Title: Managing the COVID-19 Pandemic across Geography and Demography

Speakers: Niayesh Afshordi

Series: Colloquium

Date: July 29, 2020 - 2:00 PM

URL: http://pirsa.org/20070030

Abstract: What factors drive the growth and decay of a pandemic? Can a study of community differences (in demographics, settlement, mobility, weather, and epidemic history) allow these factors to be identified? Has â€œherd immunityâ€• to COVID-19 been reached anywhere? What are the best steps to manage/avoid future outbreaks in each community? We analyzed the entire set of local COVID-19 epidemics in the United States; a broad selection of demographic, population density, climate factors, and local mobility data, in order to address these questions. What we found will surprise you! (based on arXiv:2007.00159)

Physics Colloquium, July 29
Perimeter Institute for Theoretical Physics

Managing the COVID-19 Pandemic across Geography and Demography

Niayesh Afshordi

UNIVERSITY OF WATERLOO

WATERLOO CENTRE FOR ASTROPHYSICS

PERIMETER INSTITUTE FOR THEORETICAL PHYSICS

Collaborators

- Ben Holder (Grand Valley State University)
- Mads Bahrami (Wolfram Research)
- Danny Lichtblau (Wolfram Research)

Explore Further

- Forecasts and cloud simulations for every US county: wolfr.am/COVID19Dash
- Up-to-date resources, Open data, Immunity Maps, … : nafshordi.com/covid
- Our first paper of arXiv.org and medRxiv.org:
  - https://arxiv.org/abs/2007.00159
  - https://www.medrxiv.org/content/10.1101/2020.06.30.20143636v1

wolfr.am/COVID19Dash

Managing COVID-19 Pandemic across Geography and Demography [United States Edition]

This dashboard provides important historical information and forecasts for the growth of COVID-19 epidemic, as a function of social mobility, climate, population demographics, and history of the disease in the United States communities. A 7-fold decrease in occupation density, OR widespread use of face masks is approximately equivalent to reducing Social Mobility by 24%. You can turn this on by clicking the checkbox below. The orange region shows the forecast (at 90% confidence level).

Important Note: Forecasts are subject to model, systematic, and statistical uncertainties.
If the evaluated county is different from what you had in mind, please provide more detail as County name or State.

For further information, see Dr. Afshordi's website

County or City Name: e.g., Suffolk County or Boston

US State: e.g., MA or Massachusetts

Date to Start the Forecast: 1 May

Date to Start New Social Mobility: e.g., today

New Social Mobility vs Baseline: (-100%) total lockdown .... (normal activity) 0%

Face Masks/ Social Distancing

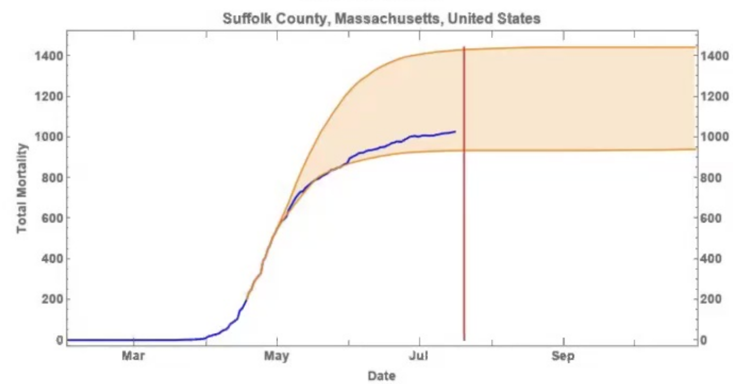
Number of days to Forecast: 30 days........ 180 days

When you click here, we will run 10 random simulations to forecast COVID-19 mortality in this community

Suffolk County, Massachusetts, United States

COVID Death per Million Population as of 16 July 2020	1412
Total Population	727194.
Population Weighted Density (per km^2)	10807.2
Population Density (per km^2)	2333.58
Population Sparsity Index	0.180026
Median Age	32.6
Pre-COVID Total Number of Deaths per Year	5277

Total COVID-19 Mortality (linear scale)
Blue Line: Reported COVID-19 Total Mortality
Orange Region: Future Forecast for Total Mortality at 90% C.L.
Vertical Red Line: Today



Canada next!

wolfr.am/COVID19Dash

Managing COVID-19 Pandemic across Geography and Demography [United States Edition]

This dashboard provides important historical information and forecasts for the growth of COVID-19 epidemic, as a function of social mobility, climate, population demographics, and history of the disease in the United States communities. A 7-fold decrease in occupation density, OR widespread use of face masks is approximately equivalent to reducing Social Mobility by 24%. You can turn this on by clicking the checkbox below. The orange region shows the forecast (at 90% confidence level).

Important Note: Forecasts are subject to model, systematic, and statistical uncertainties.
If the evaluated county is different from what you had in mind, please provide more detail as County name or State.

For further information, see Dr. Afshordi's website

County or City Name: e.g., Suffolk County or Boston

US State: e.g., MA or Massachusetts

Date to Start the Forecast: 1 May

Date to Start New Social Mobility: e.g., today

New Social Mobility vs Baseline: (-100%) total lockdown .... (normal activity) 0%

Face Masks/ Social Distancing

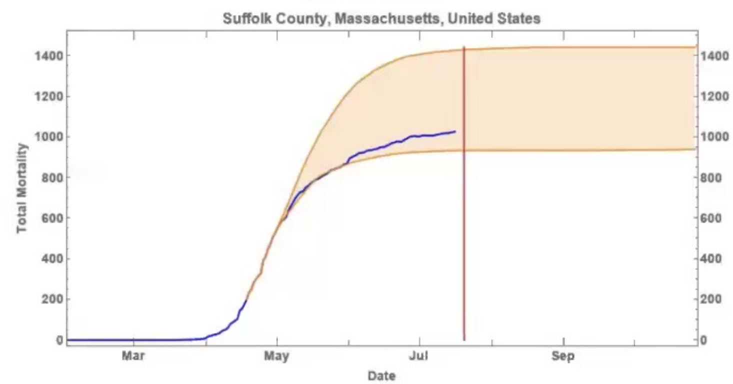
Number of days to Forecast: 30 days........180 days

When you click here, we will run 10 random simulations to forecast COVID-19 mortality in this community

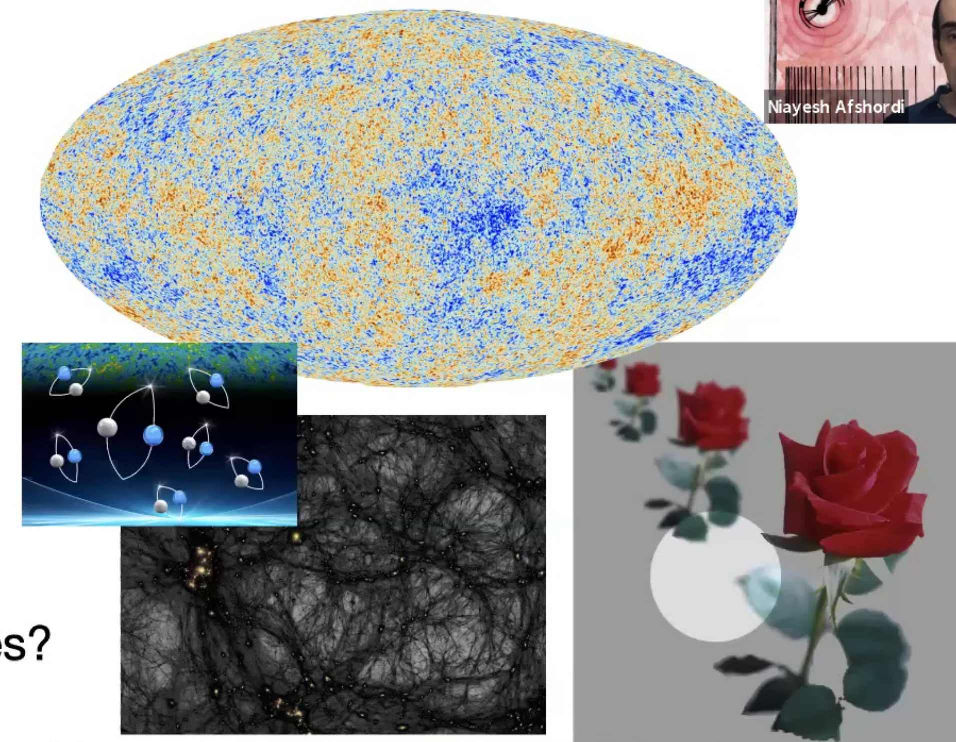
Suffolk County, Massachusetts, United States

COVID Death per Million Population as of 16 July 2020	1412
Total Population	727194.
Population Weighted Density (per km^2)	10807.2
Population Density (per km^2)	2333.58
Population Sparsity Index	0.180026
Median Age	32.6
Pre-COVID Total Number of Deaths per Year	5277

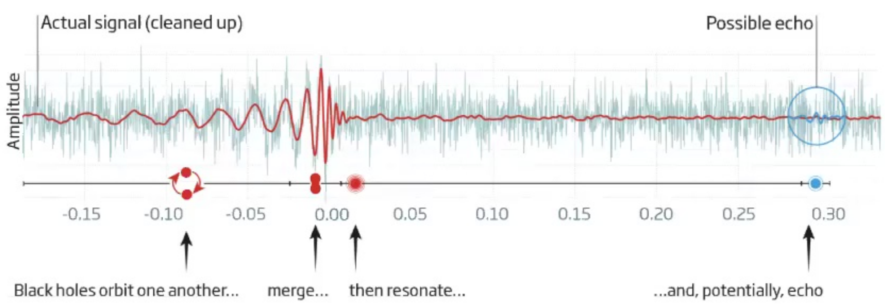
Total COVID-19 Mortality (linear scale)
Blue Line: Reported COVID-19 Total Mortality
Orange Region: Future Forecast for Total Mortality at 90% C.L.
Vertical Red Line: Today

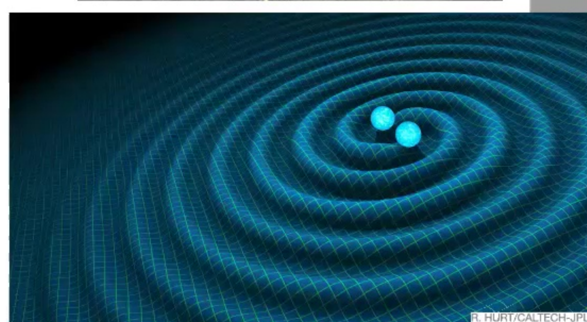


What I do for a living



- What did Big Bang look like?
- How do Quanta Gravitate?
- Can we see the Dark Universe?
- What lies at the bottom of Black Holes?





But then this happened

- Pneumonia of unknown origin first noticed in Wuhan, late-December 2019
- Cases seemed clustered around seafood market, which was closed 1 January
- Novel human coronavirus:
  - Sequenced 12 January
  - Virus: SARS-CoV-2
  - Disease: COVID-19
  - Similar to bat coronavirus (passed through intermediate)


