

# Superspreader Mitigation & A Synthetic Biology for Epidemics

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# Summary: Distributions (of virus load) Matters



# Superspreaders & COVID-19

- Considerable **heterogeneity** in infectivity
  - 5-20% of infected population may cause 80% of infections (4 “experimental/data analysis” papers before June 2020)
- Multiple reports of superspreading events
  - Choir in WA State: ~75% of 60 singers infected after 2.5 h practice
  - Bar hopper in S. Korea: ~60 cases one night
  - 1 person infect 23 on a 2 hour bus ride, + 7 on a following 2.5 hour ceremony +
  - 1 person infect 40 at wedding in Uruguai
  - An infected person only have  $p= 15\%$  to infect to spouse.



Endo A, Abbott S, Kucharski AJ, Funk S. Estimating the overdispersion in COVID-19 transmission using outbreak sizes outside China. Wellcome Open Res. 2020;5:67.

Miller D, Martin M, Harel N, Kustin T, Tirosh O, Sorek N, et al. Full genome viral sequences inform patterns of SARS-CoV-2 spread into and within Israel. Preprint [Internet]. 2020;May 22, 20. Available from: <https://doi.org/10.1101/2020.05.21.20104521>

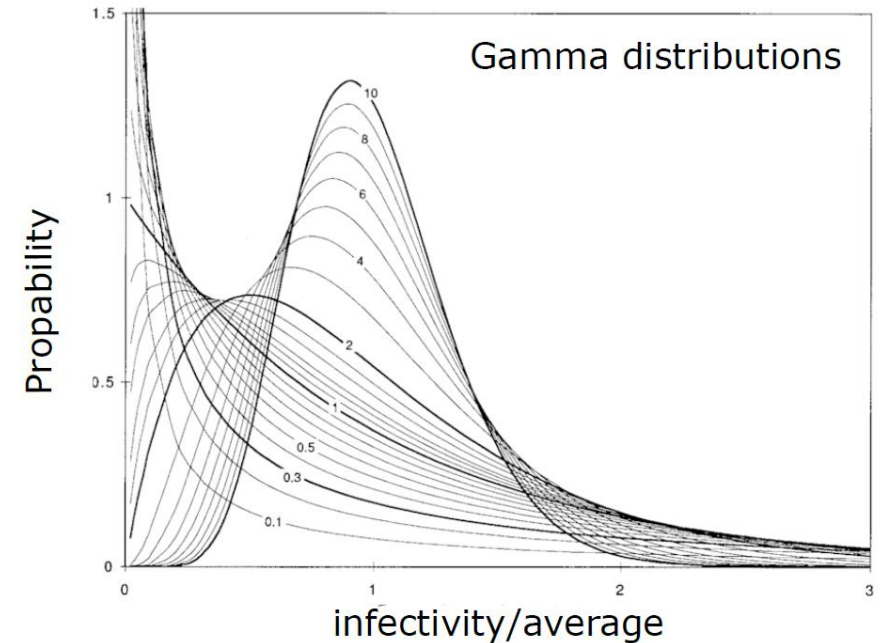
## Assumed Distribution of infectivity $r$ :

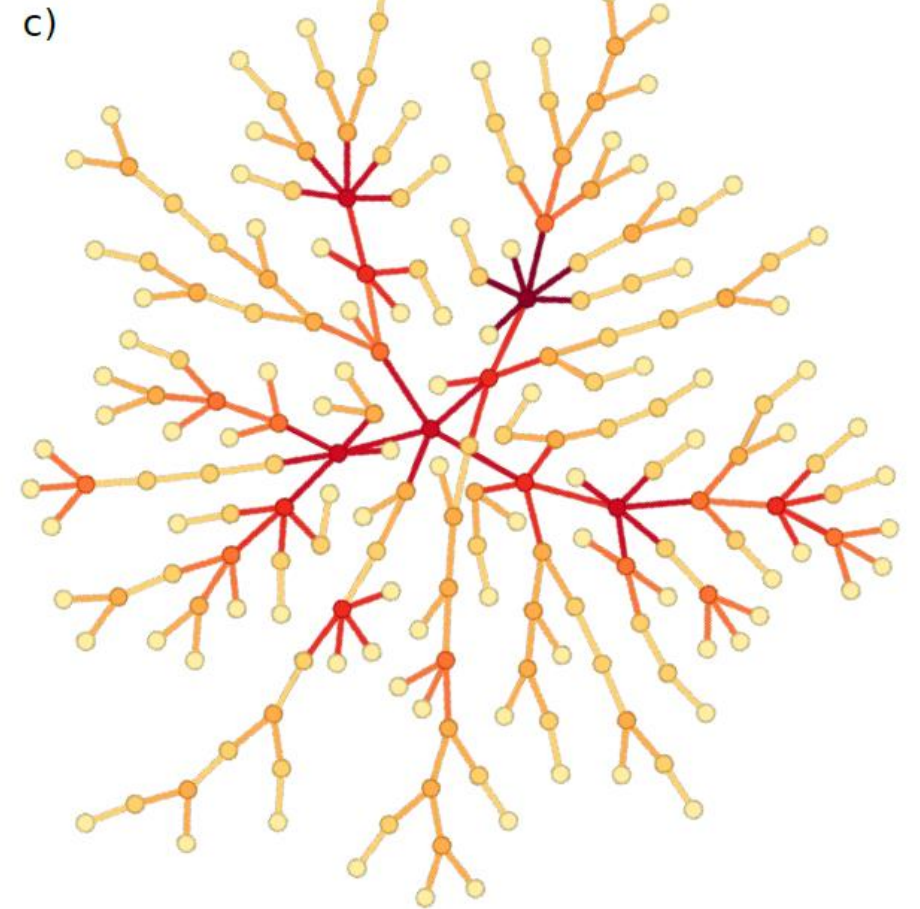
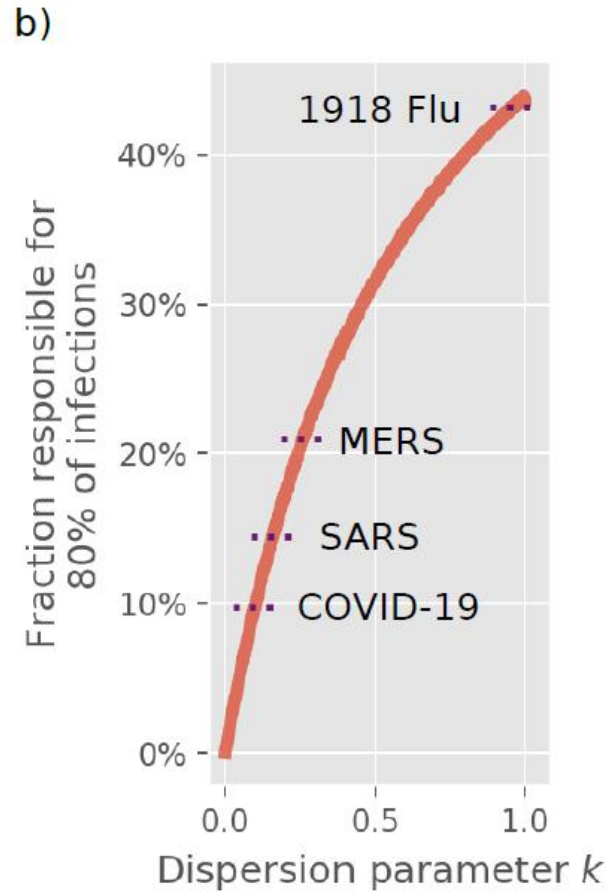
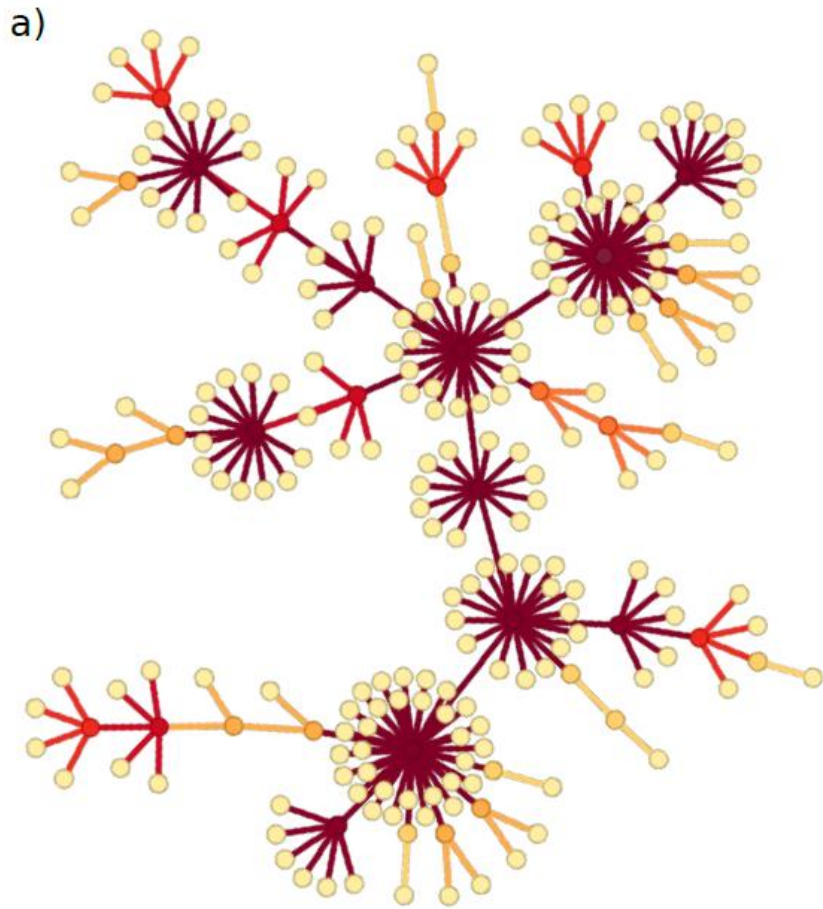
$$P_I(r) \propto r^{k-1} \cdot \exp(-kr/\mu)$$

$k=1$ ,  $\rightarrow$  exponential, seen for Influenza.

$k < 1$ ,  $\rightarrow$  for measles, SARS and covid-19, tuberculosis, many have  $r$  close to 1, few have  $r$  close to  $R_0/k$

...just mathematics, is a one parameter description of variability,  $spread/man = 1/\sqrt{k}$ ....



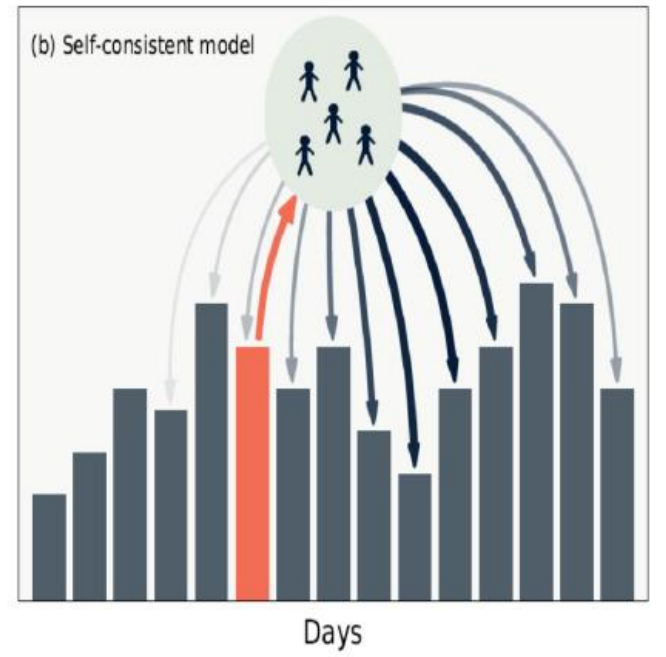
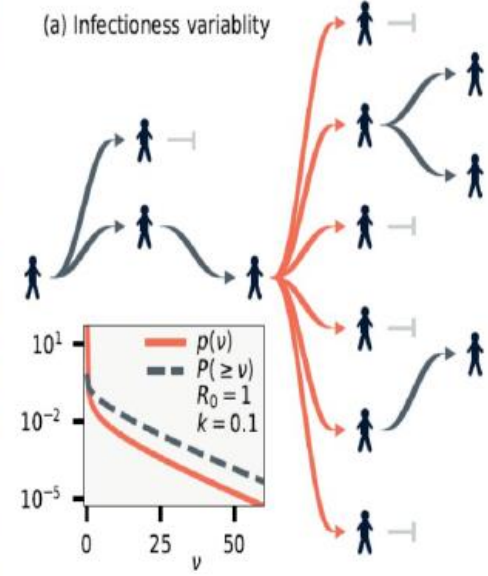
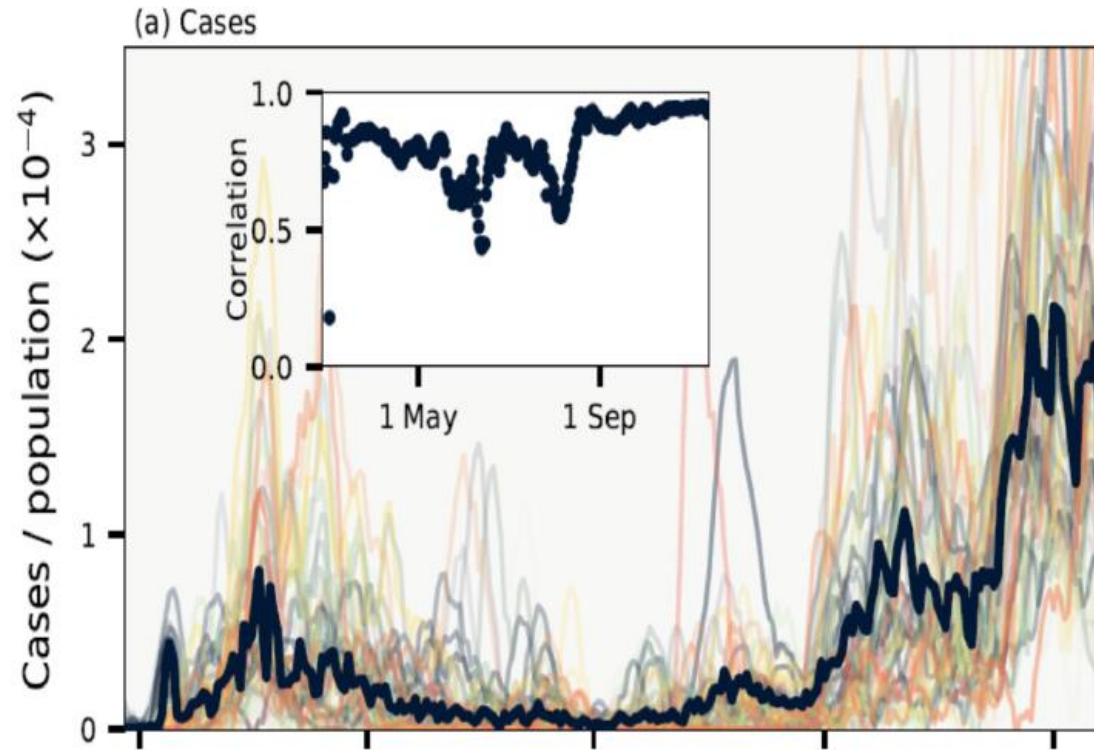


