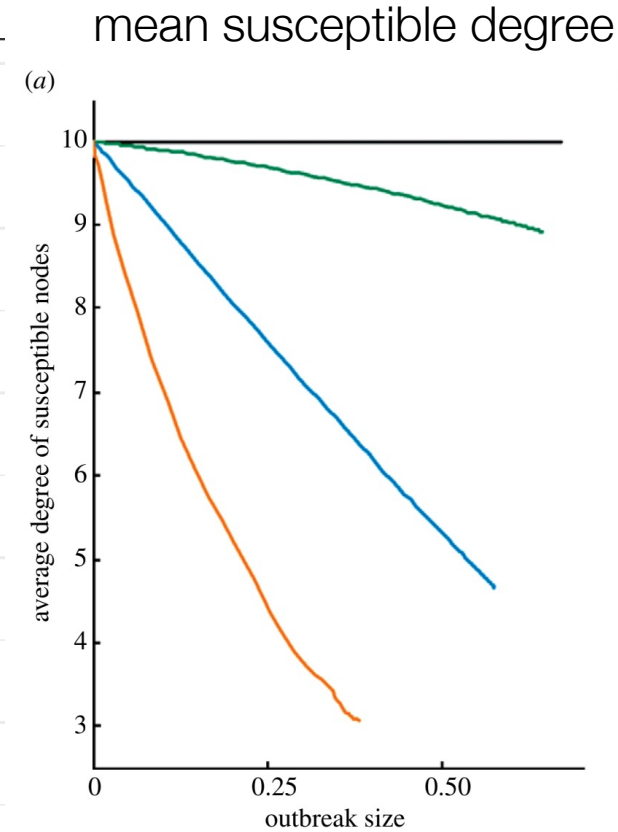
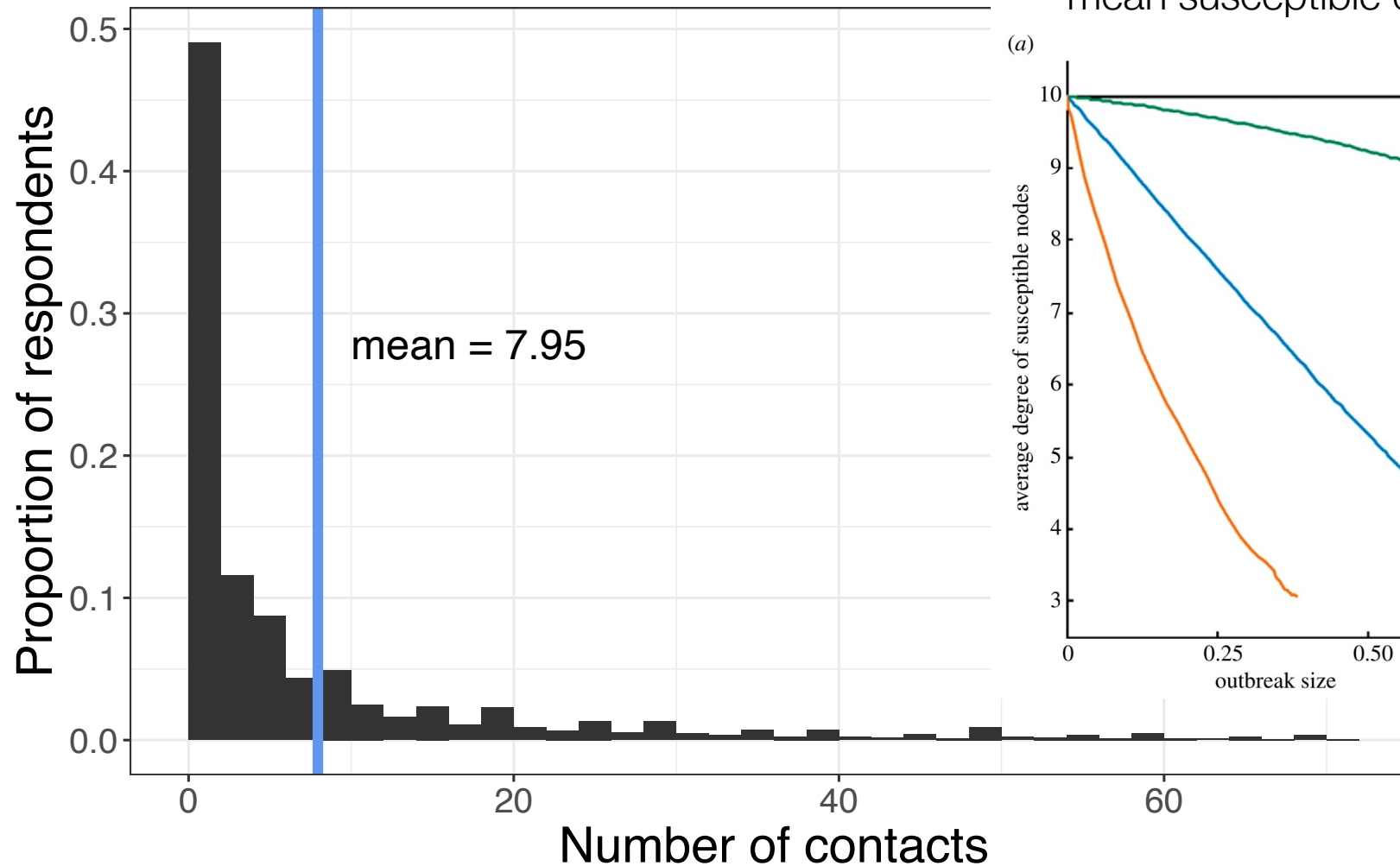
Behavior change is informed by **disease** & **perception**, especially at larger spatial scales