BBC Sign in News Sport Reel Worklife Travel Future More

NEWS

Home Video World US & Canada UK Business Tech Science Stories Entertainn

Asia China India

China pneumonia outbreak: Mystery virus probed in Wuhan

3 January 2020

Share

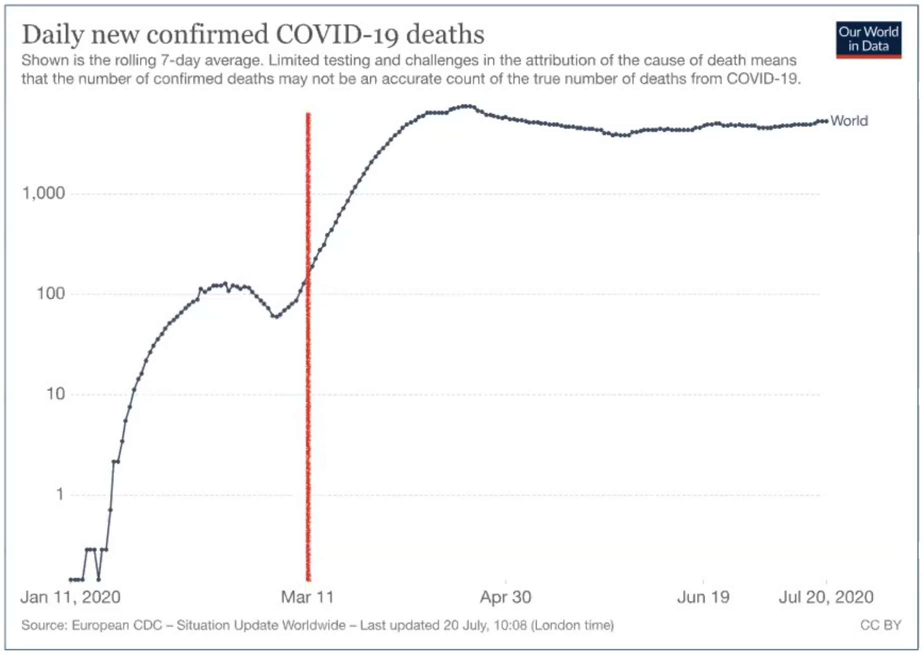
Coronavirus pandemic

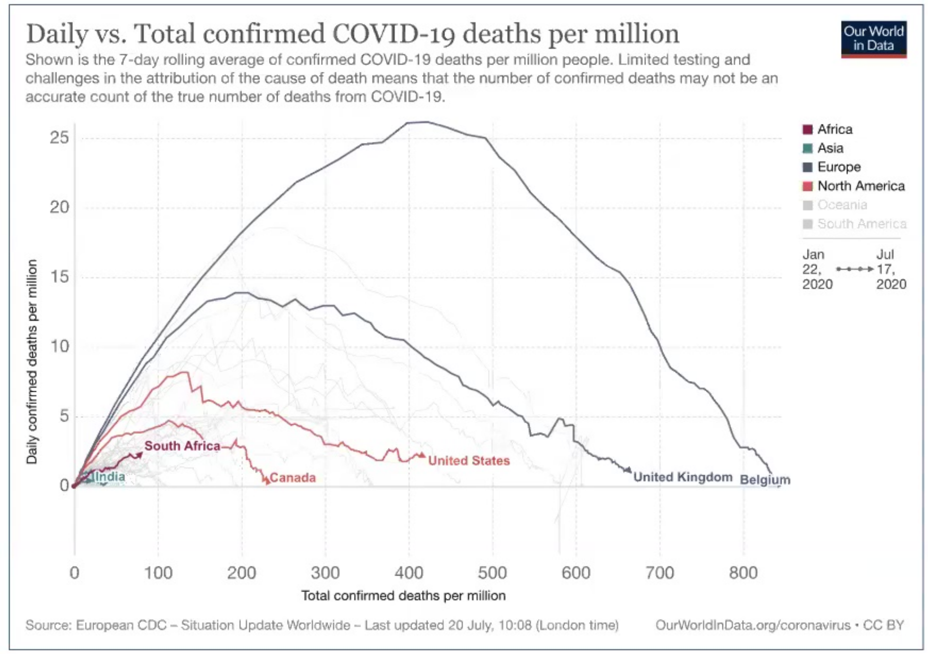
GETTY IMAGES

The outbreak has occurred in the city of Wuhan

Chinese authorities have launched an investigation into a mysterious viral pneumonia which has infected dozens of people in the central city of Wuhan.

COVID-19 Pandemic
declared on March 11, 2020





Questions

- What factors drive epidemic growth and decay?
- Can US county differences (in demographics, settlement, weather) allow these factors to be identified?
- *Correlation is not causation*: what can a mechanistic/causal model tell us?
- Has "herd immunity" been reached anywhere?
- What are the best steps to manage/avoid future outbreaks in each community?

Do both these places have to go into lockdown when a pandemic hits?

Kodiak Island, AK

Manhattan Island, NY

Outline

- Data
- Linear models
- Nonlinear mechanistic/causal model
- Herd Immunity
- Final Thoughts: How to manage a pandemic?

US County-level Data Sets

Static datasets

- Demographic Data (US Census)
- Population-weighted population density, PWD (GHS-POP raster image, EU)
- Population sparsity (PWD vs. Standard)

Time series datasets

- COVID-19 daily mortality/case incidence (JHU-CSSE and NYTimes)
- Weather: Temperature and Specific/Absolute Humidity (NOAO GSOD)
- Human Mobility in workplace/home/transit (Google)

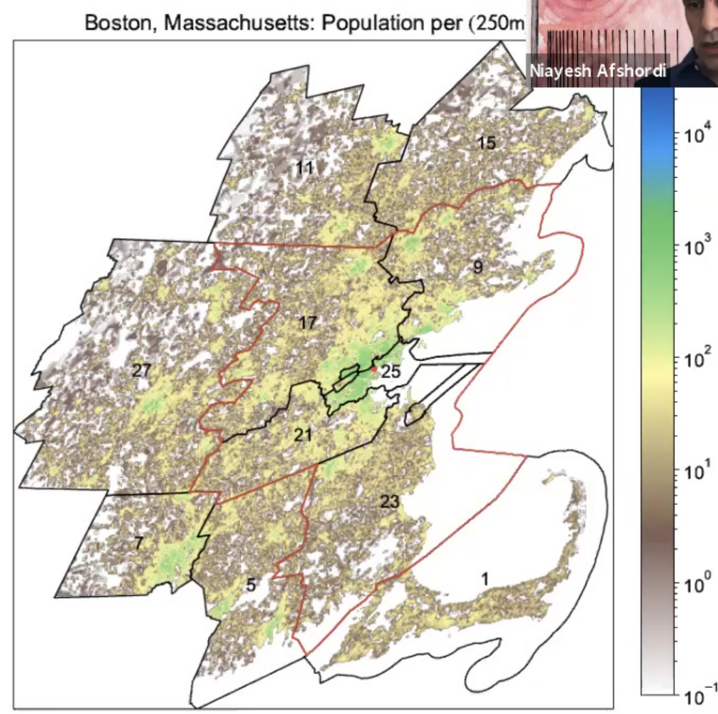
US County-level Data Sets

Static datasets

- Demographic Data (US Census)
- Population-weighted population density, PWD (GHS-POP raster image, EU)
- Population sparsity (PWD vs. Standard)

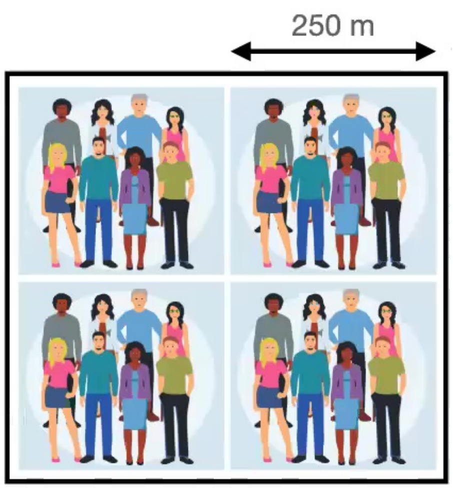
Time series datasets

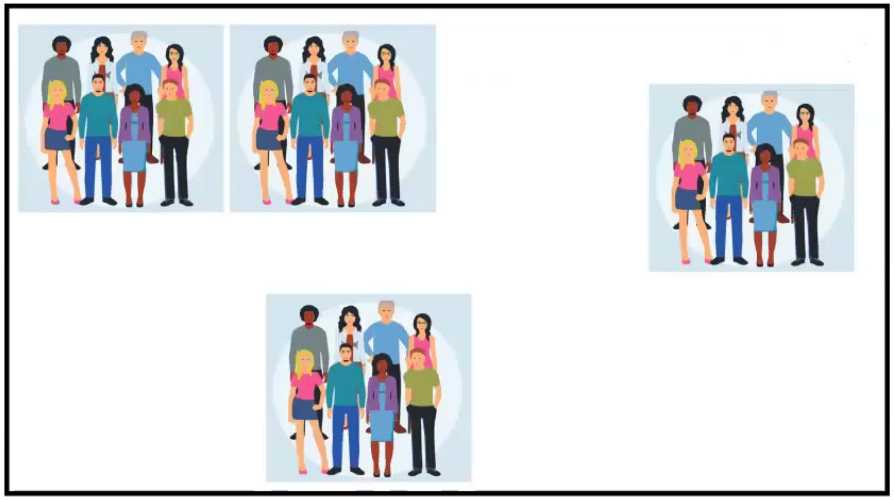
- COVID-19 daily mortality/case incidence (JHU-CSSE and NYTimes)
- Weather: Temperature and Specific/Absolute Humidity (NOAO GSOD)
- Human Mobility in workplace/home/transit (Google)



Population-Weighted Density (Lived Density), PWD

- Average density of $(250\ \mathrm{m})^2$ parcels, weighted by population in each parcel
- These counties have different densities, but **<u>same population-weighted densities</u>**



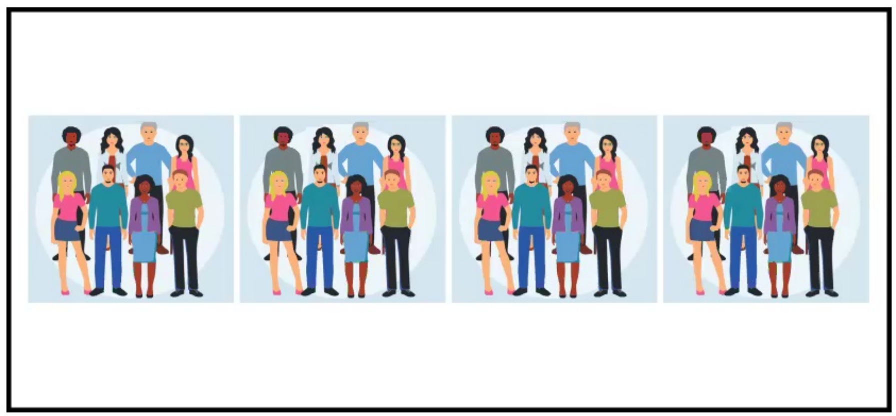


Population Sparsity, γ

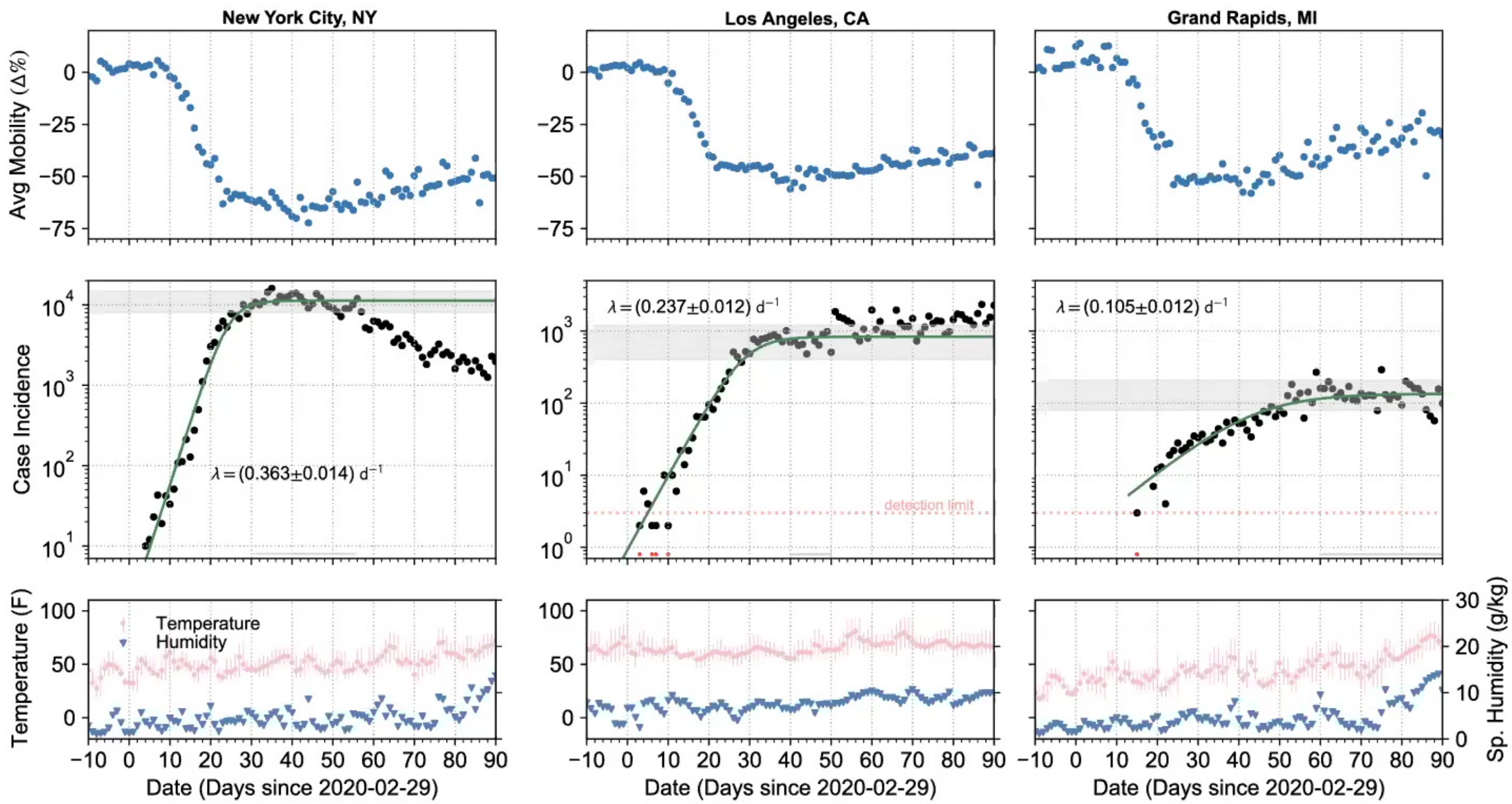
- PWD $\propto$ (parcel area)$^{-\gamma}$
- These counties have the same population-weighted densities, but **<u>different population sparsities</u>**

$\gamma = 0$

$\gamma = 1/3$



Initial growth of cases in metro regions



Outline

- Data
- Linear models
- Nonlinear mechanistic/causal model
- Herd Immunity
- Final Thoughts: How to manage a pandemic?