$$P(s) = s^{1-k} \exp(-k s/R)$$

Lloyd, Nature 2005

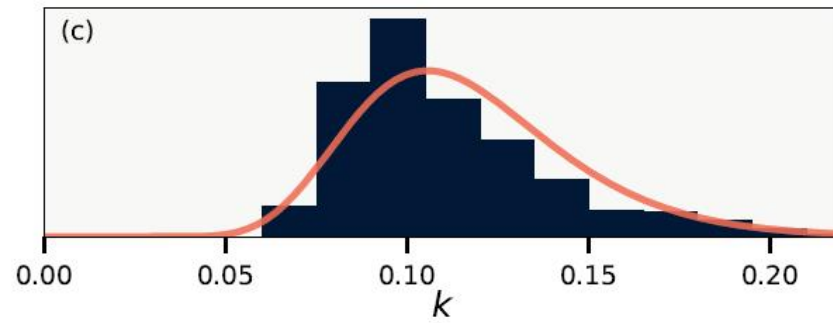
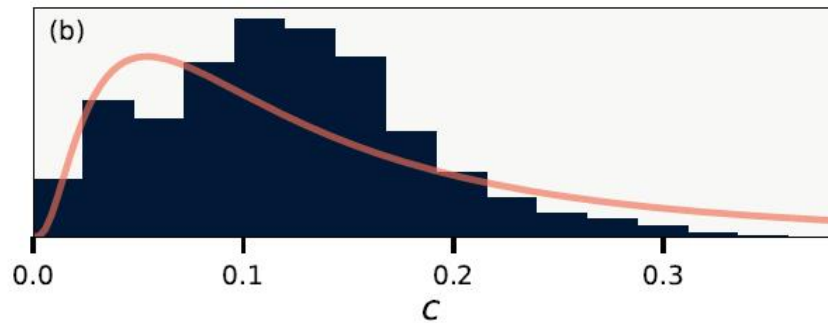
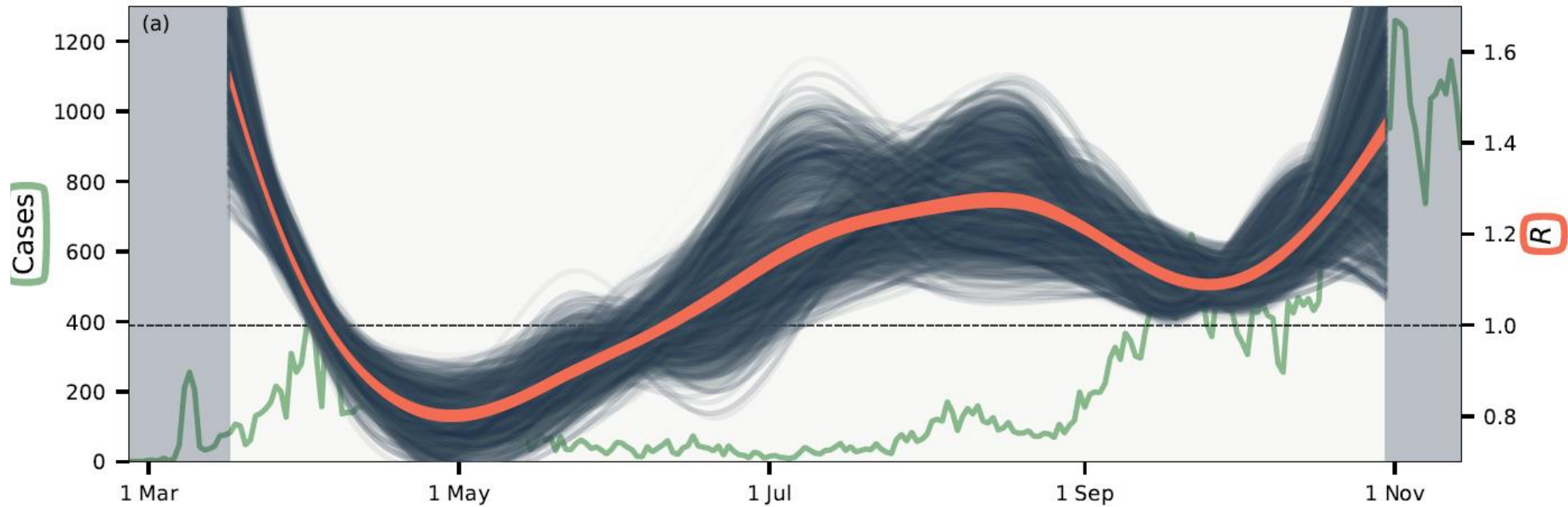
Nielsen, Bjarke Frost, Lone Simonsen, and Kim Sneppen.  
 "COVID-19 superspreading suggests mitigation by social network  
 modulation." *Physical Review Letters* 126.11 (2021): 118301.

# Measuring $k$ ... from burstiness: 99 “kommuner” in Denmark:



Variability of Individual Infectiousness  
Derived from Aggregate Statistics of COVID-19

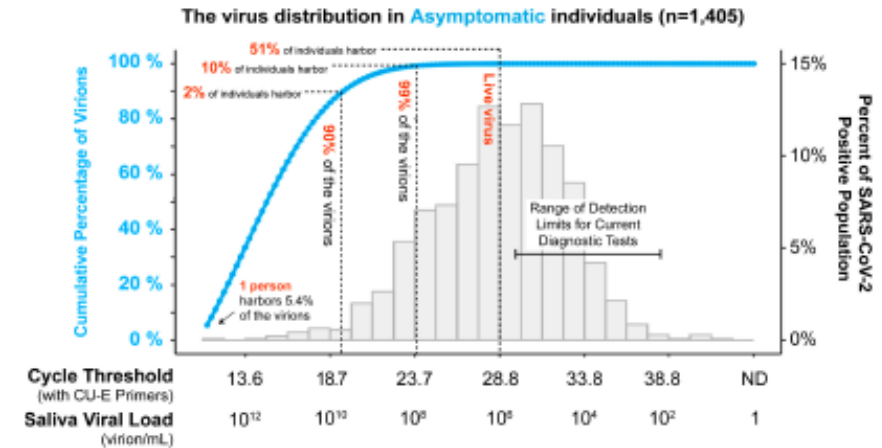
→ Result of best fit:



Variability of Individual Infectiousness  
Derived from Aggregate Statistics of COVID-19

# Supershedders in (wt) covid:

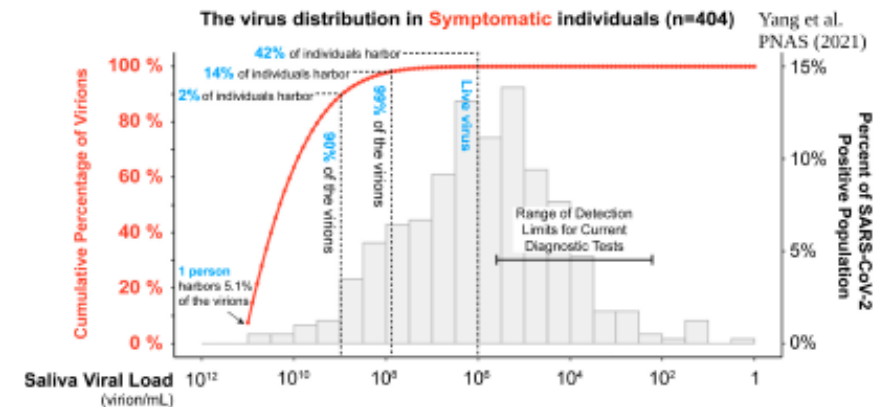
- Main argument: 2% carries 90% of virus



- Only 17% household infections (however more like 30-40% for Delta).

- → It get important to think about

**Duration of contacts, Diversity of contacts & infectivity.**





# Other (next pandemics X?) may have:

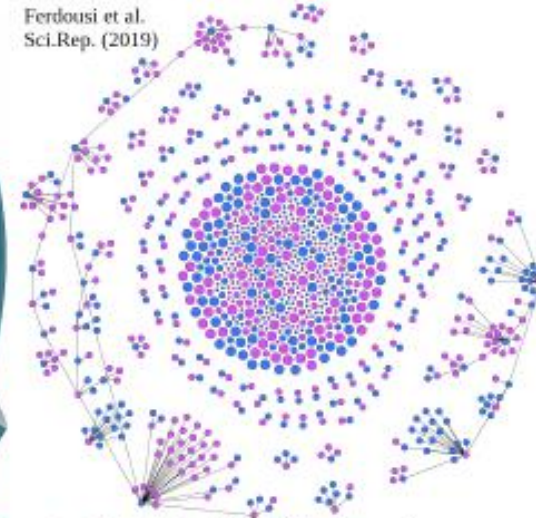
## Superspreading – different mechanisms

**Aerosol → social superspreaders**

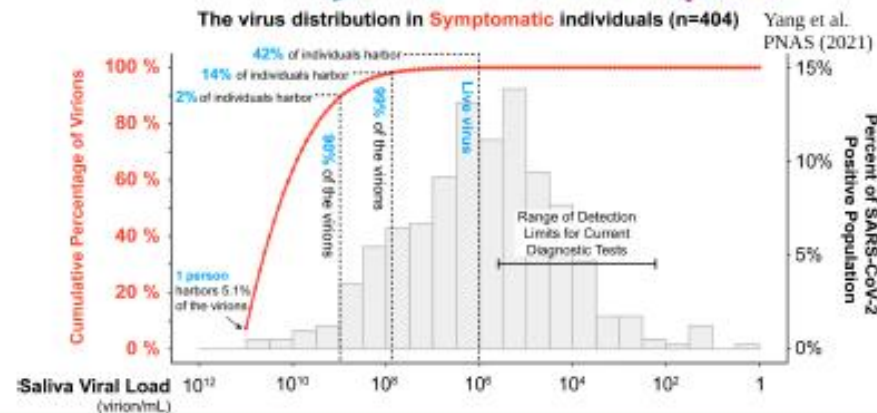
Kirkegaard et al. Sci.Rep. (2021)



Ferdousi et al. Sci.Rep. (2019)



**Extreme behavior → social superspreaders**



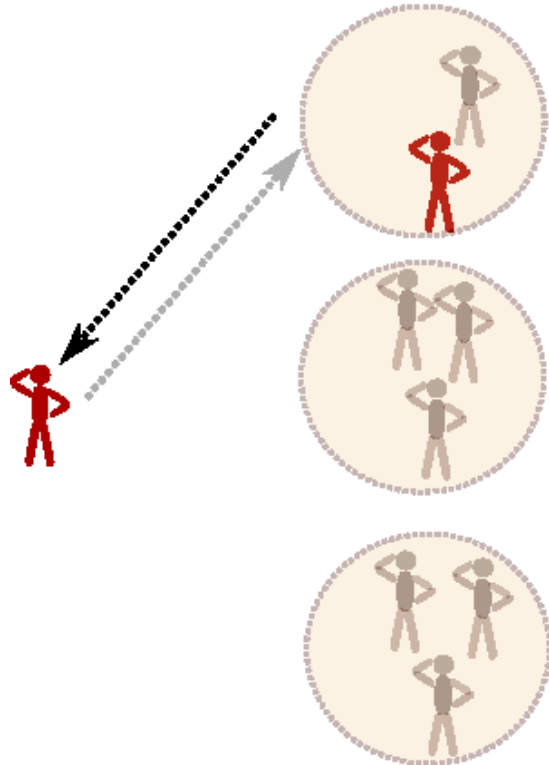
**Biological variation → superspreaders**  
Includes Tuberculosis

# SIR models wrong:

## Disease spreading needs Infectability and Opportunity

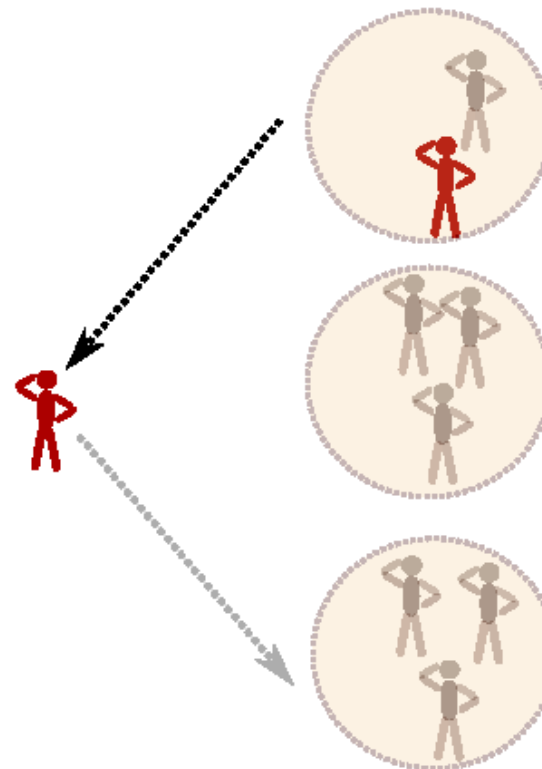
The latter nearly unlimited in SIR /compertemental models

Reality: Each man return to same home every day



Here can only infect up to 2 new susceptibles

SIR simplification: Each man return to a new home every day



Here he has unlimited infection potential (one for each timestep)