✓ prevalence-elastic

global > local

Revisiting degree heterogeneity



Bansal et al. (2007)

Do our data follow these predictions?

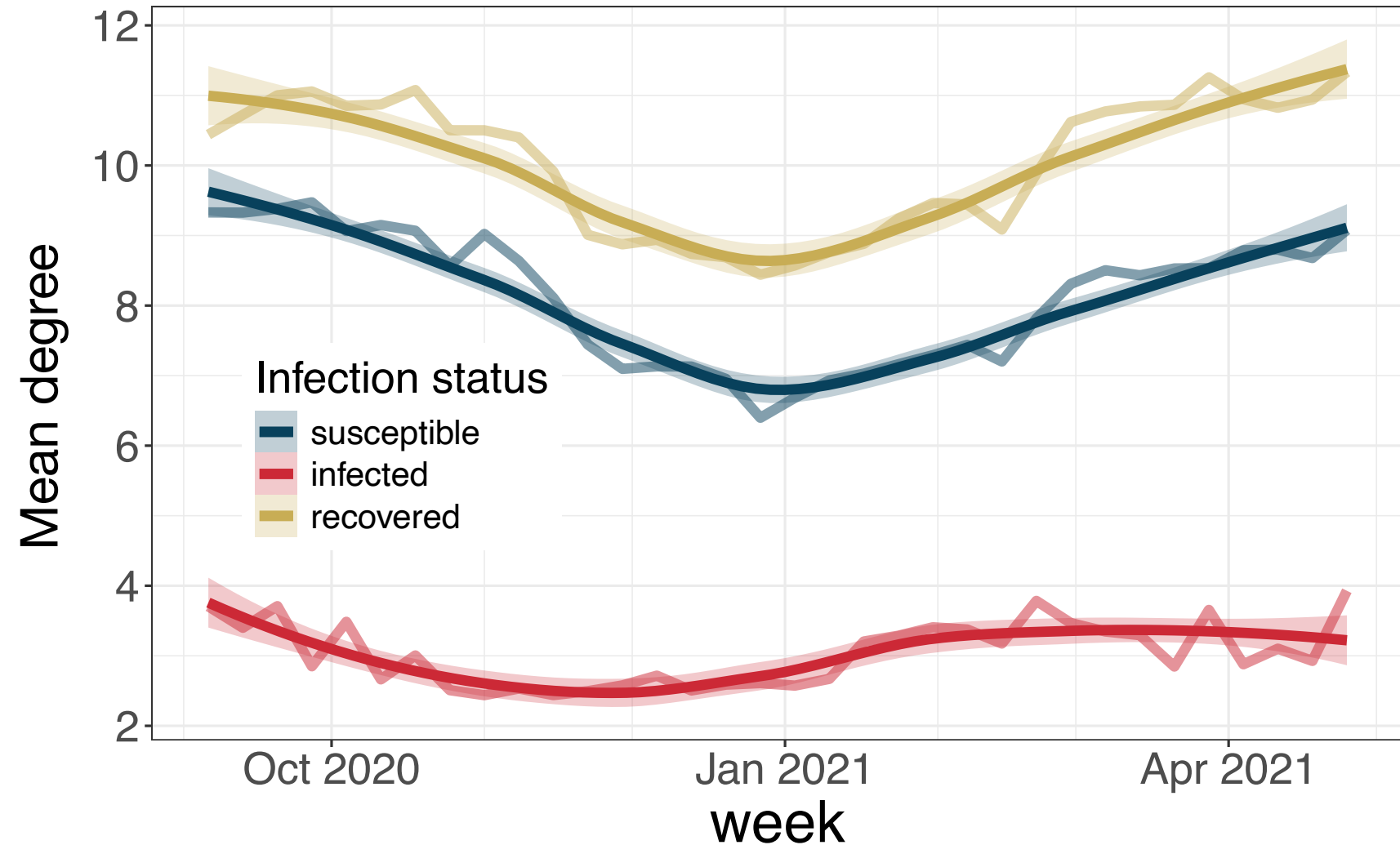
Degree varies by infection status

Asked whether (+) test:

- in the last 14 days
- ever



Classify as S, I, R



Potential drivers of degree differences

Main hypothesis:

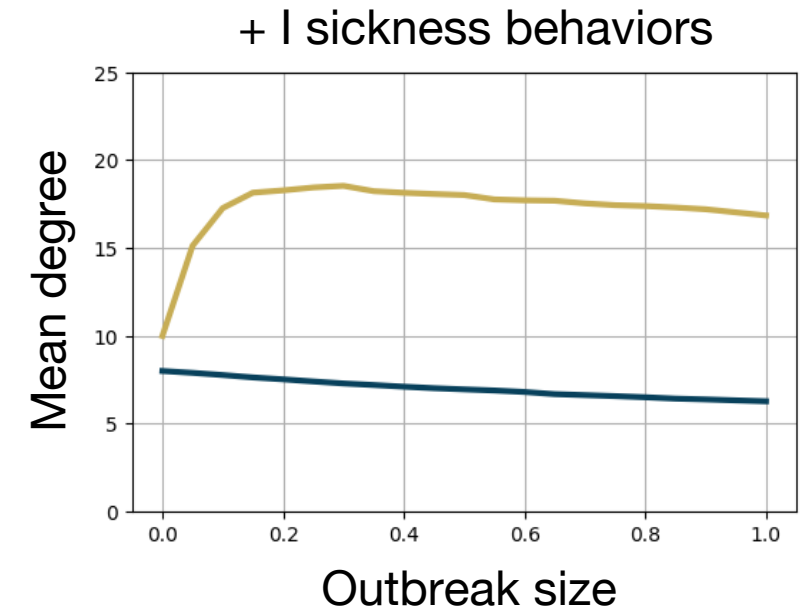
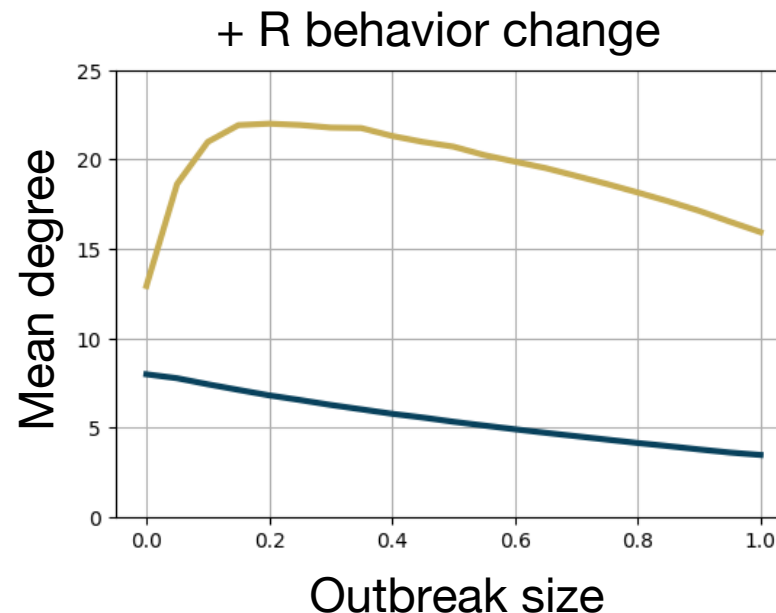
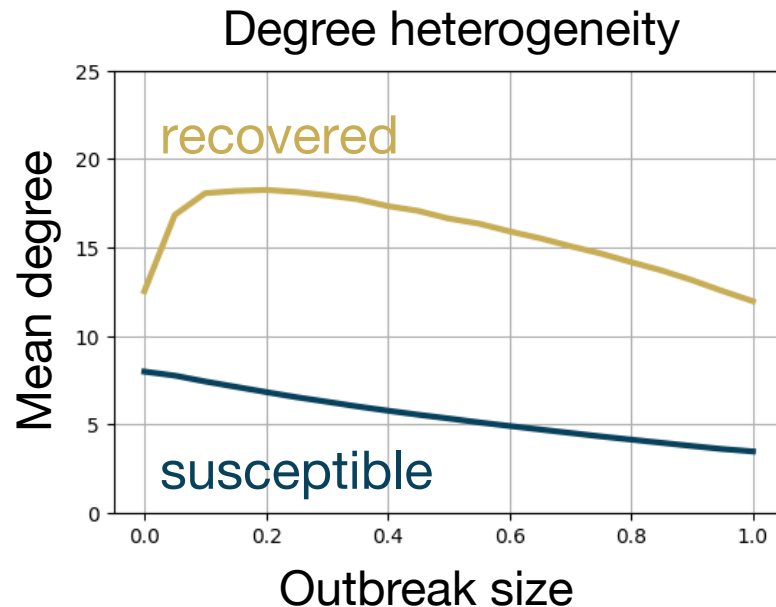
Infection process depletes high degree susceptibles

Alternative hypotheses:

1. Post-recovery behavior change
2. Sickness behaviors & downstream effects

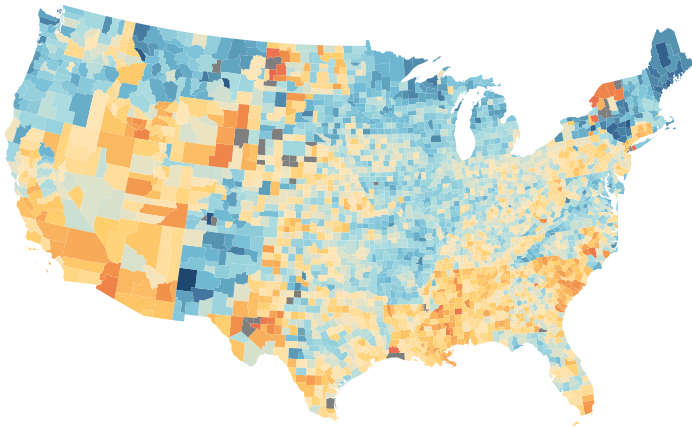
Temporal change hypotheses:

1. Social distancing
2. Local avoidance
3. Social desirability bias



Conclusions & future work

Degree varies spatially & with disease dynamics



Design models, policies, & surveillance accordingly

Mesoscale disease information drives behavior change



measured risk



perceived risk

Changes in degree across infection stages