Initial growth of cases in metro regions

Linear Fit to Growth Rate:

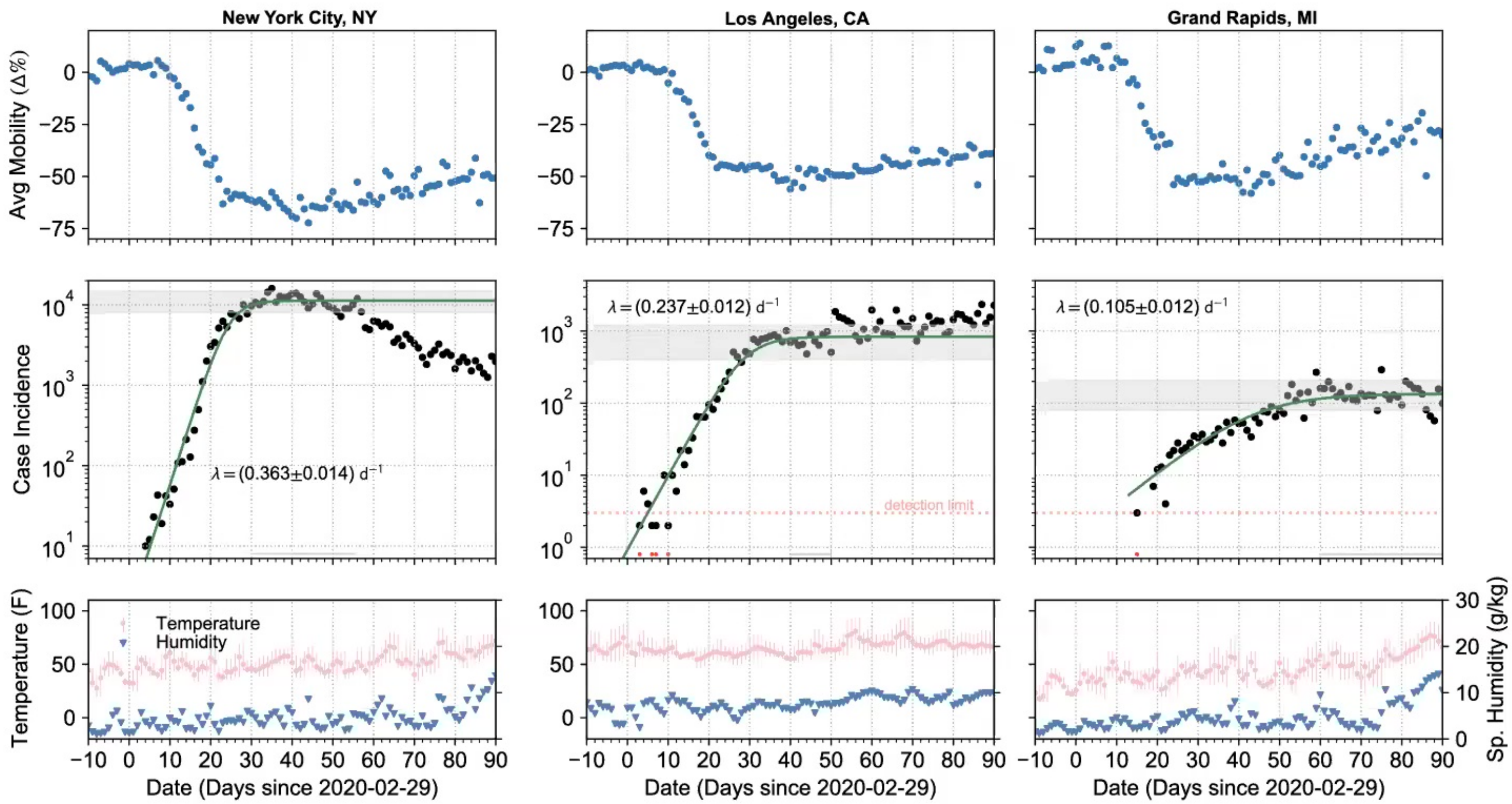
- Mobility is most significant driver
- Secondary factors: Population density (PWD), sparsity, humidity

	med. age	mob. 2wk pr.	pop. sparsity	hum. 2wk pr.	lnpwpd	λ_{mod}	λ_{exp}	λ_{exp} err
ny_newyorkcity	0.004	0.011	0.007	0.021	0.069	0.343	0.363	0.014
il_chicago	-0.002	0.022	0.02	0.018	0.017	0.307	0.316	0.017
mi_detroit	0.008	0.044	0.019	0.02	-0.023	0.301	0.412	0.035
oh_cleveland	0.014	0.035	0.02	0.018	-0.024	0.294	0.298	0.027
pa_philadelphia	0.004	0.01	0.015	0.014	0.012	0.286	0.291	0.009
ma_boston	0.003	-0.03	0.015	0.021	0.017	0.258	0.222	0.013
ct_hartford	0.012	-0.003	0.01	0.019	-0.014	0.255	0.287	0.019
co_denver	-0.009	0.022	-0.018	0.027	-0.002	0.252	0.24	0.014
wa_seattle	-0.003	0.02	0.002	0.007	-0.006	0.252	0.223	0.019
ma_worcester	0.009	0.003	0.001	0.024	-0.02	0.248	0.237	0.026
tx_dallas	-0.015	0.027	0.011	-0.016	0.001	0.24	0.252	0.021
ga_atlanta	-0.008	0.022	0.025	-0.006	-0.025	0.24	0.242	0.019
ca_losangeles	-0.007	0.0	-0.006	-0.016	0.027	0.229	0.237	0.012
dc_washington	-0.002	-0.047	0.008	0.003	0.012	0.206	0.213	0.009
mi_grandrapids	-0.005	-0.12	-0.001	0.015	-0.038	0.083	0.105	0.012

positive contribution, negative contribution

Variable		Mean value	Coef.	Std. Err.	t	95% CI
average growth rate, λ_{avg}			0.232	0.005	43.1	[0.220, 0.242]
avg mobility, 2wk prior	–	+2.2%	0.0063	0.0006	10.8	[0.0051,0.0074]
ln[PWD]	–	8.1	0.048	0.010	4.7	[0.028,0.069]
sp. humidity, 2wk prior	–	4.9 g/kg	-0.010	0.0027	-3.7	[-0.016, -0.005]
pop. sparsity, γ	–	0.21	-0.33	0.11	-3.0	[-0.55, -0.11]
median age	–	35.7	0.0049	0.0024	2.1	[0.0002,0.0096]

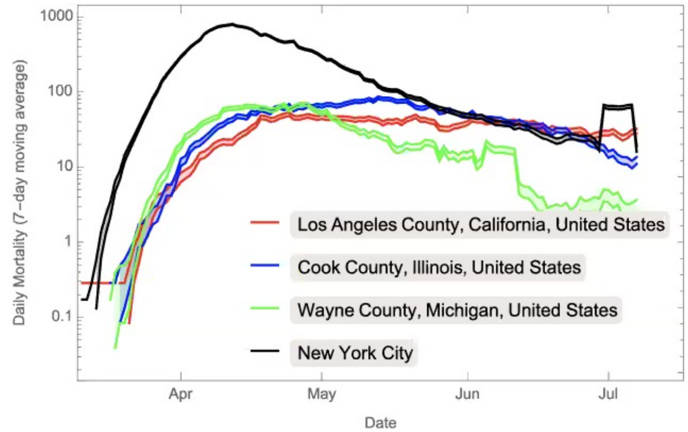
Initial growth of cases in metro regions

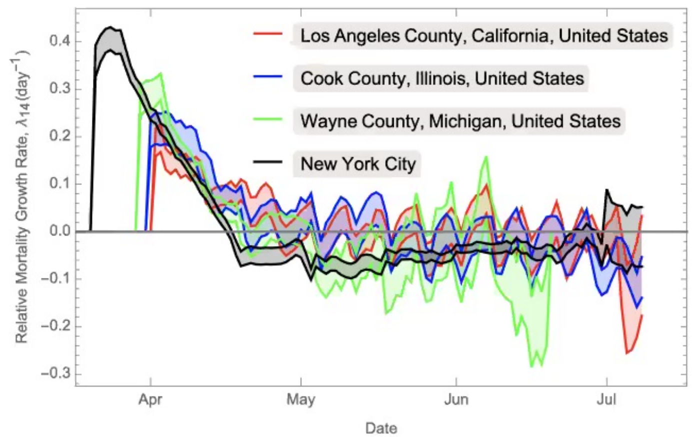


US-County Analysis: Philosophy & Methods

- Use time series of **exponential growth rate** as measure; estimate over 14d window
- Rely only on **mortality statistics**:
  - Traces incidence growth rate, with delay
  - Not dependent on testing rates/bottlenecks
  - Fewer issues with reporting, methodology
- **Data set**: >5000 growth rate values (time, county)

1. **Linear regression** → significant factors
2. **Mechanistic/Causal model (renewal equation)** → nonlinear expression for growth rate





Growth rate linear analysis: All counties, all days

- Identify the most significant drivers

Joint Fit to All potential drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.195	0.011	17.2
COVID Death Fraction	-59.4	6.1	-9.7
Social Mobility (2wks prior)	0.00238	0.00028	8.5
$\ln$(Population Weighted Density)-8.24	0.0412	0.0058	7.1
Social Mobility (4wks prior)	0.00122	0.00019	6.6
Population Sparsity-0.188	-0.249	0.063	-3.9
$\log$(Annual Death)-4.04	-0.0301	0.0091	-3.3
Median Age-37.47	0.0038	0.0012	3.0
People per Household-2.76	0.023	0.014	1.6
Specific Humidity (2wks prior)-5.92 g/kg	-0.0033	0.0031	-1.1
Temperature (2wks prior)-13.11 C	-0.00083	0.0013	-0.6
Temperature (4wks prior)-11.60 C	-0.00060	0.0014	-0.4
Specific Humidity (4wks prior)-5.53 g/kg	0.00058	0.0032	0.2

Joint Fit to statistically significant drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.198	0.011	18.7
COVID Death Fraction	-56.7	5.9	-9.7
Social Mobility (2wks prior)	0.00236	0.00027	8.8
Social Mobility (4wks prior)	0.00131	0.00017	7.6
$\ln$(Population Weighted Density)-8.24	0.0413	0.0058	7.2
Population Sparsity-0.188	-0.260	0.061	-4.3
Specific Humidity (2wks prior)-5.92 g/kg	-0.0047	0.0011	-4.1
$\log$(Annual Death)-4.04	-0.0324	0.0088	-3.7
Median Age-37.48	0.0040	0.0012	3.3

Growth rate linear analysis: All counties, all days

- Identify the most significant drivers
- Similar dependencies on the analysis of metro regions (initial cases growth)

Joint Fit to All potential drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.195	0.011	17.2
COVID Death Fraction	-59.4	6.1	-9.7
Social Mobility (2wks prior)	0.00238	0.00028	8.5
ln(Population Weighted Density)-8.24	0.0412	0.0058	7.1
Social Mobility (4wks prior)	0.00122	0.00019	6.6
Population Sparsity-0.188	-0.249	0.063	-3.9
log(Annual Death)-4.04	-0.0301	0.0091	-3.3
Median Age-37.47	0.0038	0.0012	3.0
People per Household-2.76	0.023	0.014	1.6
Specific Humidity (2wks prior)-5.92 g/kg	-0.0033	0.0031	-1.1
Temperature (2wks prior)-13.11 C	-0.00083	0.0013	-0.6
Temperature (4wks prior)-11.60 C	-0.00060	0.0014	-0.4
Specific Humidity (4wks prior)-5.53 g/kg	0.00058	0.0032	0.2

Joint Fit to statistically significant drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.198	0.011	18.7
COVID Death Fraction	-56.7	5.9	-9.7
Social Mobility (2wks prior)	0.00236	0.00027	8.8
Social Mobility (4wks prior)	0.00131	0.00017	7.6
ln(Population Weighted Density)-8.24	0.0413	0.0058	7.2
Population Sparsity-0.188	-0.260	0.061	-4.3
Specific Humidity (2wks prior)-5.92 g/kg	-0.0047	0.0011	-4.1
log(Annual Death)-4.04	-0.0324	0.0088	-3.7
Median Age-37.48	0.0040	0.0012	3.3

Growth rate linear analysis: All counties, all days

- Identify the most significant drivers
- Similar dependencies on the analysis of metro regions (initial cases growth)
- *Additionally:* dependence on COVID death fraction, and total annual death *(RG scale?!)*

Joint Fit to All potential drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.195	0.011	17.2
COVID Death Fraction	-59.4	6.1	-9.7
Social Mobility (2wks prior)	0.00238	0.00028	8.5
ln(Population Weighted Density)-8.24	0.0412	0.0058	7.1
Social Mobility (4wks prior)	0.00122	0.00019	6.6
Population Sparsity-0.188	-0.249	0.063	-3.9
log(Annual Death)-4.04	-0.0301	0.0091	-3.3
Median Age-37.47	0.0038	0.0012	3.0
People per Household-2.76	0.023	0.014	1.6
Specific Humidity (2wks prior)-5.92 g/kg	-0.0033	0.0031	-1.1
Temperature (2wks prior)-13.11 C	-0.00083	0.0013	-0.6
Temperature (4wks prior)-11.60 C	-0.00060	0.0014	-0.4
Specific Humidity (4wks prior)-5.53 g/kg	0.00058	0.0032	0.2

Joint Fit to statistically significant drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.198	0.011	18.7
COVID Death Fraction	-56.7	5.9	-9.7
Social Mobility (2wks prior)	0.00236	0.00027	8.8
Social Mobility (4wks prior)	0.00131	0.00017	7.6
ln(Population Weighted Density)-8.24	0.0413	0.0058	7.2
Population Sparsity-0.188	-0.260	0.061	-4.3
Specific Humidity (2wks prior)-5.92 g/kg	-0.0047	0.0011	-4.1
log(Annual Death)-4.04	-0.0324	0.0088	-3.7
Median Age-37.48	0.0040	0.0012	3.3