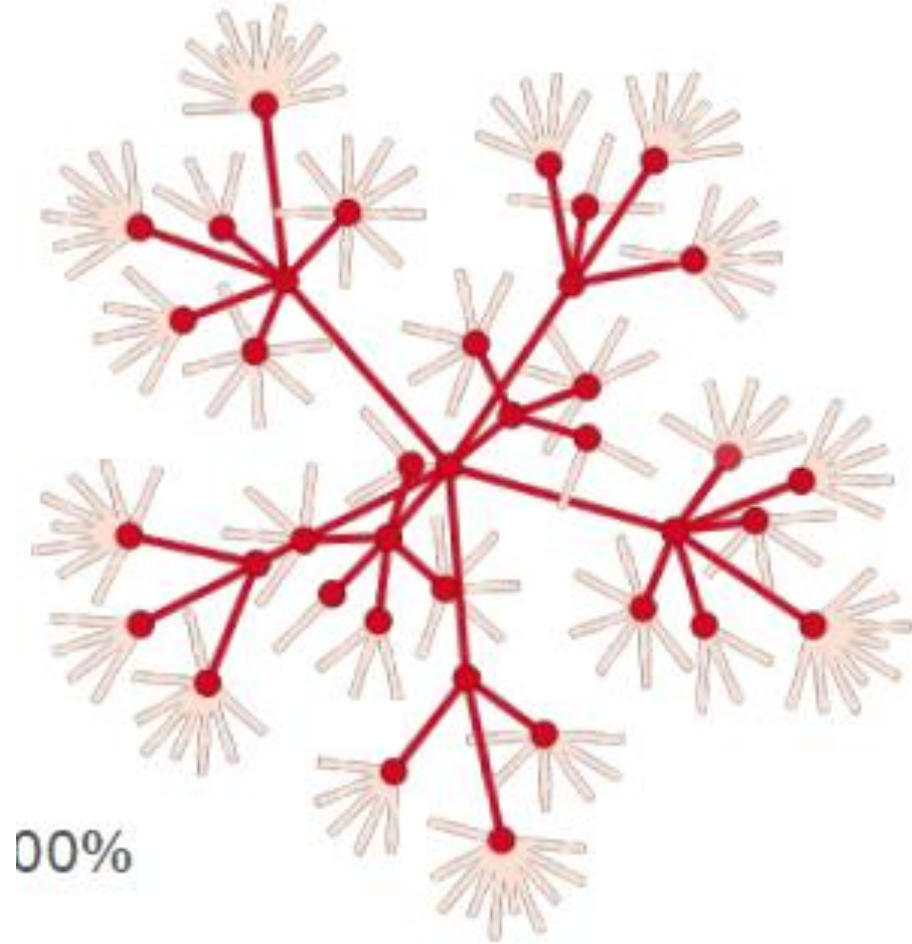
# Agent based model:

- Follow individuals as nodes in a network:
- Can give people real homes & work, don't give them a new family every evening (as done in SEIR models)
- Can give people individual properties.... ``Quenched noise''

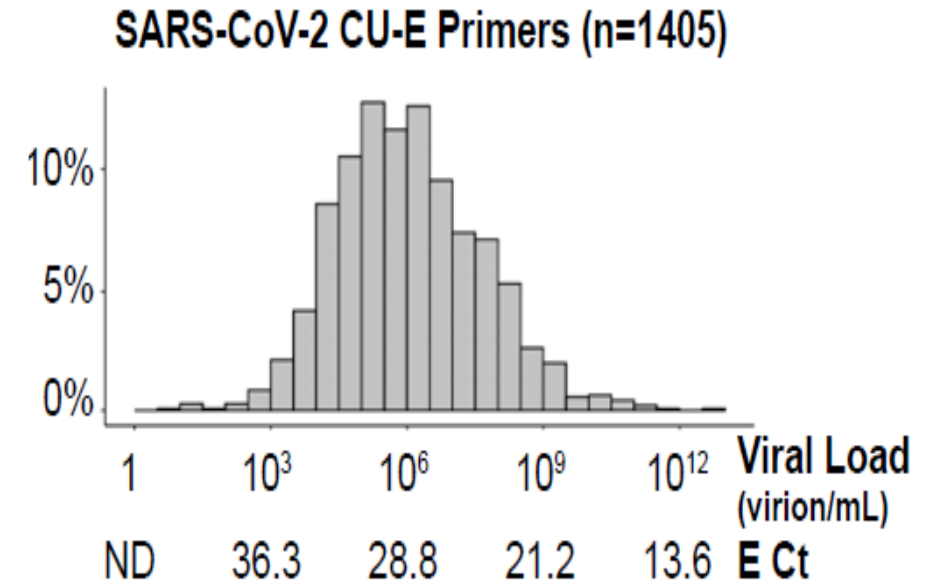
• **DOES NOT NEED TO BE COMPLICATED!!!!**

.....e.g. same 2 basic parameters as SIR model

# Put people on a network:



+



**Main idea: you cannot infect more than you are connected to**

# Agent based: Disease on a social network:

Repeat N times:

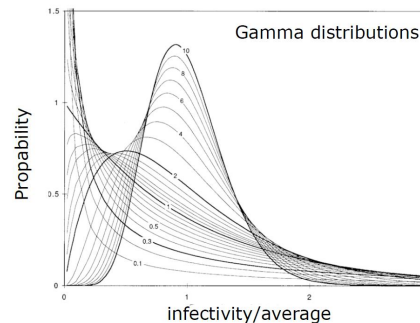
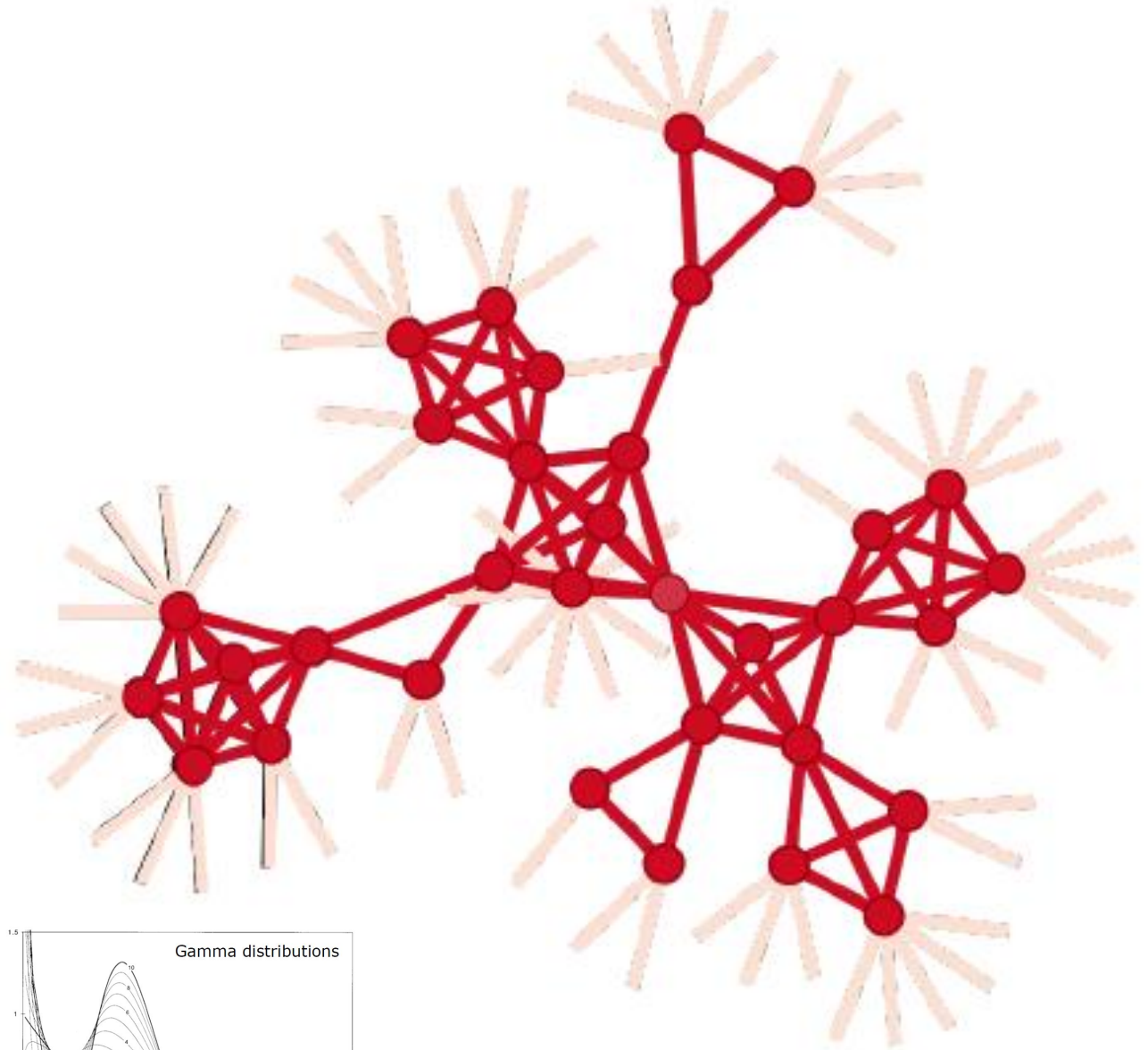
Take random agent  $i$ .

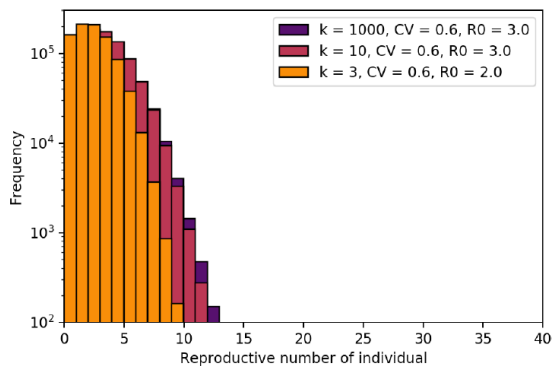
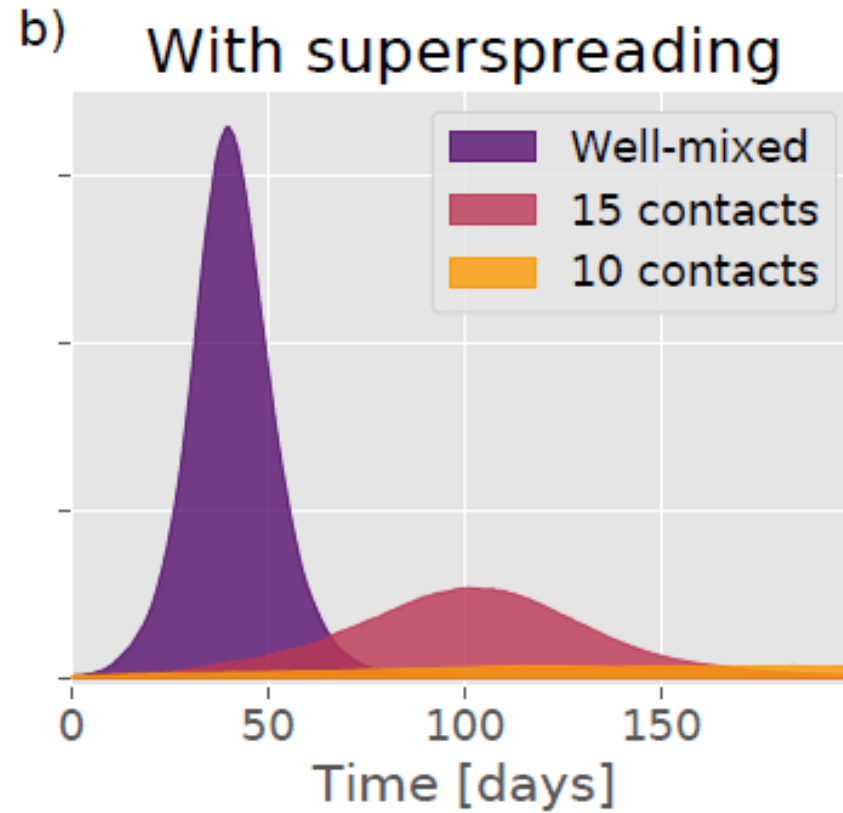
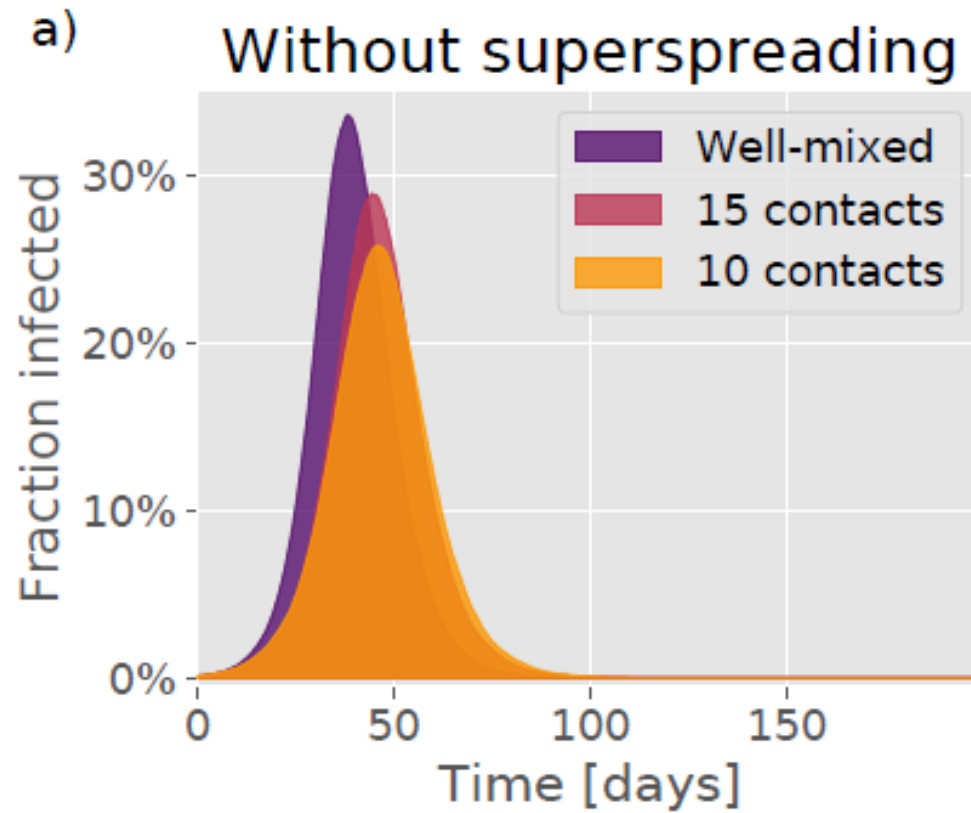
If in  $I$ -state, take one of its neighbors. If this is in  $S$ -state then it is infected with probability  $= \beta_i \cdot dt$

For each sites in state  $I$   
convert it to state  $R$  with

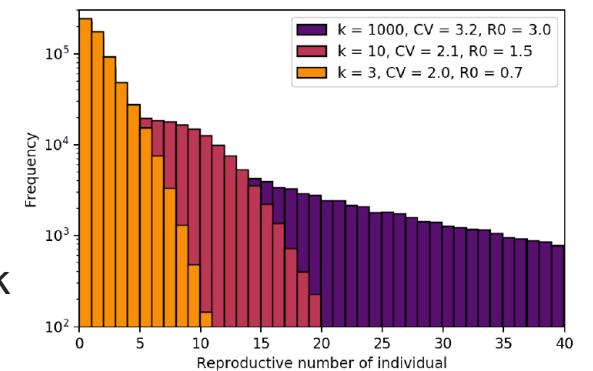
Probability  $= dt/\tau$  (duration of in  $I$ -state)

...NB: Notice each person assigned a different  $\beta_i$ ... that is different infectivity, that is selected from a gamma distribution with form factor  $k$

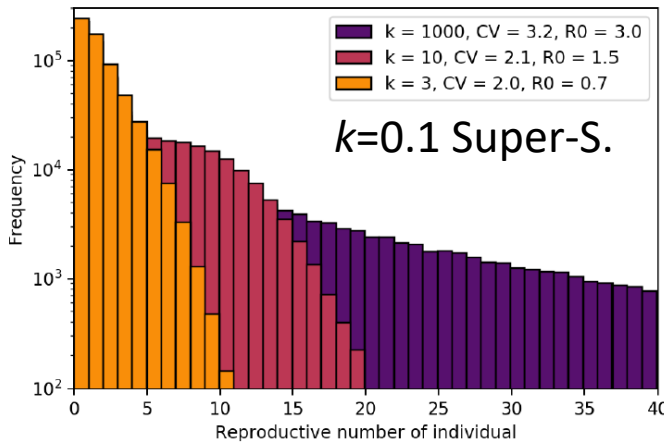
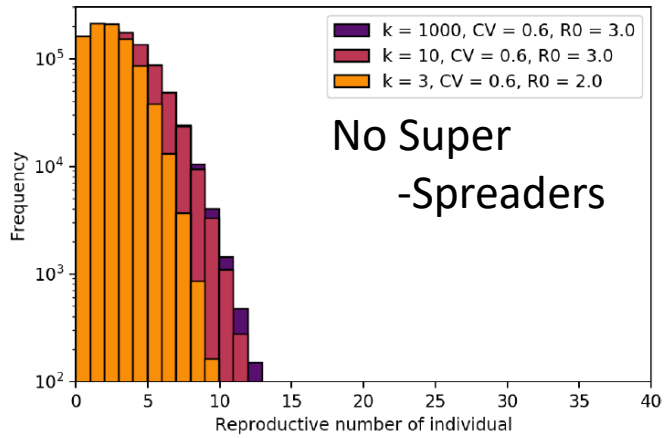




Nielsen, Bjarke Frost, Lone Simonsen, and Kim Sneppen.  
 "COVID-19 superspreading suggests mitigation by social network modulation." *Physical Review Letters* 126.11 (2021): 118301.

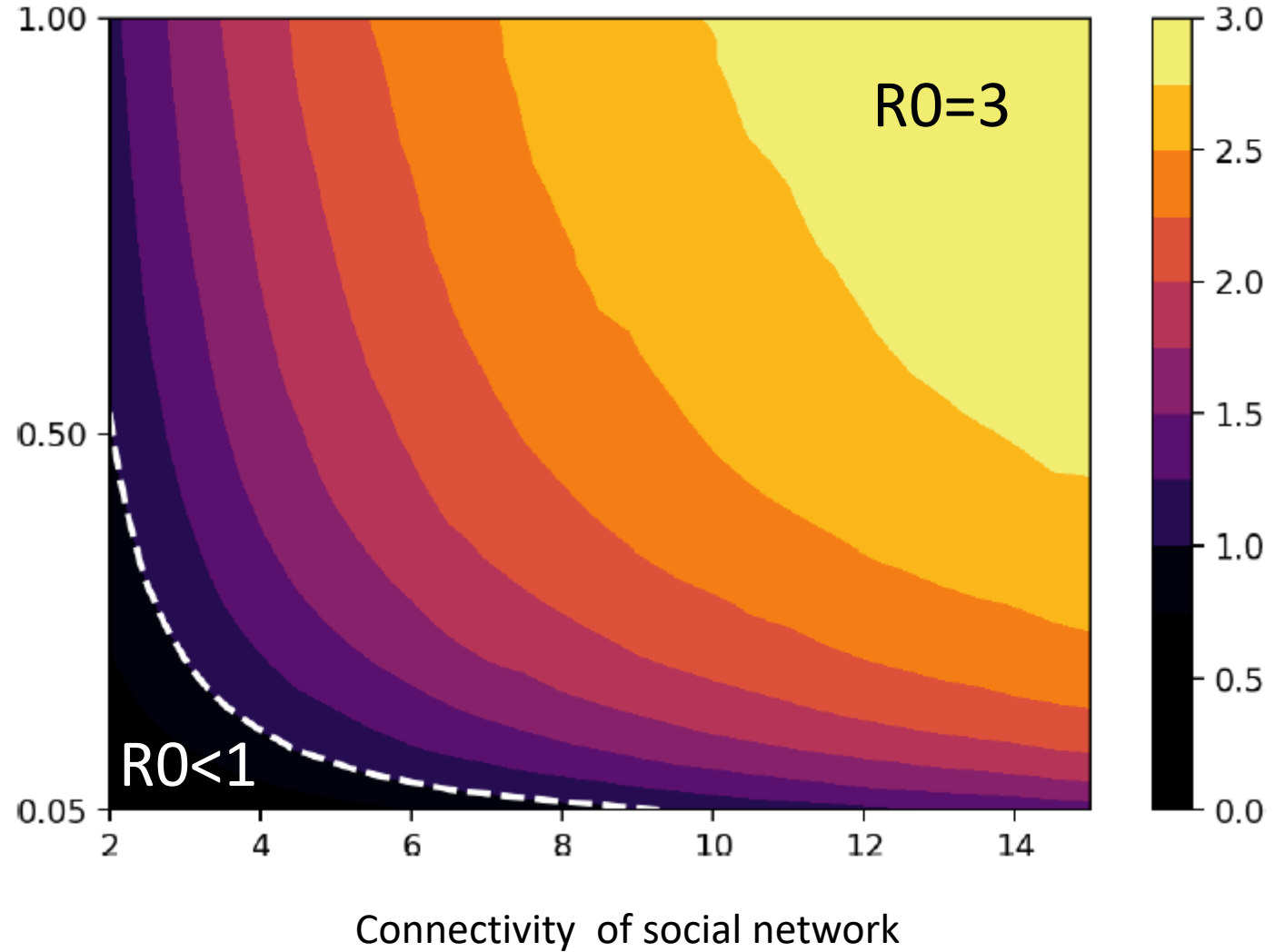


# Systematics of social network constraints on superspreaders



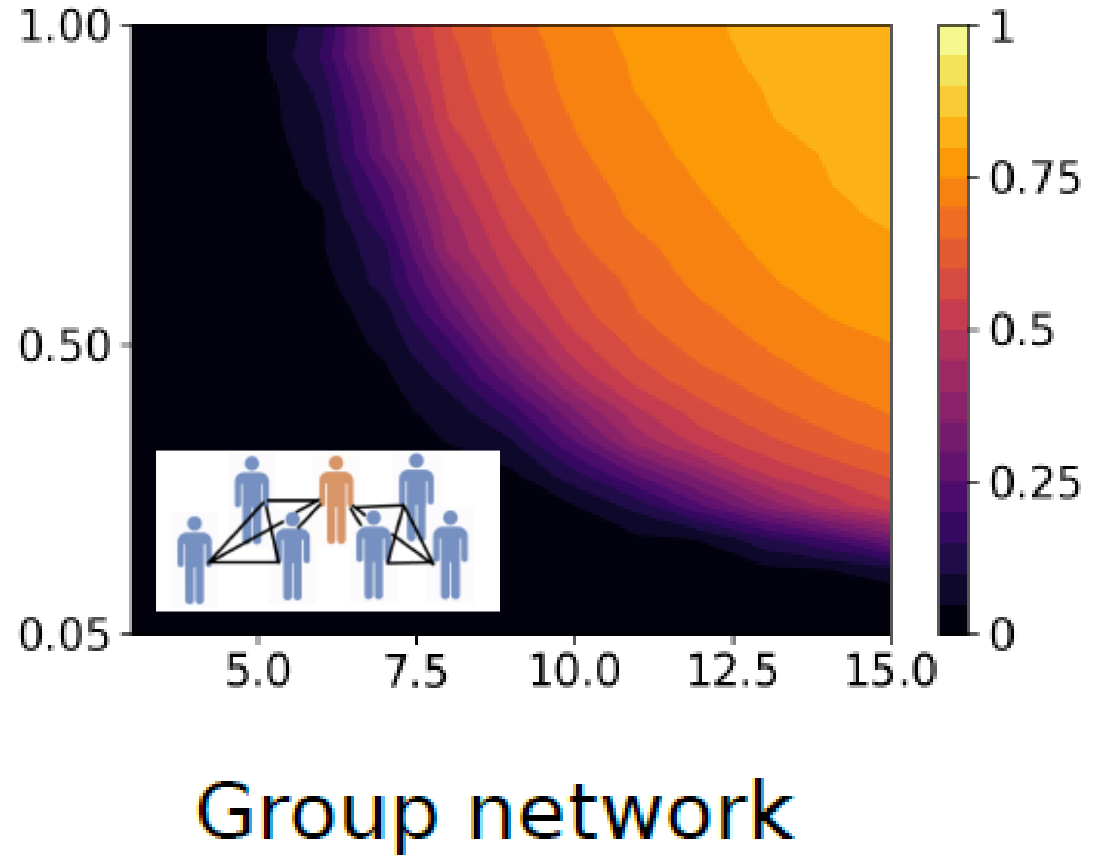
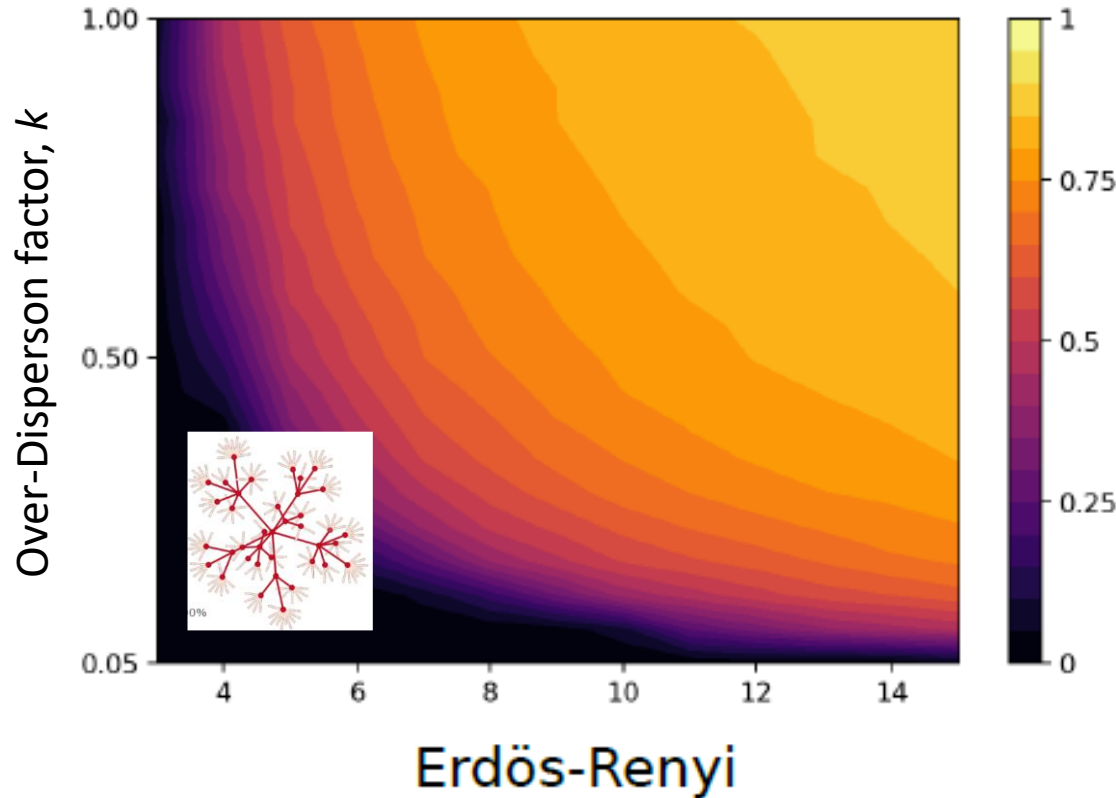
$$P(s) = s^{k-1} \exp(-k s/3)$$

Overdispersion between 0.05 and 1



Main idea: Limit connectivity on your network stops the epidemic... already a limit of 10 works fairly well