Growth rate linear analysis: All counties, all days

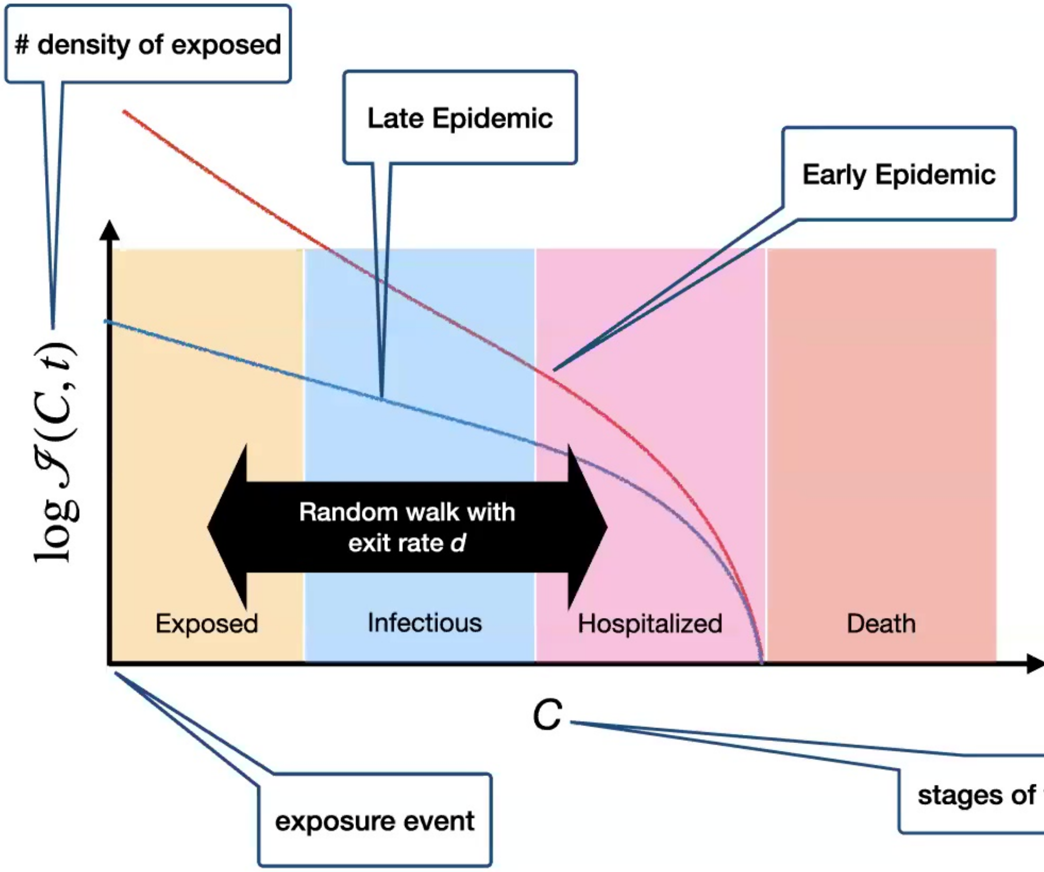
- Identify the most significant drivers
- Similar dependencies on the analysis of metro regions (initial cases growth)
- *Additionally:* dependence on <u>COVID death fraction</u>, and <u>total annual death *(RG scale?!)*</u>
- **But correlation is not causation!**

Joint Fit to All potential drivers	Estimate	Std Err	t-Statistic
Baseline Mortality Growth Rate λ_{14}	0.195	0.011	17.2
COVID Death Fraction	-59.4	6.1	-9.7
Social Mobility (2wks prior)	0.00238	0.00028	8.5
ln(Population Weighted Density)-8.24	0.0412	0.0058	7.1
Social Mobility (4wks prior)	0.00122	0.00019	6.6
Population Sparsity-0.188	-0.249	0.063	-3.9
log(Annual Death)-4.04	-0.0301	0.0091	-3.3
Median Age-37.47	0.0038	0.0012	3.0
People per Household-2.76	0.023	0.014	1.6
Specific Humidity (2wks prior)-5.92 g/kg	-0.0033	0.0031	-1.1
Temperature (2wks prior)-13.11 C	-0.00083	0.0013	-0.6
Temperature (4wks prior)-11.60 C	-0.00060	0.0014	-0.4
Specific Humidity (4wks prior)-5.53 g/kg	0.00058	0.0032	0.2
Joint Fit to statistically significant drivers	**Estimate**	**Std Err**	**t-Statistic**
Baseline Mortality Growth Rate λ_{14}	0.198	0.011	18.7
COVID Death Fraction	-56.7	5.9	-9.7
Social Mobility (2wks prior)	0.00236	0.00027	8.8
Social Mobility (4wks prior)	0.00131	0.00017	7.6
ln(Population Weighted Density)-8.24	0.0413	0.0058	7.2
Population Sparsity-0.188	-0.260	0.061	-4.3
Specific Humidity (2wks prior)-5.92 g/kg	-0.0047	0.0011	-4.1
log(Annual Death)-4.04	-0.0324	0.0088	-3.7
Median Age-37.48	0.0040	0.0012	3.3

Outline

- Data
- Linear models
- Nonlinear mechanistic/causal model
- Herd Immunity
- Final Thoughts: How to manage a pandemic?

Disease progress as a continuous random walk



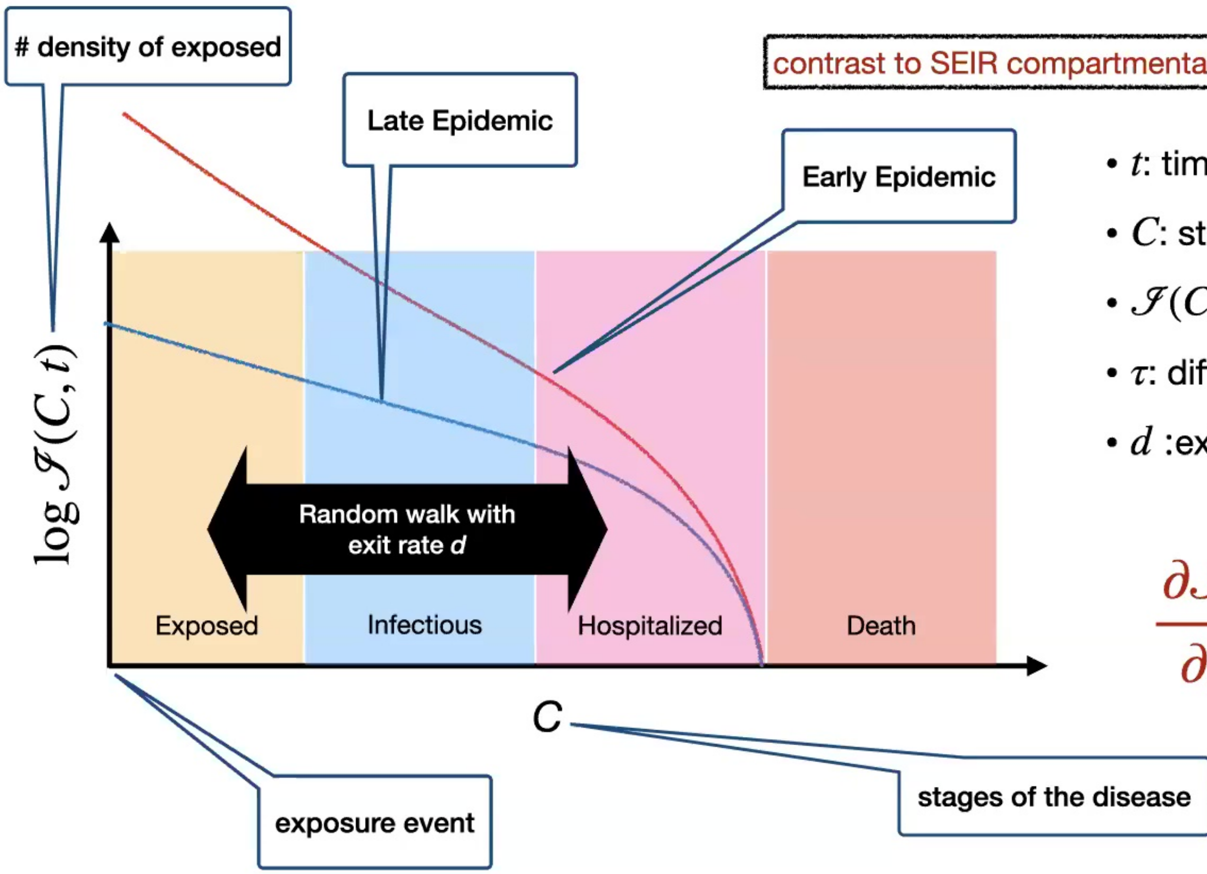
- t: time
- C: stage of the disease (*C*>*1* infectious)
- $\mathcal{I}(C,t)$: # density of infected @ stage *C*
- τ: diffusion time (incubation period)
- d :exit rate (quarantine/recovery)

$$\frac{\partial \mathcal{I}}{\partial t} = \frac{1}{2\tau}\frac{\partial \mathcal{I}}{\partial C^2} - d\mathcal{I}$$

Diffusion+Decay Equation

Disease progress as a continuous random walk

contrast to SEIR compartmental models, where progress only goes one way

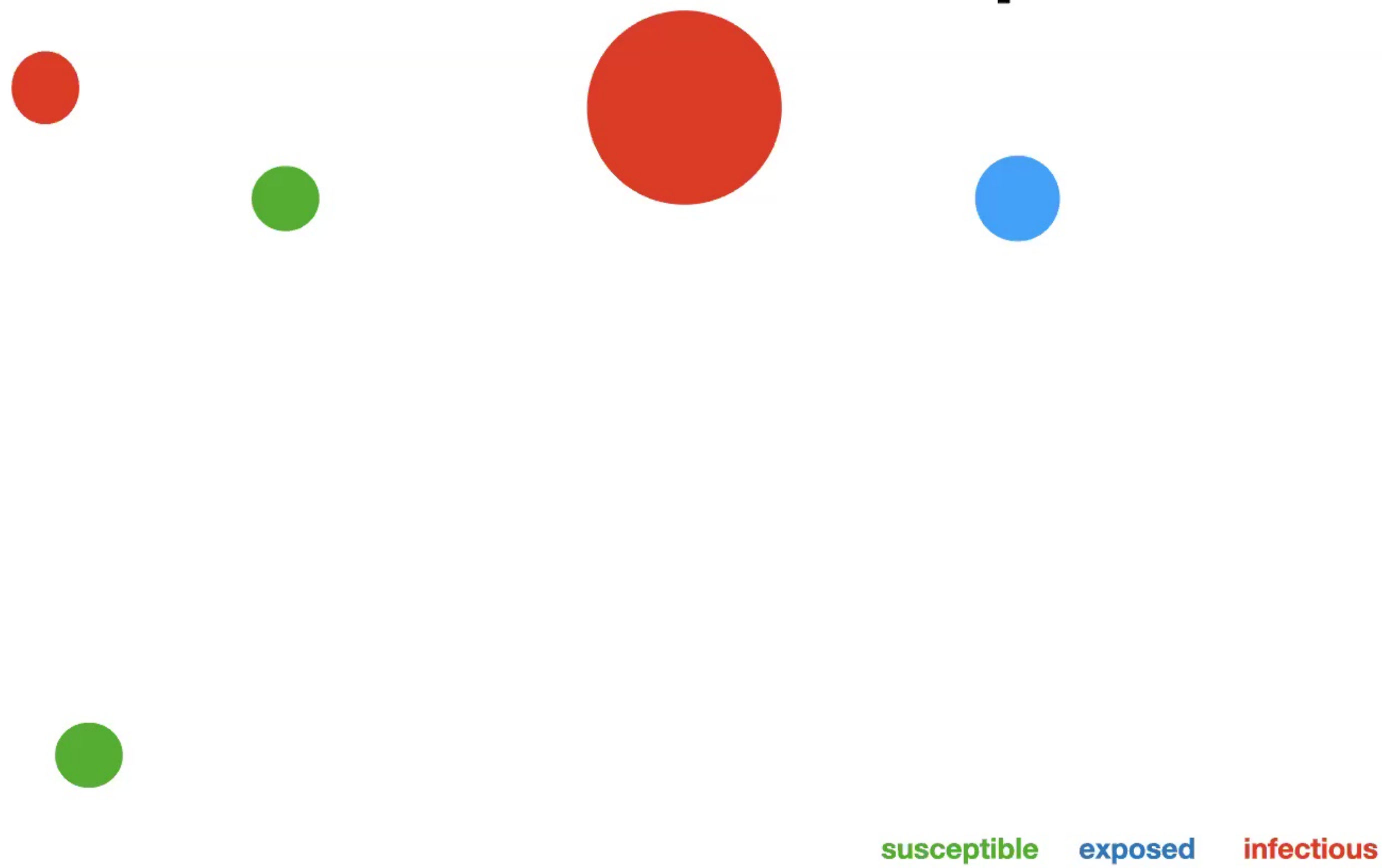


- t: time
- C: stage of the disease ($C>1$ infectious)
- $\mathscr{I}(C,t)$: # density of infected @ stage C
- τ: diffusion time (incubation period)
- d :exit rate (quarantine/recovery)