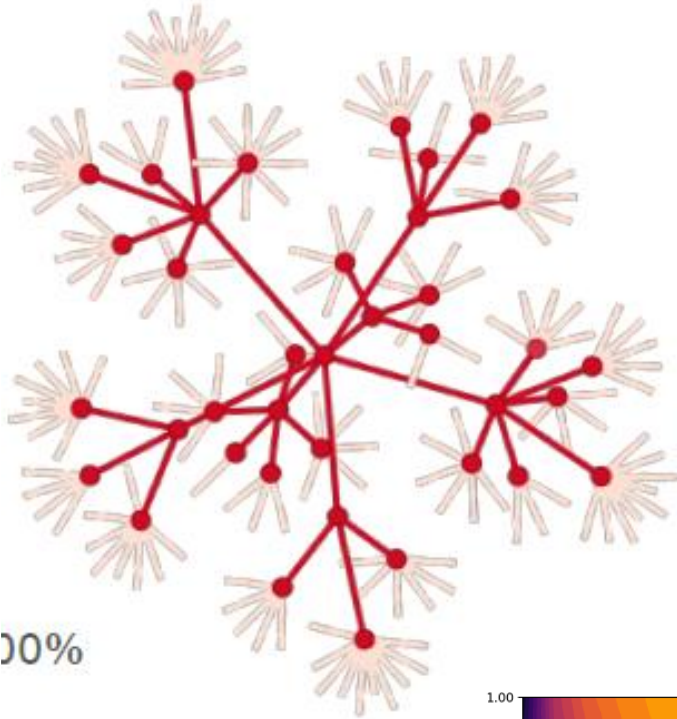
# Attack rate for superspreaders ( $k=0.1$ ):



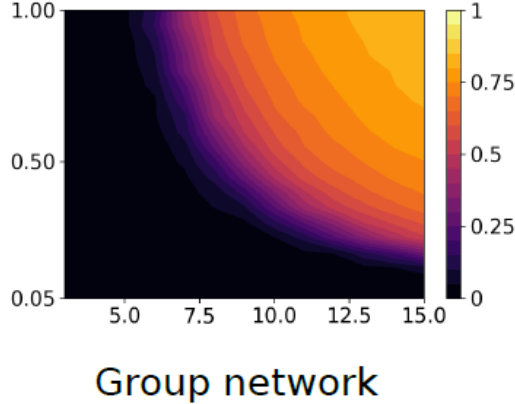
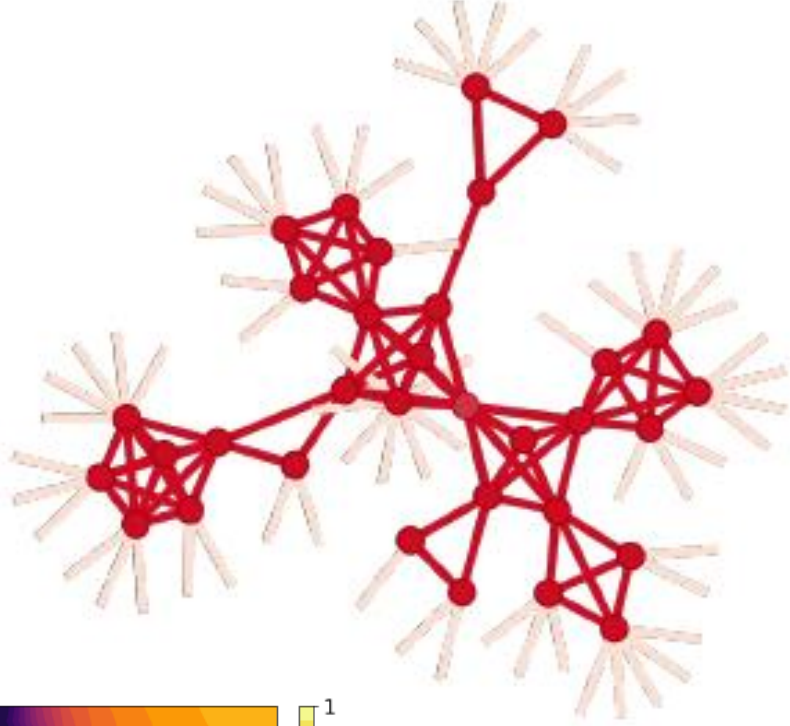
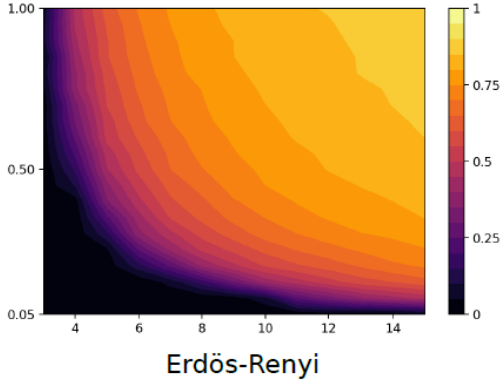
→ Limits on propagation much higher if people you connect to connect to each other (cluster network)  
.....local saturation, if you are infected, most of your surroundings are already infected.



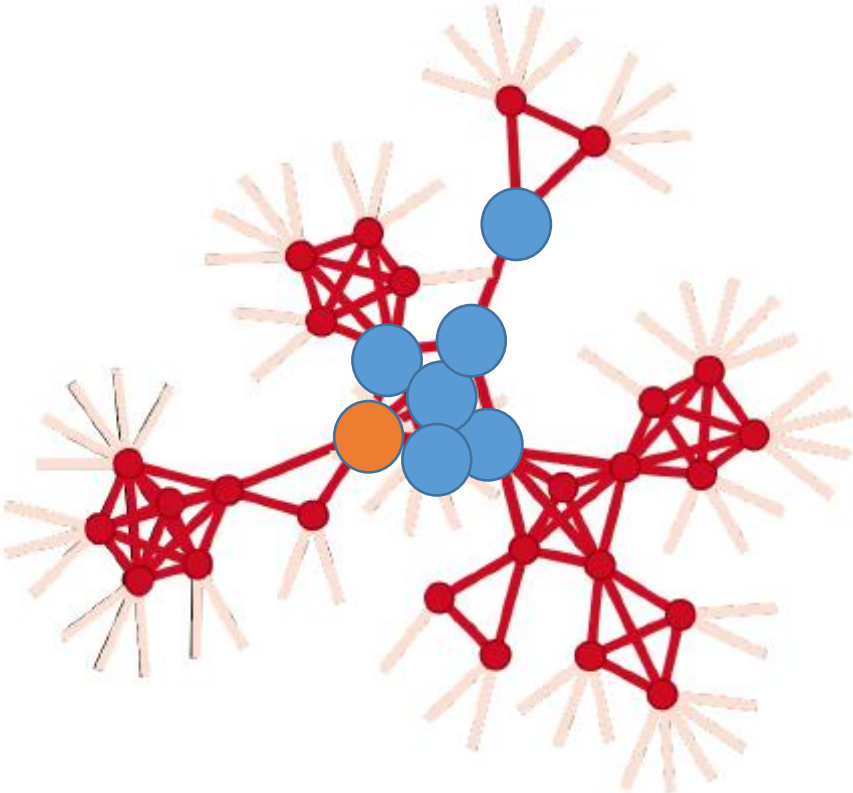
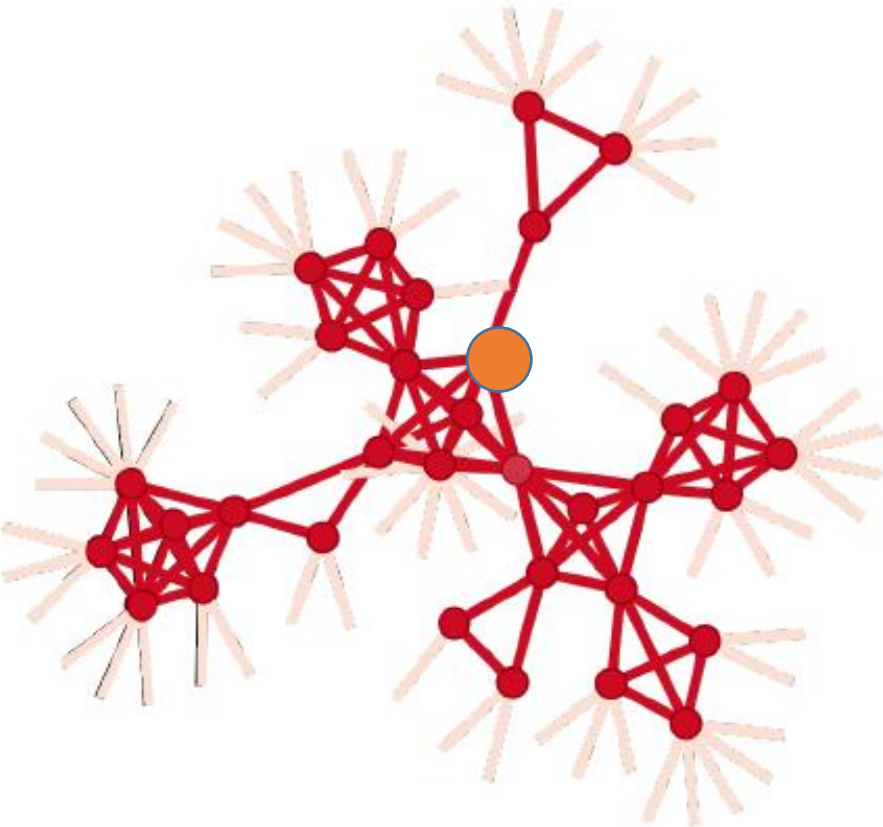
# Social bubbles easier to mitigate than “open” networks



10%



# Diseases on networks, beta high $\rightarrow$ Local Saturation



# Mechanism of bubble battles:

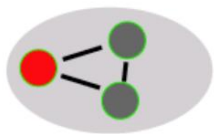
- With social bubbles, like your workplace, then when you get infected, most likely other also got it, and you thus cannot spread more at that workplace.
- When you get disease from a single contact, on the other hand, no local ``micro-herd'' immunity.

Nielsen, Bjarke Frost, Lone Simonsen, and Kim Sneppen.  
"COVID-19 superspreading suggests mitigation by social network modulation." *Physical Review Letters* 126.11 (2021): 118301.

# More realism:

- Different type of social networks
- Also meet some people outside networks:

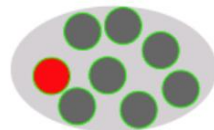
## Social interactions



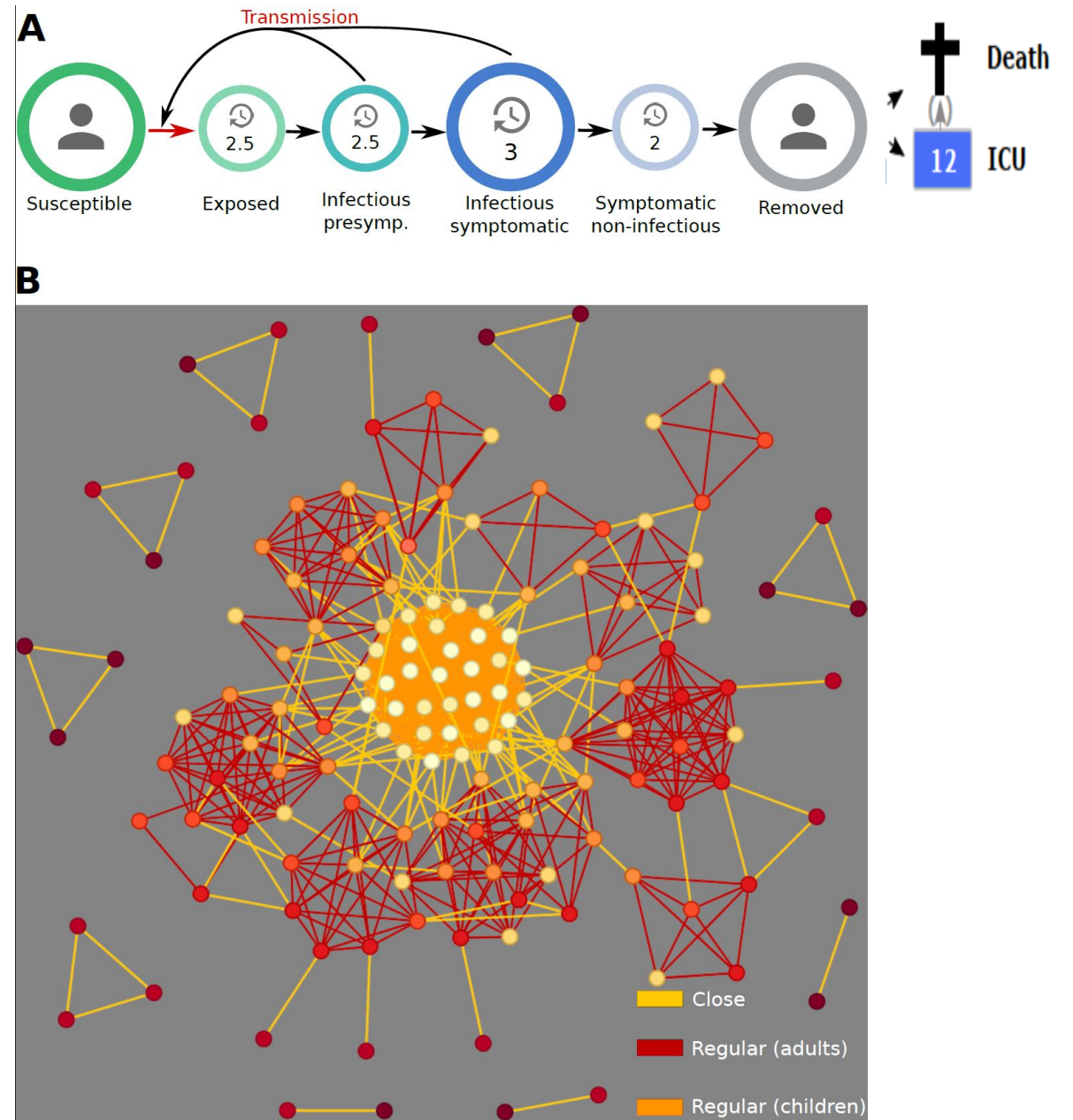
Home: 33%



Work/school: 33%



Other: Transport, Religious services, bars, leisure, shopping, sporting events, concerts: 33%



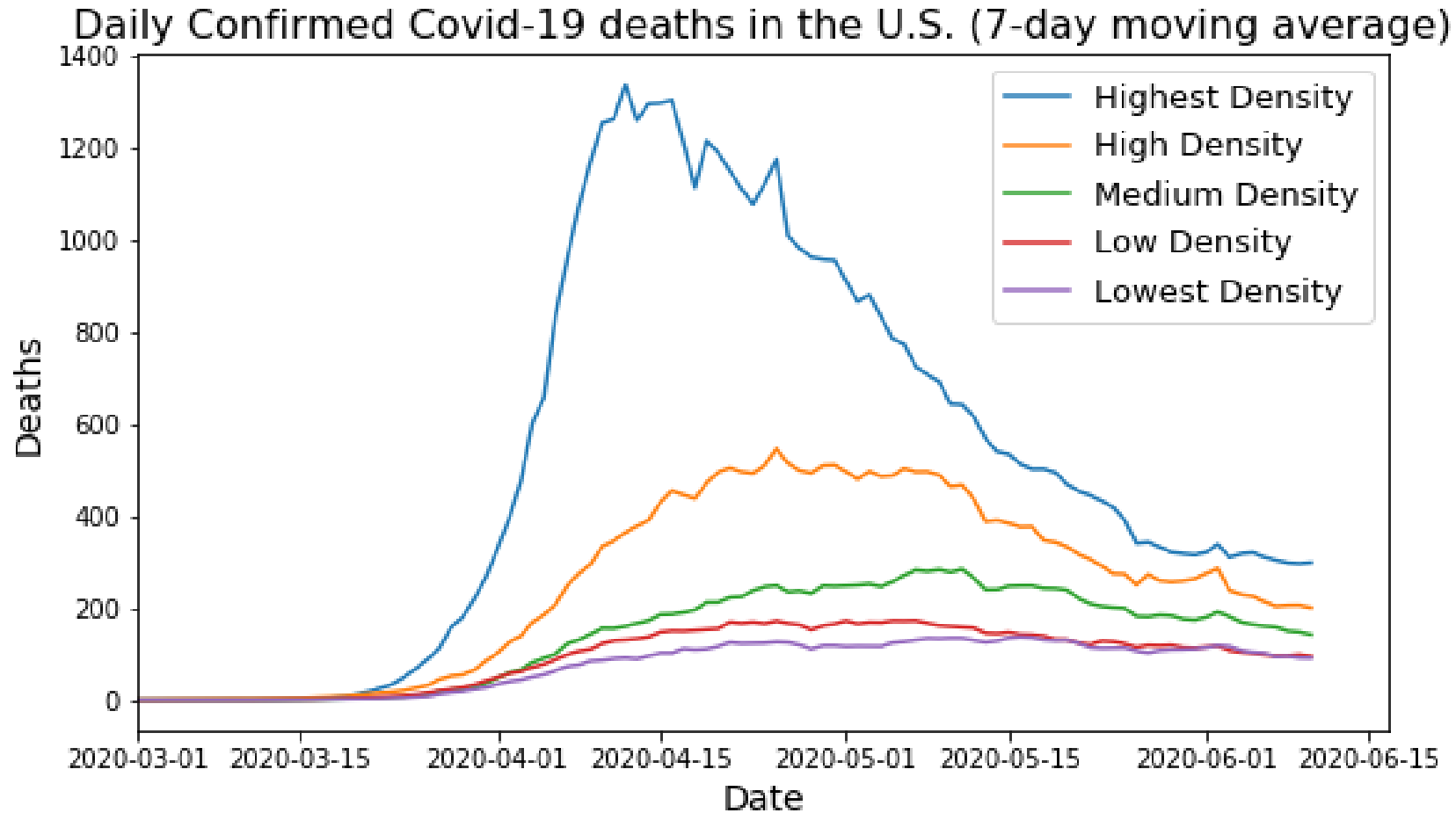
Sneppen, K., Nielsen, B. F., Taylor, R. J., & Simonsen, L. (2021). Overdispersion in COVID-19 increases the effectiveness of limiting nonrepetitive contacts for transmission control. *Proceedings of the National Academy of Sciences*, 118(14).

# Here we just remove 1 of 3 different sectors



→ The only thing that matters is to remove the random connections = occasional encounters

Superspreading *potentially* explain why Covid-19 spreads more at high population density:

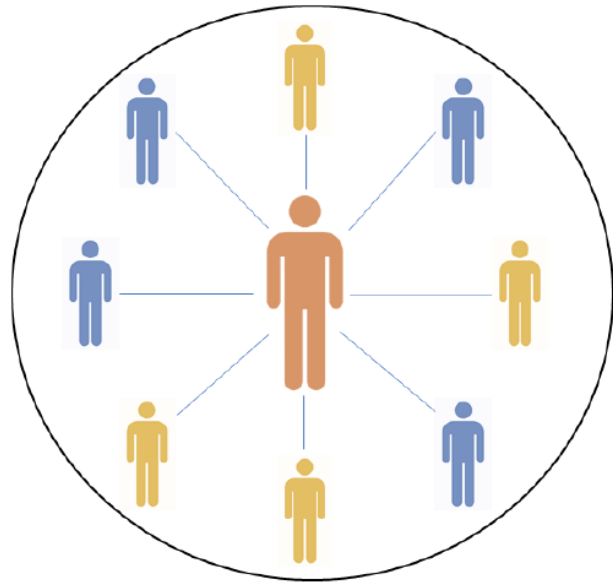


Eilersen, Andreas, and Kim Sneppen. "SARS-CoV-2 superspreading in cities vs the countryside." *Apmis* (2021).

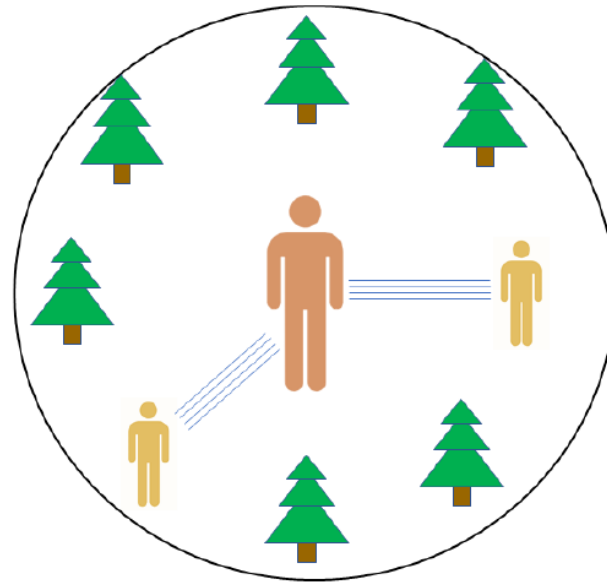
.....Influenza does not

# Superspreaders and geography:

- 99% infection was indoors (in China, ref 1, 2))
- Few infections within households, → only visits facilitate spreading



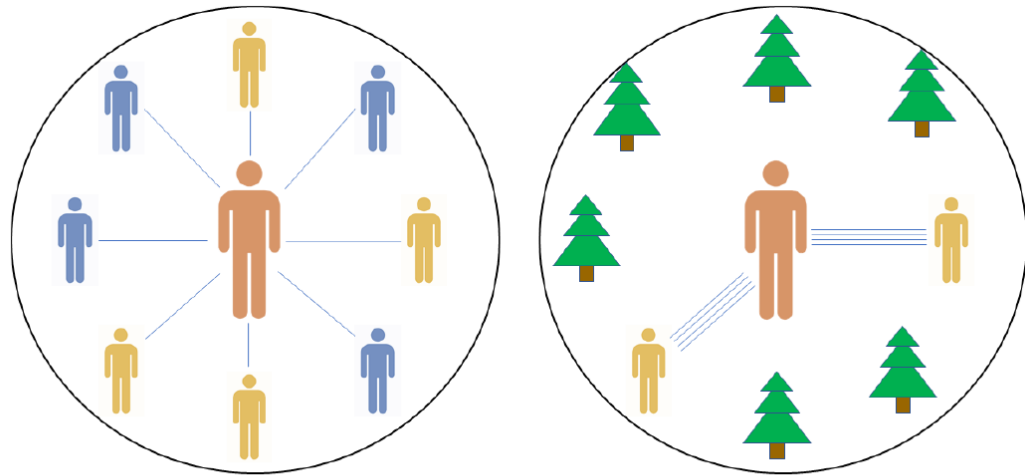
Superspreader in a city



Superspreader outside the city

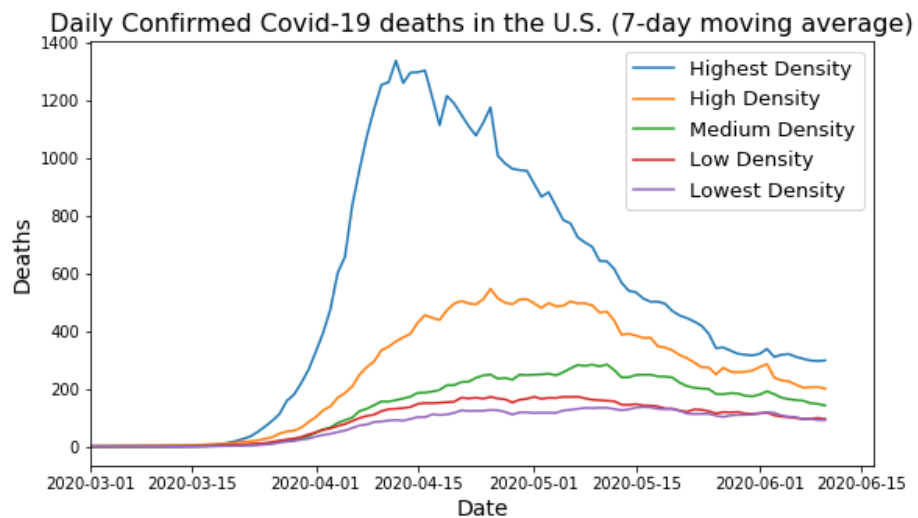
- 1) C. J. Carlson et al. *Species distribution models are inappropriate for covid-19, Nature Ecology & Evolution* 4, 770 (2020).
- 2) H. Nishiura, et al. *Closed environments facilitate secondary transmission of coronavirus disease 2019 (covid-19), medRxiv* (2020).
- 3) S. Y. Park et al. et al. *Early release-coronavirus disease outbreak in call center,*