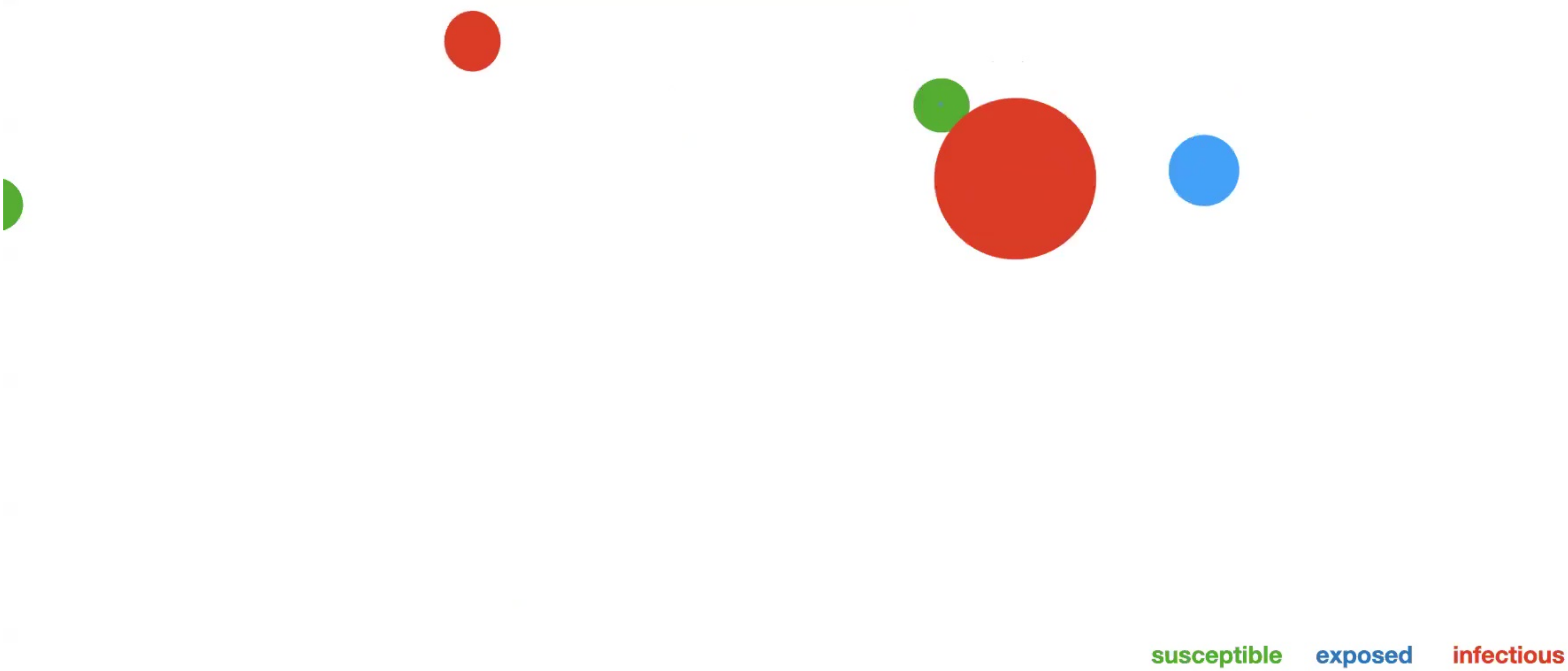
$$\frac{\partial \mathscr{I}}{\partial t} = \frac{1}{2\tau}\frac{\partial \mathscr{I}}{\partial C^2} - d\mathscr{I}$$

Diffusion+Decay Equation

Disease transmission as a collisional process



Disease transmission as a collisional process



Disease transmission as a collisional process

"incidence"

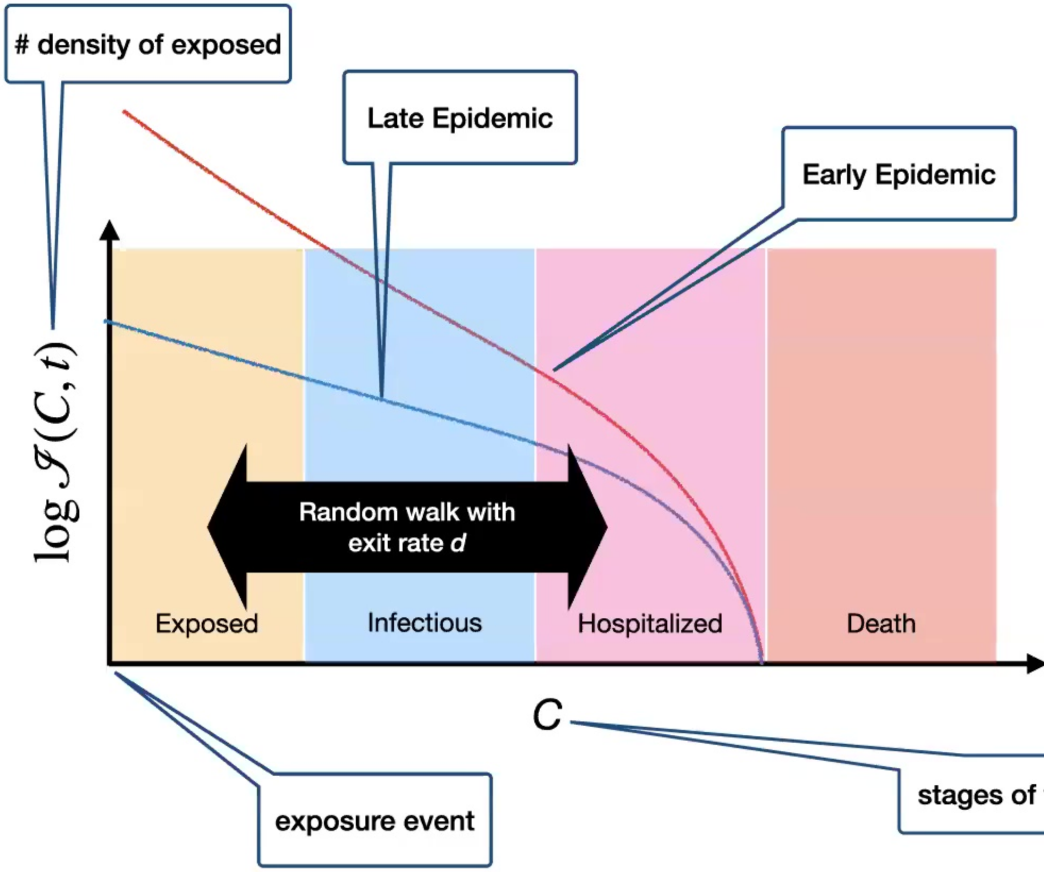
- $$\frac{\text{new infections}}{\text{time} \times \text{area}} = \text{susceptible density} \times \text{infected density} \times \beta(C)$$
- $$\beta(C) : \text{infection rate} = \langle (\text{cross} - \text{section}) \times (\text{relative velocity}) \rangle$$

$$= 0 \text{ for } C < 1$$

$$= \bar{\beta} \text{ for } C \geq 1$$

susceptible exposed infectious

Disease progress as a continuous random walk



- t: time
- C: stage of the disease ($C>1$ infectious)
- $\mathscr{I}(C,t)$: # density of infected @ stage C
- τ: diffusion time (incubation period)
- d :exit rate (quarantine/recovery)

$$\frac{\partial \mathscr{I}}{\partial t} = \frac{1}{2\tau}\frac{\partial \mathscr{I}}{\partial C^2} - d\mathscr{I}$$

Diffusion+Decay Equation

Nonlinear model for exponential growth rate

$$\lambda + d = \frac{2}{\tau}\left[\mathrm{W}\left(\sqrt{\frac{\bar{\beta}\bar{S}\tau}{2}}\right)\right]^2$$

- λ: exponential growth rate
- d: exit rate (quarantine/recovery)
- $\bar{\beta}$: infection rate
- $\bar{S}$: susceptible density
- τ: diffusion time
- $\mathrm{W}(x)$: Lambert W-function

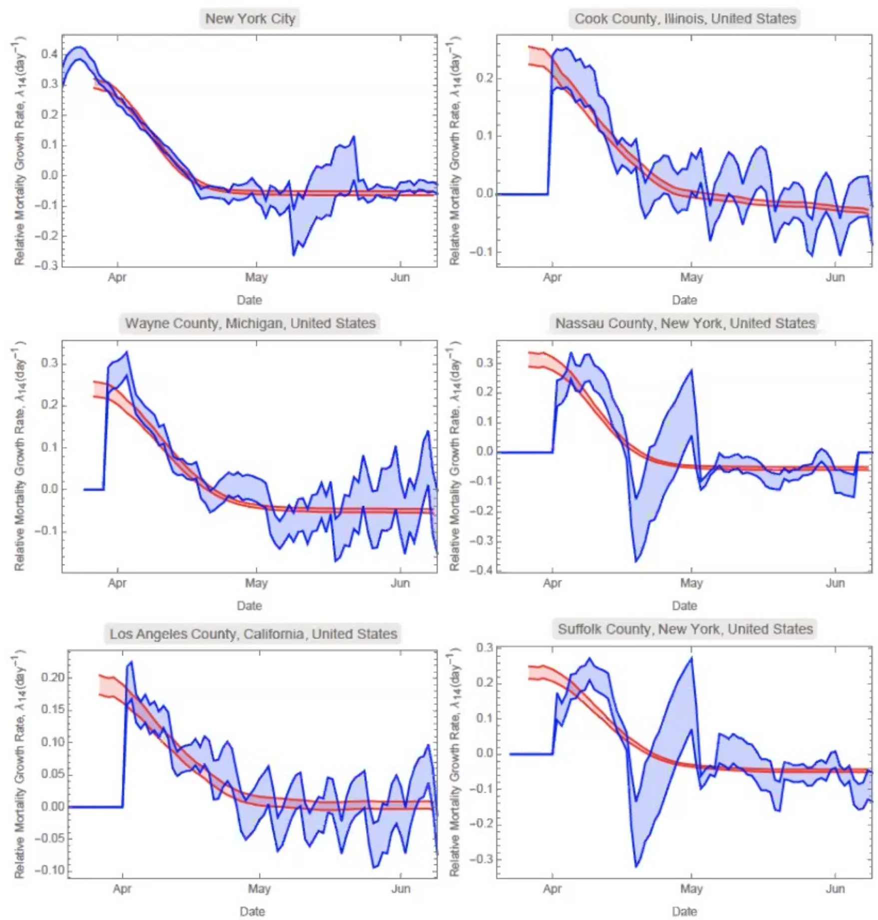
$$\mathrm{W}(x) \simeq \ln(x) \text{ for } x \gg 1$$

$$\mathrm{W}(x) \simeq x \text{ for } x \ll 1$$

Nonlinear Model Results: Parameters and F

- Well fit to all counties, $\chi^2_{\rm red} \simeq 1.3$
- Late-time constant exponential decline (1/*d* ≈ 18 day) is universal in hard-hit regions.

Parameter	Best-Fit ± Std Err	Description
$\tau = \tau_0(\text{Median Age}/26.2\ \text{years})^{C_A}$		Time from exposure to contagiousness
τ_0(day)	160 ± 58	Normalization
C_A	-2.26 ± 0.95	Age dependence
d^{-1}(day)	17.6 ± 2.2	Time from exposure to quarantine/recovery
C_D	3460 ± 610	Conversion constant, $f_D \to f_I$
β: Equation (2)		Rate constant for infection
$\ln\left[k\beta_0\tau_0^{-2}(\text{m}^2/\text{day}^3)\right]$	0.37 ± 1.25	Normalization
$100C_{\mathcal{M}}$	8.08 ± 1.76	Dependence on Social Mobility
$C_{\mathcal{H}}$	-0.154 ± 0.055	Dependence on specific humidity
C_γ	-5.52 ± 2.35	Dependence on population sparsity
C_{A_D}	-1.05 ± 0.25	Dependence on total annual deaths



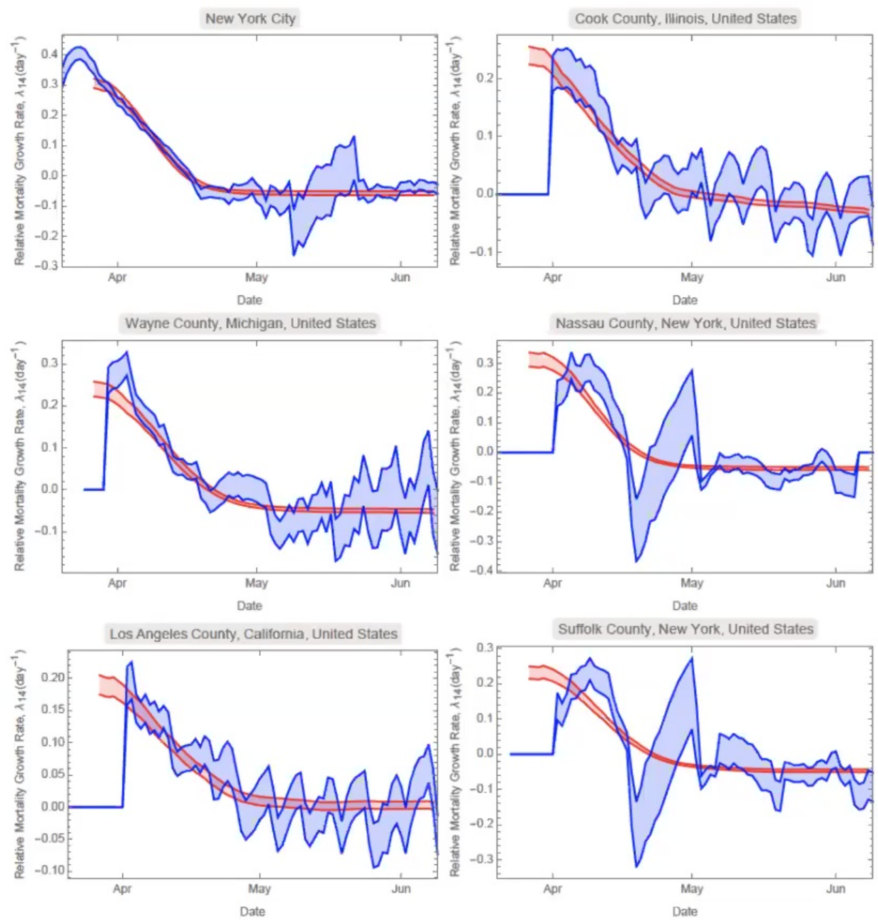
Nonlinear Model Results: Parameters and F

- Well fit to all counties, $\chi^2_{\rm red} \simeq 1.3$
- Late-time constant exponential decline ($1/d \approx 18$ day) is universal in hard-hit regions.