# Superspreader & City $\leftrightarrow$ Countryside

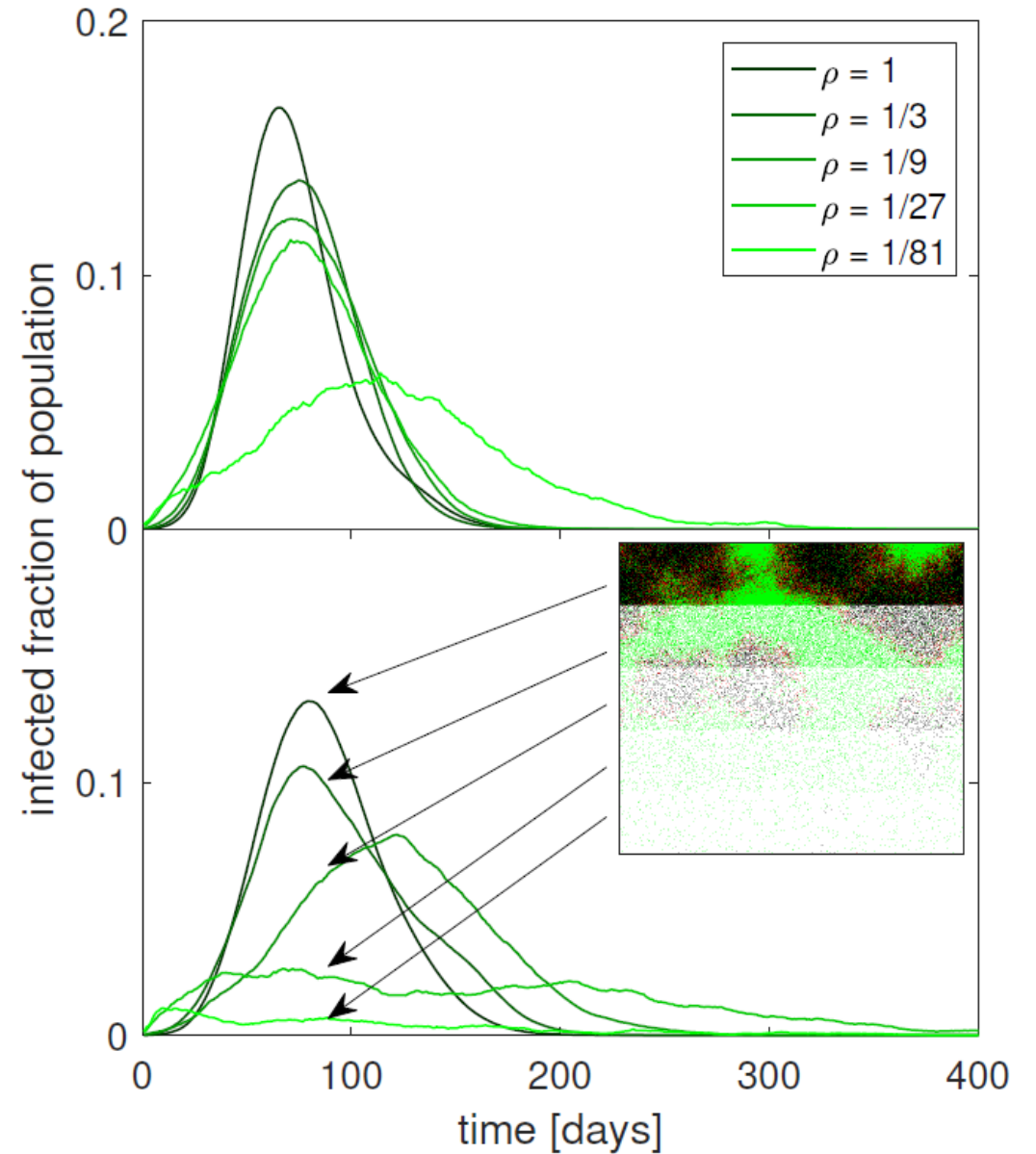


Superspreader in a city

Superspreader outside the city



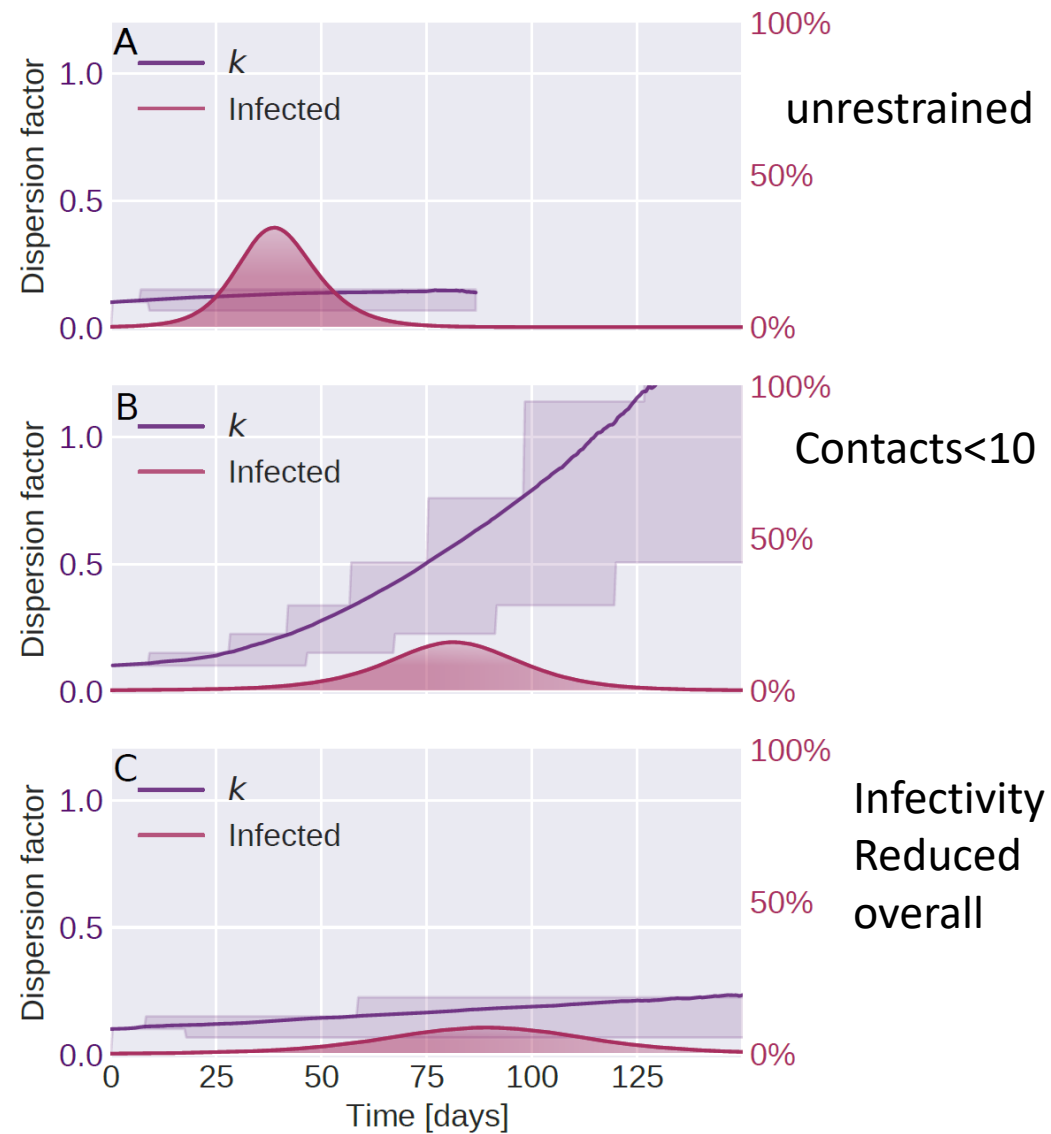
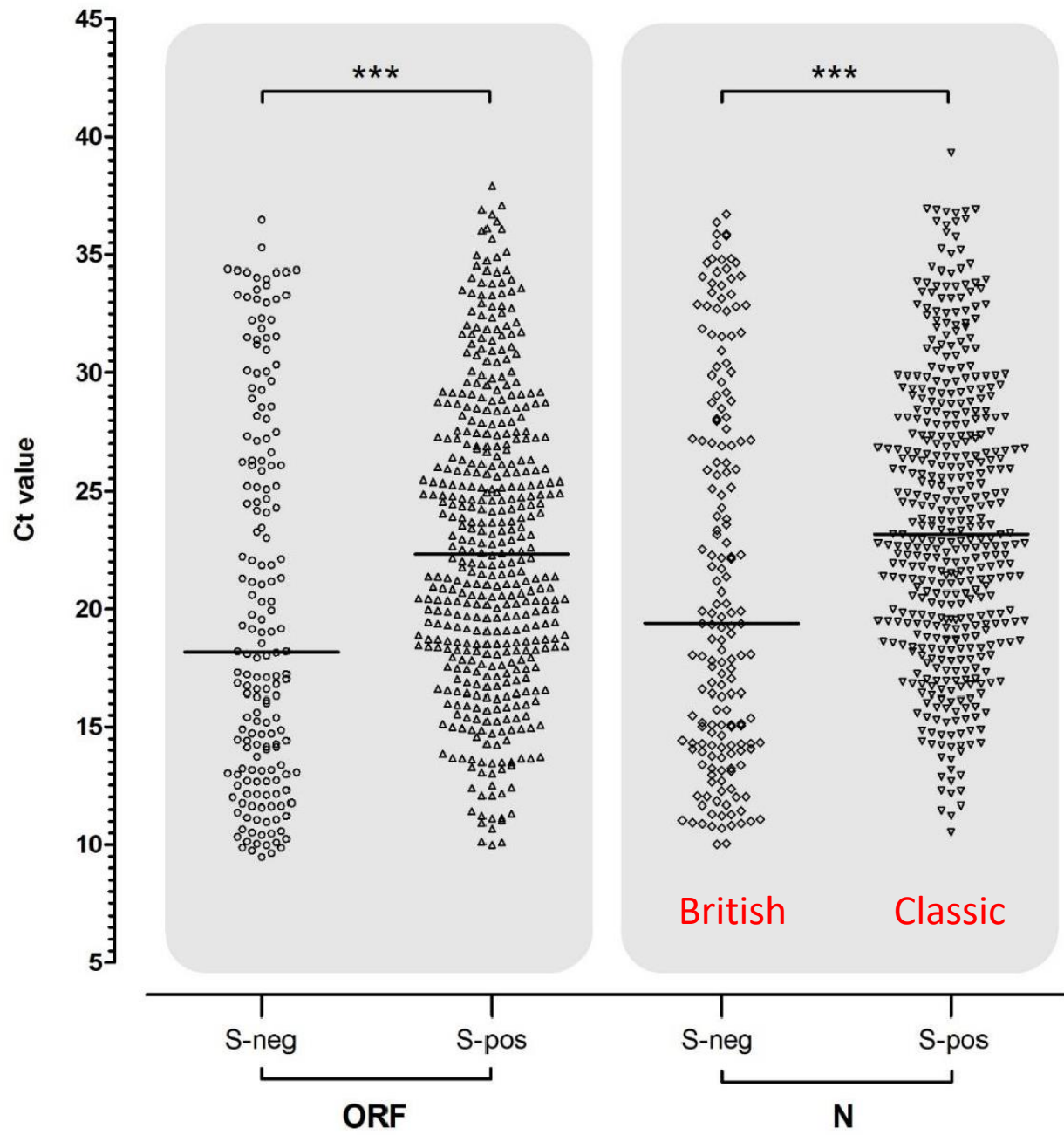
N. Mehdi.  
June 2020.





→ Evolution pressure:  $k$  should increase  
( $R$  of course also)

### Comparative Ct values for viral targets



Nielsen, B. F., Eilersen, A., Simonsen, L., & Sneppen, K. (2021). Lockdowns exert selection pressure on overdispersion of SARS-CoV-2 variants. *medRxiv*.

# → Shedding Summary:

- The more extreme the superspreader phenomenon, the easier it is to contain a COVID-19 epidemic !!!
- With 10%/75% superspreading, one can largely stop the Covid-19 epidemic by removing diffuse contacts
  - large events, public transportation, fitness centers etc
- And this will also be true in the middle of an epidemic!!!!
- Consider heterogeneity when modelling COVID-19 mitigation
- Superspreading explain large initial contrast between city and countryside.
- →→ Stay with you friends....
- Delta variant worse! 1000 times more virus,...
- Omicron lighter, infect upper part of lungs...

# Thanks to:

- **Andreas Eilersen**
- **Mathias Heltberg**
- **Bjarke Frost Nielsen**
- **Julius Kirkegaard**
- **Joachim Mathiesen**
- **Lone Simonsen**
- **Robert Taylor**
- **Xu Xiaochan**

## Publications:

### Cost–benefit of limited isolation and testing in COVID-19 mitigation

Andreas Eilersen, Kim Sneppen, [Scientific Reports 10.1 \(2020\): 1-7.](#)

### Overdispersion in COVID-19 increases the effectiveness of limiting nonrepetitive contacts for transmission control

K. Sneppen, BF. Nielsen, RJ Taylor, L. Simonsen, [PNAS, 118.14 \(2021\): e2016623118.](#)

### **Social network heterogeneity is essential for contact tracing**

Bjarke Frost Nielsen, Kim Sneppen, Lone Simonsen, Joachim Mathiesen  
[The European Physical Journal B 94 \(2021\): 1-11.](#)

### **Superspreading in cities vs the countryside.**

Andreas Eilersen, Kim Sneppen, [Apmis \(2021\) 2021, 129.7: 401-407.](#)

### **Superspreading quantified from bursty epidemic trajectories.**

Julius Kirkegaard & Kim Sneppen (2021). [Scientific Reports, 11\(1\), 24124.](#)

### **COVID-19 Superspreading Suggests Mitigation by Social Network Modulation**

Bjarke Frost Nielsen, Lone Simonsen, Kim Sneppen, [Phys. Rev. Letter 126.11 \(2021\): 118301.](#)

### Superspreading of airborne pathogens in a heterogeneous world

Julius B Kirkegaard, J. Mathiesen, Kim Sneppen, [Scientific reports 11.1 \(2021\): 1-9](#)

### **Lockdowns exert selection pressure on overdispersion of SARS-CoV-2 variants.**

Nielsen, B. F., Eilersen, A., Simonsen, L., & Sneppen, K. [Epidemics 40 \(2022\): 100613.](#)

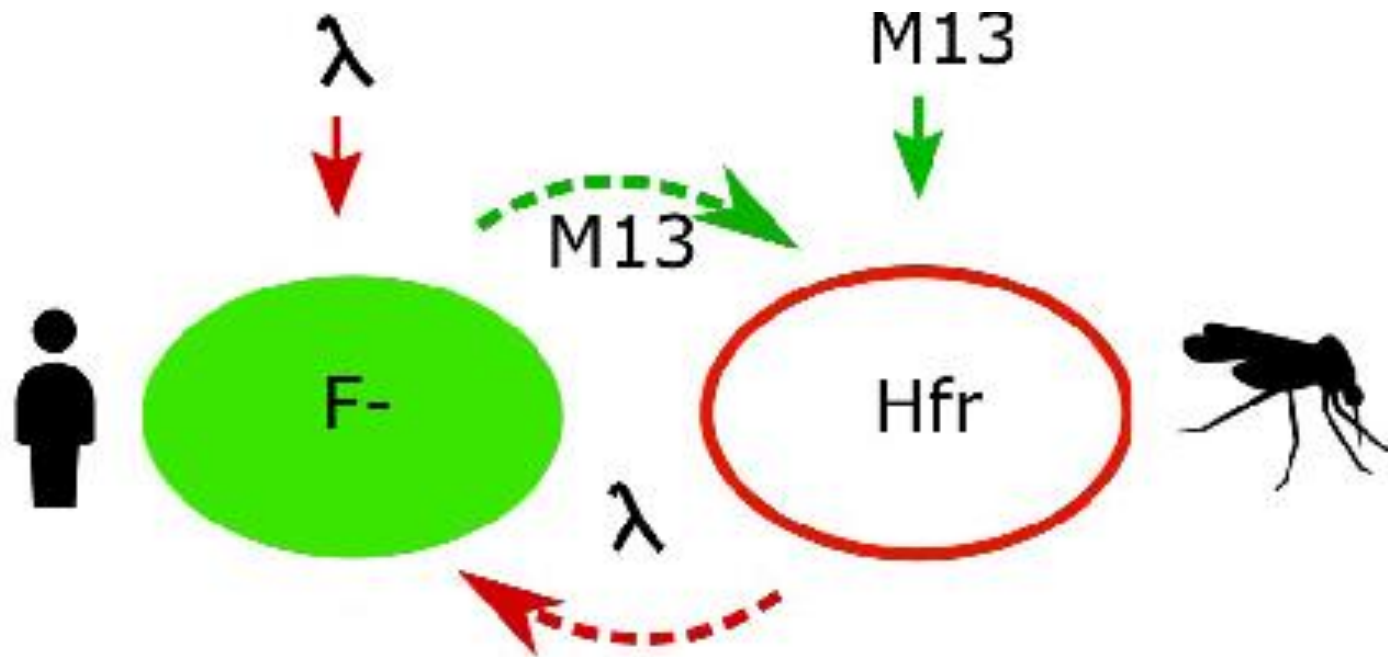
### **The timing of natural killer cell response in coronavirus infection: a concise model perspective.**

Xu, X., & Sneppen, K. (2021). [bioRxiv.](#)