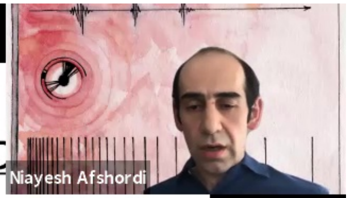
Parameter	Best-Fit ± Std Err	Description
$\tau = \tau_0(\text{Median Age}/26.2\text{ years})^{C_A}$		Time from exposure to contagiousness
τ_0(day)	160 ± 58	Normalization
C_A	-2.26 ± 0.95	Age dependence
d^{-1}(day)	17.6 ± 2.2	Time from exposure to quarantine/recovery
C_D	3460 ± 610	Conversion constant, $f_D \to f_I$
β: Equation (2)		Rate constant for infection
$\ln\left[k\beta_0\tau_0^{-2}(\text{m}^2/\text{day}^3)\right]$	0.37 ± 1.25	Normalization
$100C_{\mathcal{M}}$	8.08 ± 1.76	Dependence on Social Mobility
$C_{\mathcal{H}}$	-0.154 ± 0.055	Dependence on specific humidity
C_γ	-5.52 ± 2.35	Dependence on population sparsity
C_{A_D}	-1.05 ± 0.25	Dependence on total annual deaths

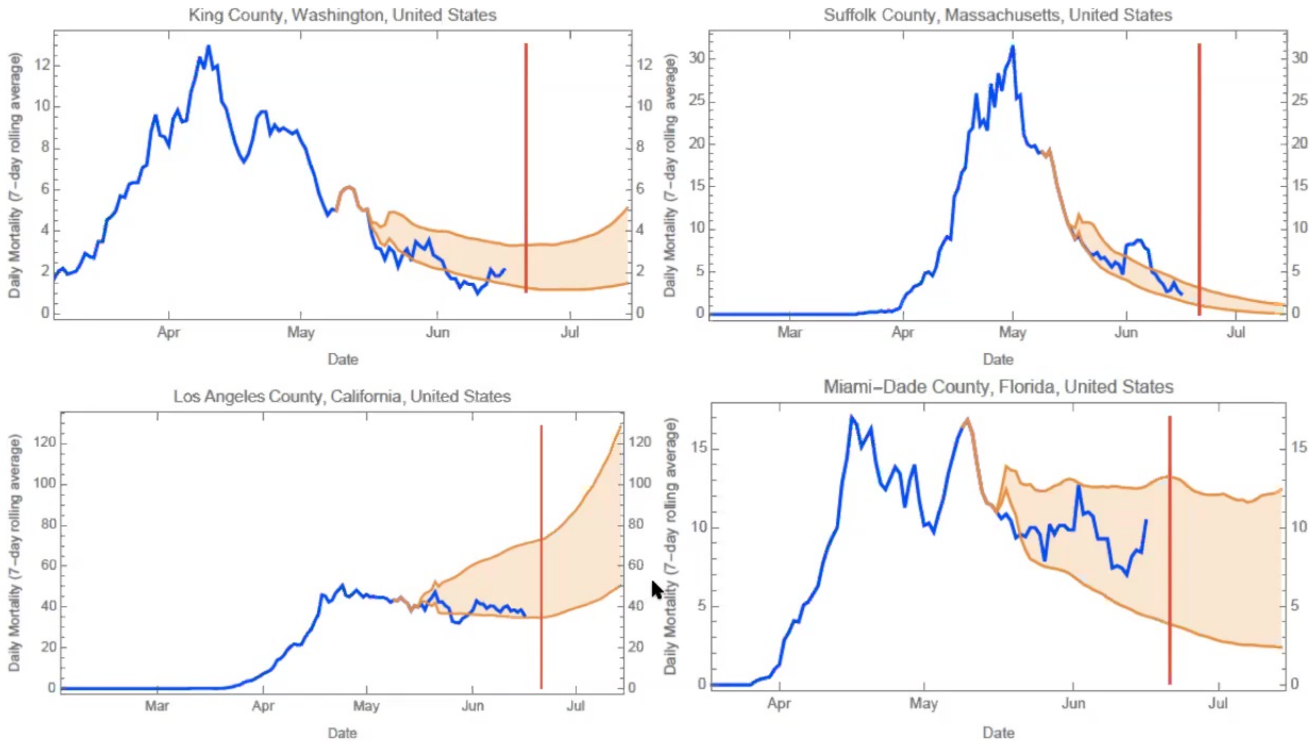
depletion of susceptible population, a.k.a. "herd immunity"

$$\bar{S}(t) \propto (\text{pop.} - \text{weighted} - \text{density}) \times \exp\left(-C_D \times \frac{\text{total COVID death}}{\text{county population}}\right)$$

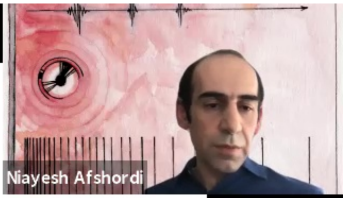


Nonlinear Model Results: Predictions (wolfr.am/COVID19D

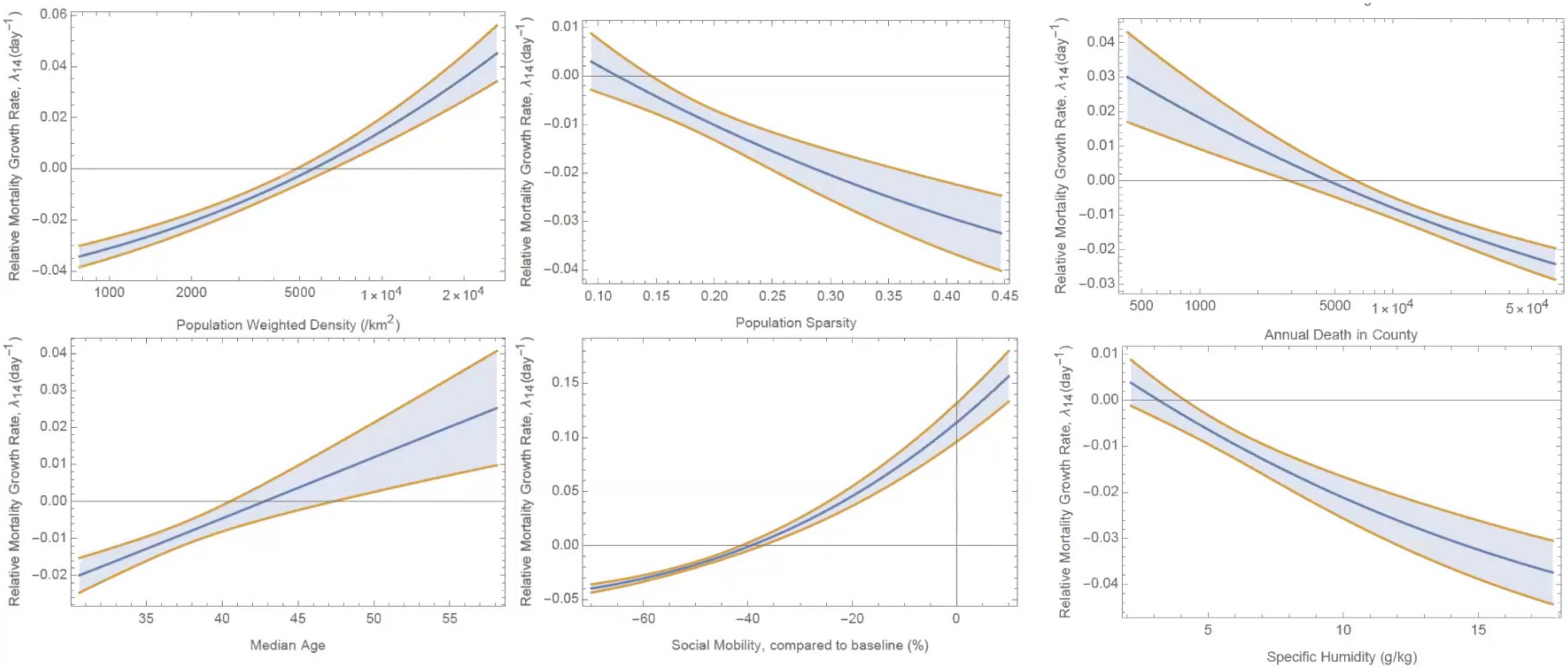




Assuming future weather (temperature or humidity) and social mobility, model accurately predicts future mortality incidence for local community (Dashboard)



What drives a Pandemic



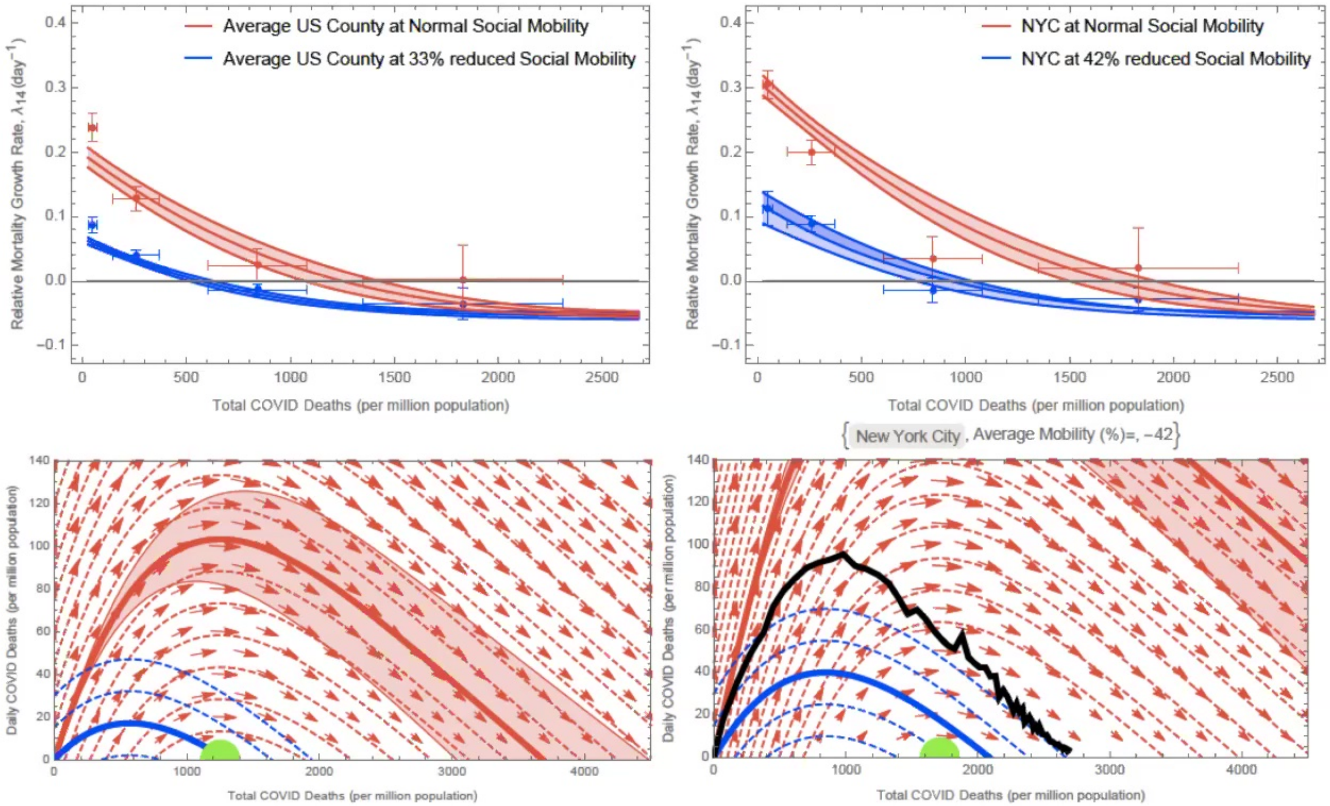
Outline

- Data
- Linear models
- Nonlinear mechanistic/causal model
- Herd Immunity
- Final Thoughts: How to manage a pandemic?

On Depletion of Susceptibles, a.k.a. “Herd Immunity

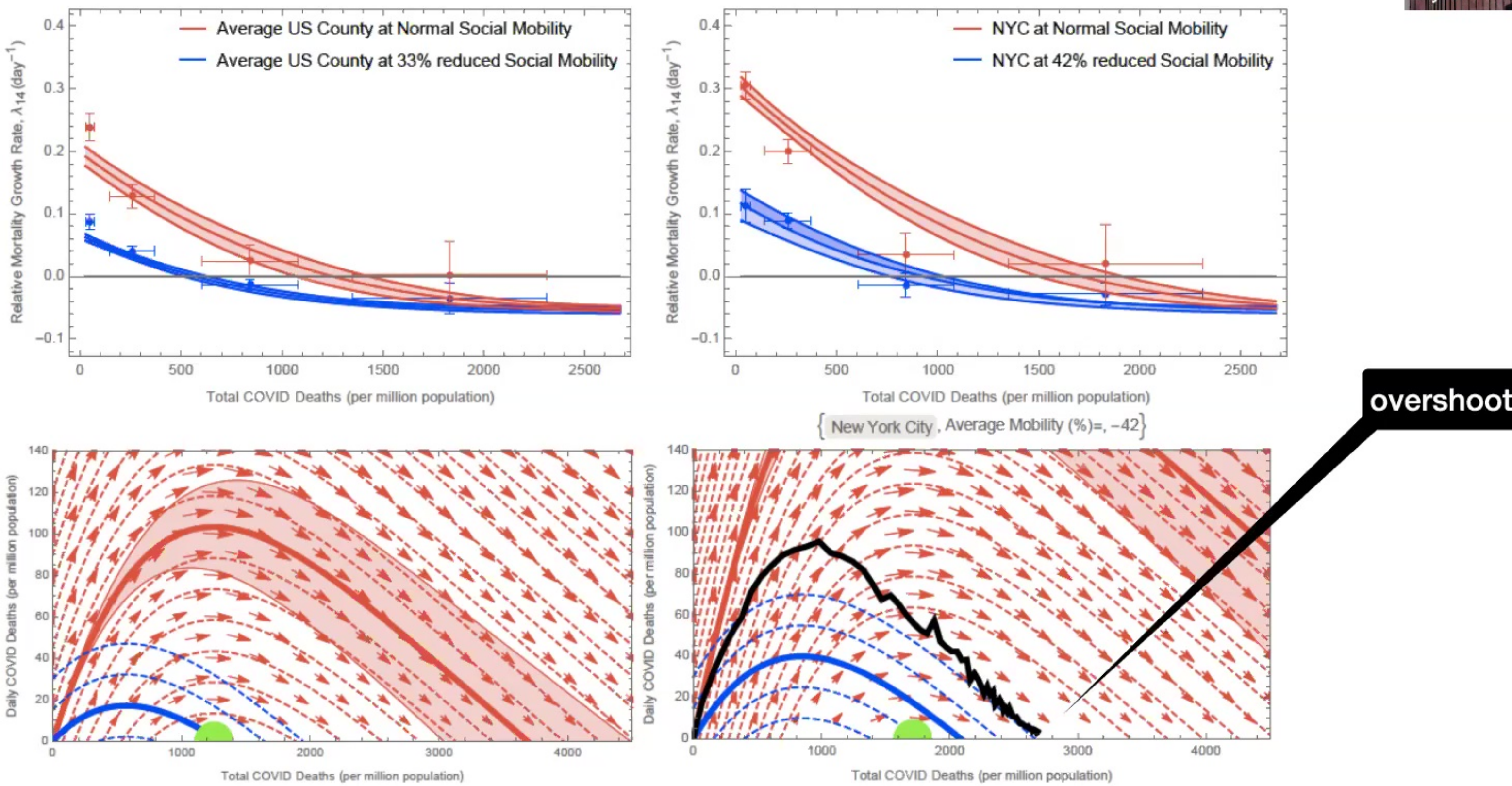
- **Classical “herd immunity”**: If large enough fraction of population achieve immunity through infection/vaccine, reproduction number falls below one: *R(t)<1*, i.e. the disease decays: $\lambda(t) < 0$ *(but beware of “overshoot”)*
- Estimates for COVID-19 “Herd Immunity Threshold”: 20% to 70% (Gomes et al. 2020), lower values for “heterogenous” population
- How to accurately test immunity (T-cell v antibody)? Is it permanent?
- **Correlation with COVID death fraction is a more objective and quantifiable probe**

Predictions for "Herd Immunity"



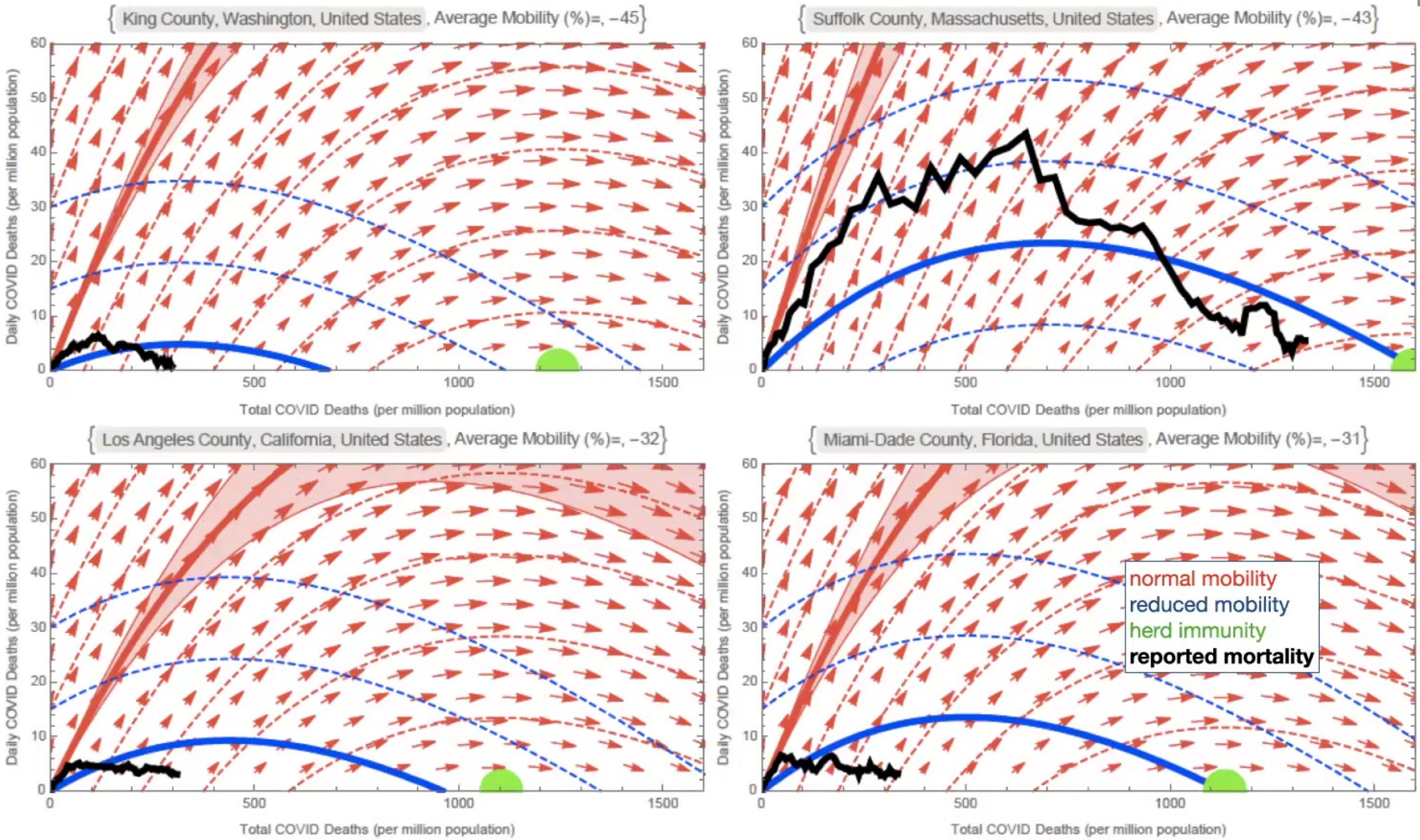
By "turning off" social mobility intervention (red), nonlinear model can predict the **herd immunity threshold** (λ = 0, green discs) for local communities.

Predictions for “Herd Immunity”



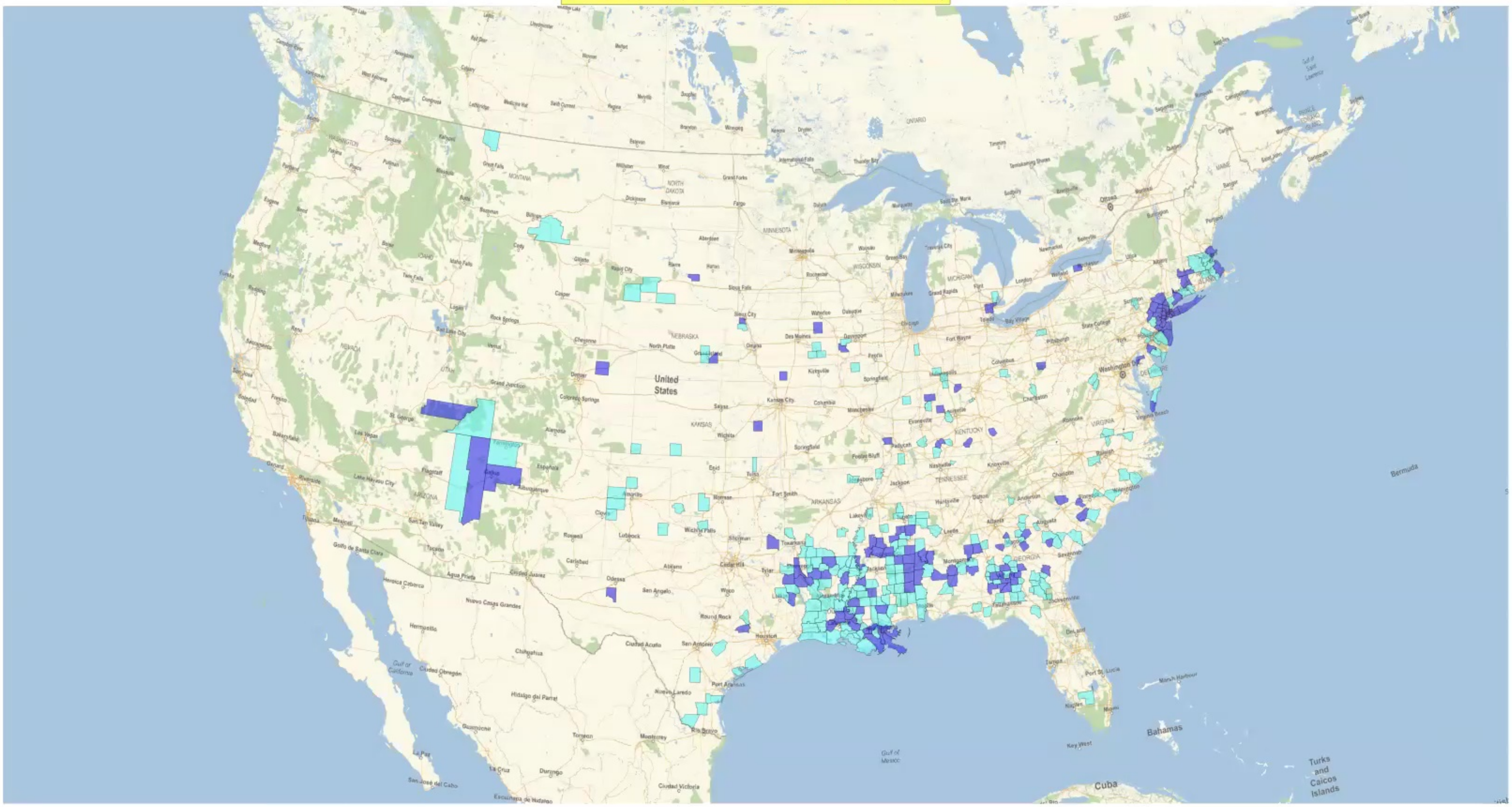
By “turning off” social mobility intervention (red), nonlinear model can predict the **herd immunity threshold** ($\lambda = 0$, green discs) for local communities.

Predictions for “Herd Immunity”



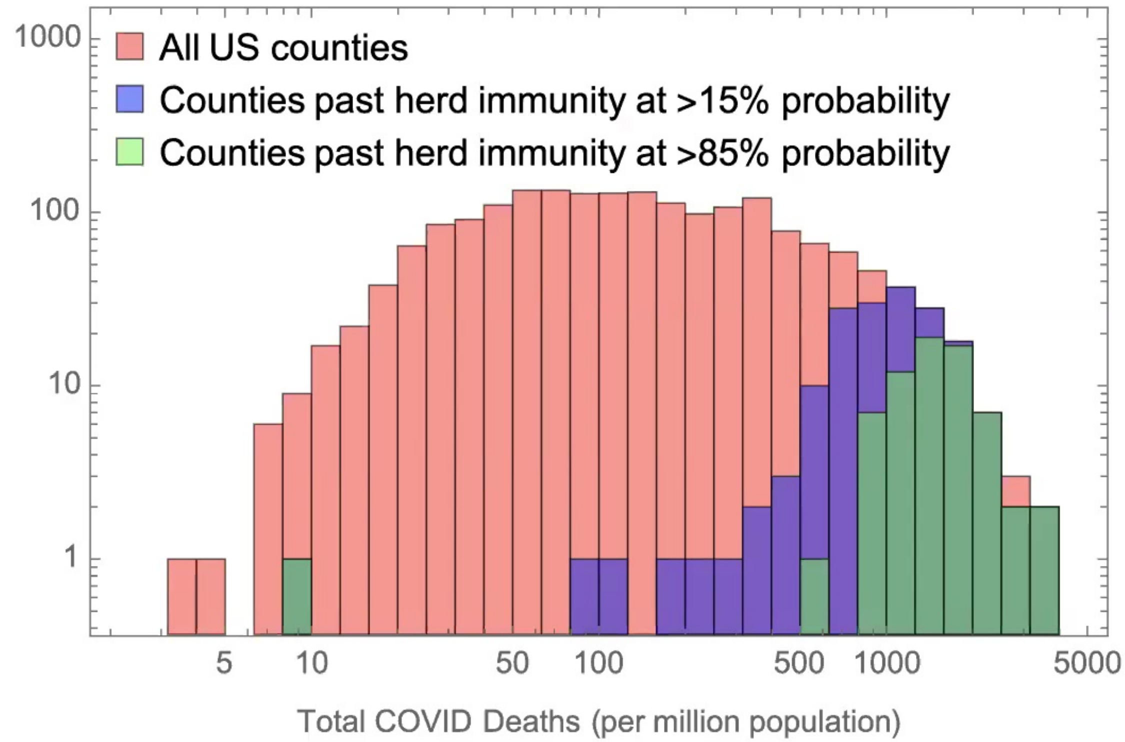
Predictions for “Herd Immunity” (as of July 7

Passed Herd Immunity, Within 1σ of Herd Immunity (as of July 7, 2020)



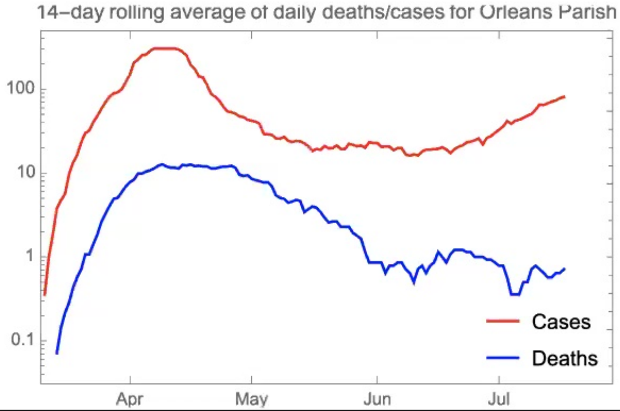
Predictions for "Herd Immunity"

- A few hard-hit counties (e.g., NYC, Detroit, New Orleans) w/ 0.1-0.3% COVID mortality/population, reached the herd immunity threshold
- **Vast majority of counties** (comprising 90% of US population) **remain susceptible**



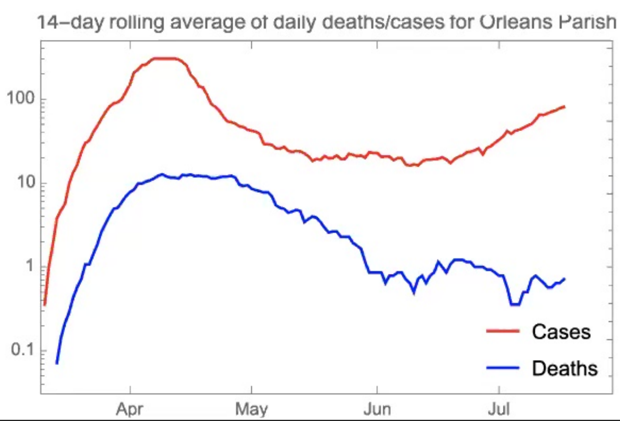
Case Study: New Orleans

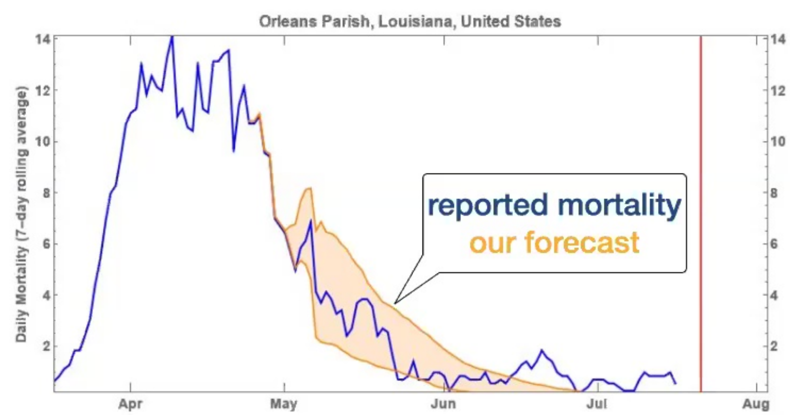
- Some counties in Louisiana/Georgia/Mississippi have reached herd immunity



Case Study: New Orleans

- Some counties in Louisiana/Georgia/Mississippi have reached herd immunity
- What if a county reaches herd immunity, but its neighbours have not?
- Cases across the US South have been rising steadily, where population is mostly susceptible. Will the outbreak spill over to counties that have reached "herd immunity"?
- ***Prediction:*** *mortality will plateau in New Orleans ($\lambda(t) = 0$) but no community outbreak (case rise due to increased testing),* ***Alternative:*** *immunity doesn't last* 😟





Superspreader vs Vulnerable

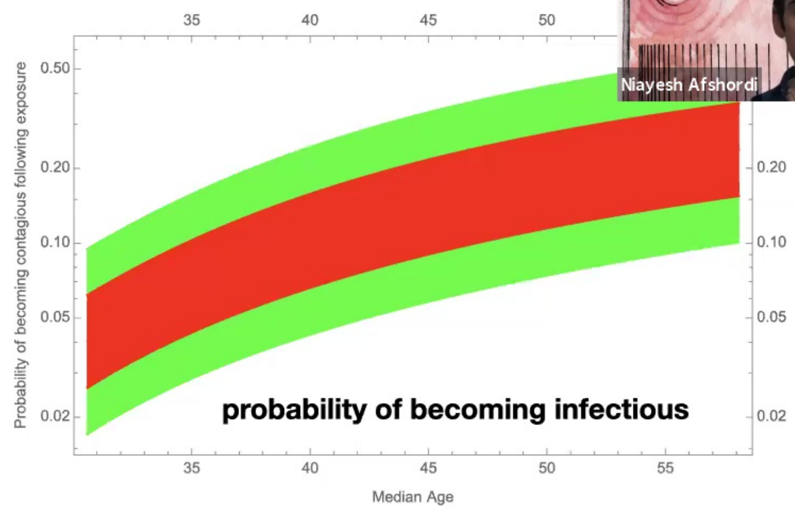
- Exponential suppression of susceptible fraction, derived for heterogeneous population:
- superspreaders drive the epidemic, but vulnerables are most likely to die from it
- $\dfrac{\text{superspreader infection rate}}{\text{vunerable infection rate}} = \text{Infection Fatailty Rate (IFR)} \times C_D$
- $C_D \simeq 3500 \pm 600$, $\text{IFR} \simeq 0.01 - 0.03$
- superspreaders are 30-100 times more likely to get infected (and reach immunity) than the vulnerable population
- ***Possible strategy: can we maximize this ratio?***

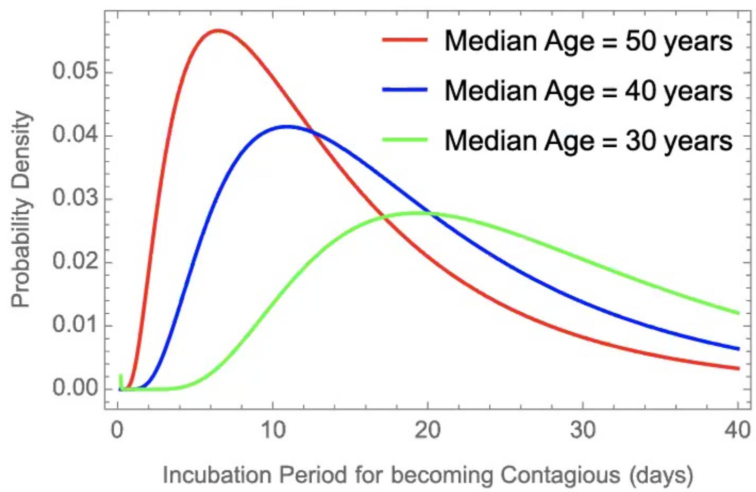
Outline

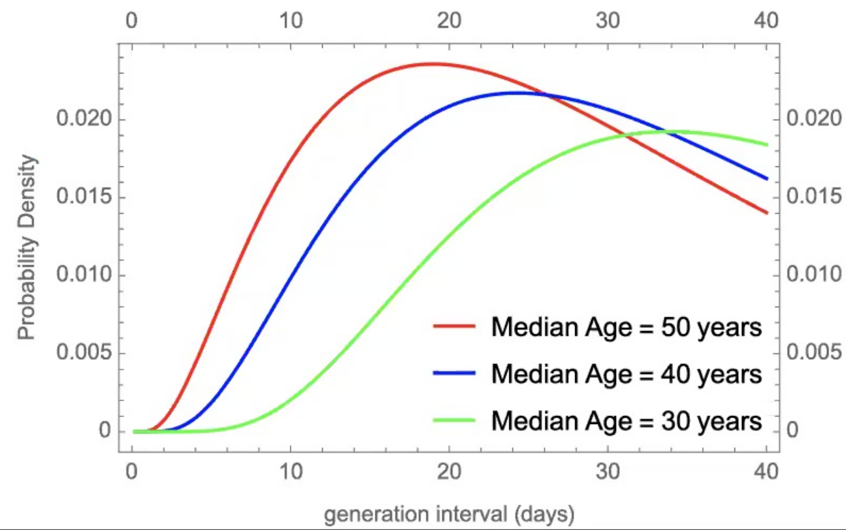
- Data
- Linear models
- Nonlinear mechanistic/causal model
- Herd Immunity
- Final Thoughts: How to manage a pandemic?

Incubation Probability and Period

- <10% of exposed will ever become infectious
- Generation intervals 10x longer than clinical estimates of 3-7 days (e.g., Ganyani, et al.), esp. for younger counties
- COVID long-haulers?







How to manage a pandemic?

1. Find out what drives it in YOUR community (e.g., population density, age, social mobility, weather, herd immunity)

2. Find out the human costs of mitigations (e.g., lockdown, school closure, face mask)

3. Identify potential endpoints and their likelihoods (vaccine, herd immunity)

4. Can you separate the superspreaders from the vulnerable population?

5. Optimize your strategy accordingly, *based on Evidence, NOT Politics*

wolfr.am/COVID19Dash

Final Thoughts

- A physical approach to epidemiology: more realistic than "*SEIR compartmental models*", more identifiable/tractable than "*social networks*"
- Community-specific epidemic intervention: depends on population distribution, demographics, and climate *(e.g., Kodiak Island doesn't need a lockdown for COVID, Manhattan does)*.
- Herd Immunity happens through depletion of susceptible superspreaders. Can they be identified through demography, biology?
- Counties are not islands, thus herd immunity is not localized/perfect → data on mobility between counties needed to model this (cooperation of mobile carriers?)
- Incubation and "long-haulers": much longer quarantine/tracking periods?

What keeps me up at night

- Evidence for immunity is decisive, *but does it last?*
- What are best ways to track social distancing, and/or PPE use?
- How to balance the harms due to COVID-19 against the adverse effects of lockdowns on mental health, economies, education, working parents, etc. ?
- Scientists (yes, even Astrophysicists) have responsibility to their societies. Should they roll up their sleeves, when millions of lives are at stake, or just stay out and “leave it up to the experts” to handle the situation?

Heterogeneous Populations: Susceptible Density from Death Fractic

- The infection of susceptibles is governed by

$$\dot{S} = -\beta\, S\, I_* \quad \longrightarrow \quad S(t) = S(0) \exp\left[-\beta \int^t I_*(s)\,\mathrm{d}s\right]$$

and the susceptible fraction can also be expressed in terms of fraction infected:

$$S(t) = S(0)\,[1 - f_I(t)]$$

- Given two populations with different rate constants (e.g., mobile vs immobile)

$$\frac{S_A(t)}{S_A(0)} = \left[\frac{S_B(t)}{S_B(0)}\right]^{\beta_A/\beta_B}$$

which implies that

$$\frac{S_A(t)}{S_A(0)} = \left[1 - f_I^{(B)}(t)\right]^{\beta_A/\beta_B} \xrightarrow[\boxed{f_D(t) = \mathrm{IFR} \times f_I(t-\Delta t)}]{} \frac{S_A(t-\Delta t)}{S_A(0)} \approx \exp\left[-\frac{\beta_A}{\beta_B\,\mathrm{IFR}}\, f_D^{(B)}(t)\right]$$

leaving an exponential relationship between susceptibles and dead if $\beta_A \gg \beta_B$ and if the mortality statistics are dominated by the “B” population.