# Synthetic Biology of Epidemics:

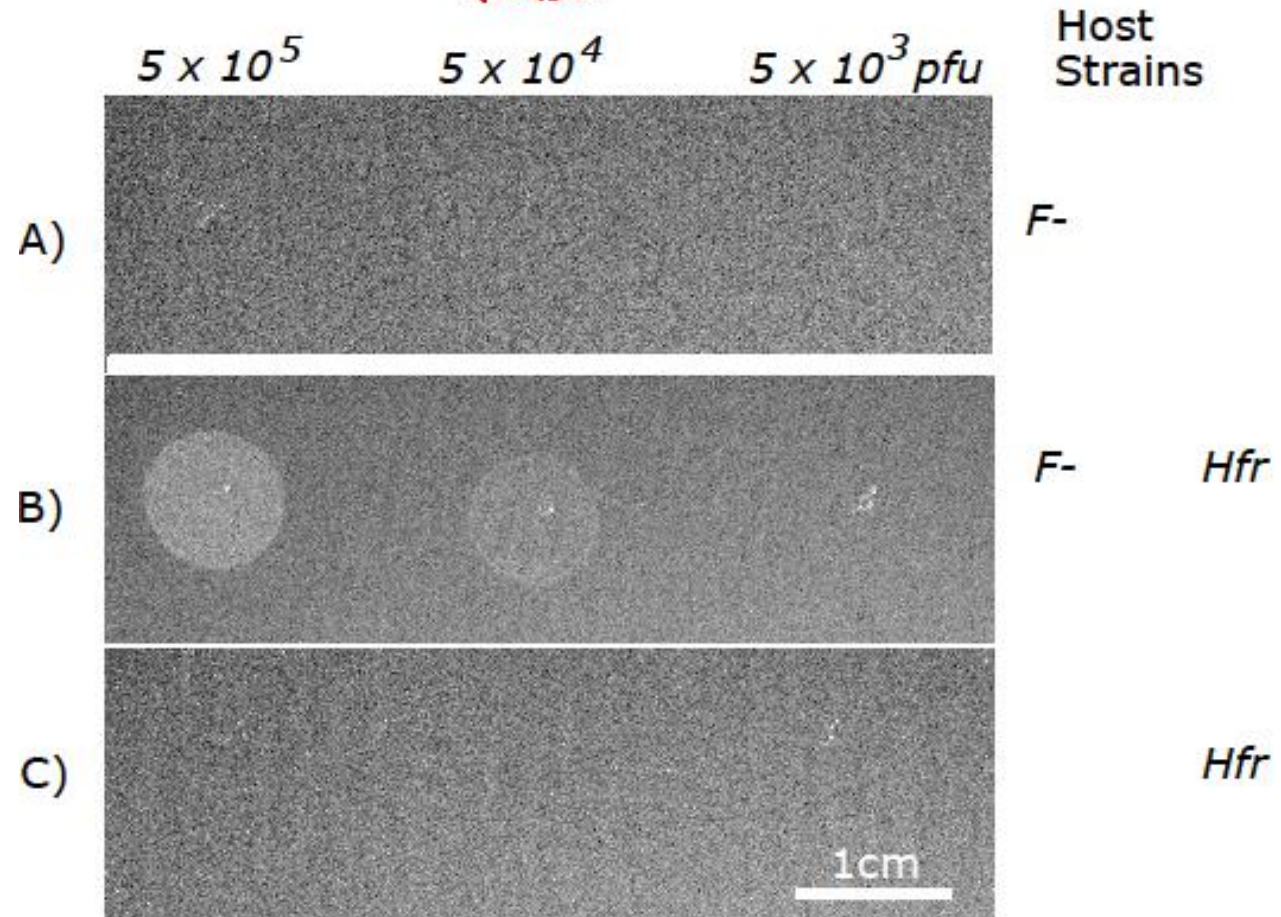
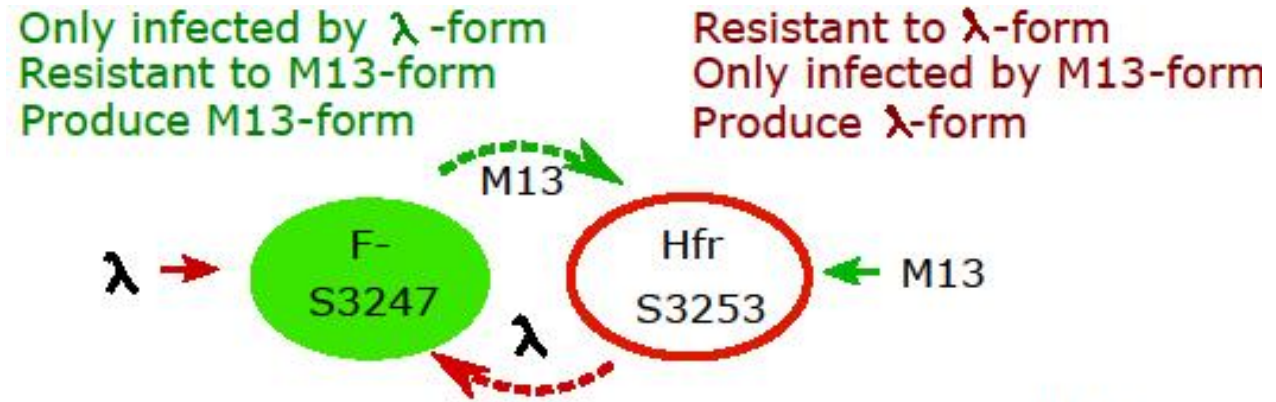
making lab models for exploring diseases X

Here of Vector borne diseases:



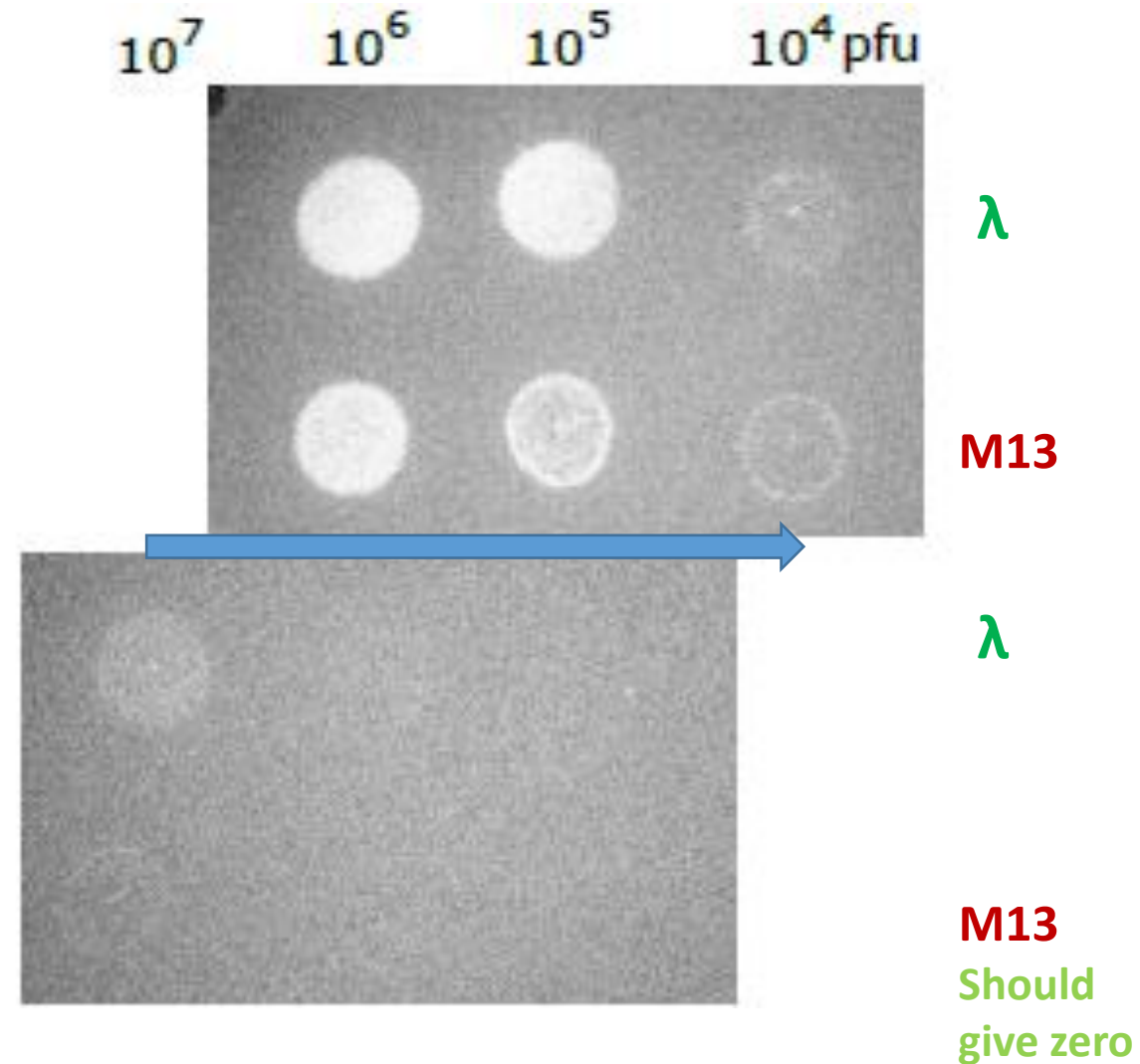
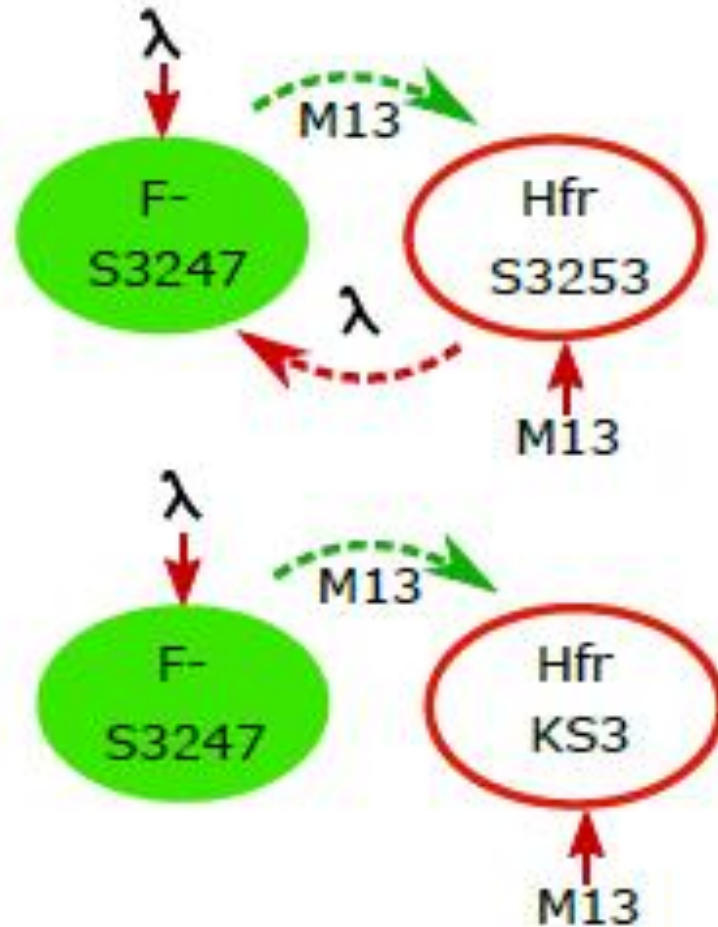
Done with bacterial constructed (gain of function) bacterial viruses & two mutant strains of E.coli

# Proof Of Construction:



# One cycle experiments:

1000-fold less spreading if only one cycle



# Model & parameters:

**S (prey)**

**E**

**I (predator)**

**R**

$$\frac{df}{dt} = \Gamma_f \cdot f \cdot C - \eta_\lambda \cdot P_\lambda \cdot f_{avai} + \Gamma_{cure} \cdot f^* \cdot C$$

$$\frac{df_1}{dt} = \eta_\lambda \cdot P_\lambda \cdot f_{avai} - f_1 \cdot \frac{n_m}{\tau_m} + \Gamma_f \cdot f_1 \cdot C$$

$$\frac{df_i}{dt} = f_{i-1} \cdot \frac{k_m}{\tau_m} - f_i \cdot \frac{k_m}{\tau_m} + \Gamma_f \cdot f_i \cdot C, \quad i = 2, 3, \dots$$

$$\frac{df^*}{dt} = f_n \cdot \frac{k_m}{\tau_m} + \Gamma_f \cdot f^* \cdot C - \Gamma_{cure} \cdot f^* \cdot C$$

$$\frac{dP_m}{dt} = \Omega_m \cdot f^* \cdot C - \eta_m \cdot P_m \cdot v_{abs} - Loss_m \cdot P_m$$

$$\frac{dv}{dt} = \Gamma \cdot v \cdot C - \eta_m \cdot P_m \cdot v_{avai}$$

$$\frac{dv_1}{dt} = \eta_m \cdot P_m \cdot v_{avai} - v_1 \frac{k_\lambda}{\tau_\lambda}$$

$$\frac{dv_i}{dt} = v_{i-1} \cdot \frac{k_\lambda}{\tau_\lambda} - v_i \cdot \frac{k_\lambda}{\tau_\lambda} \quad \text{for } i = 2, 3, \dots, n_\lambda$$

$$\frac{dP_\lambda}{dt} = \beta \cdot C \cdot v_{n_\lambda} \frac{k_\lambda}{\tau_\lambda} - \eta_\lambda \cdot P_\lambda \cdot f_{abs} - Loss \cdot P_\lambda$$

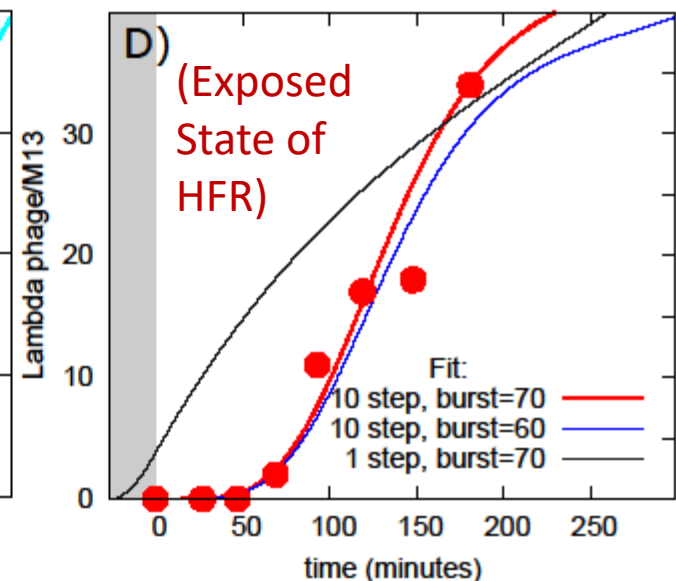
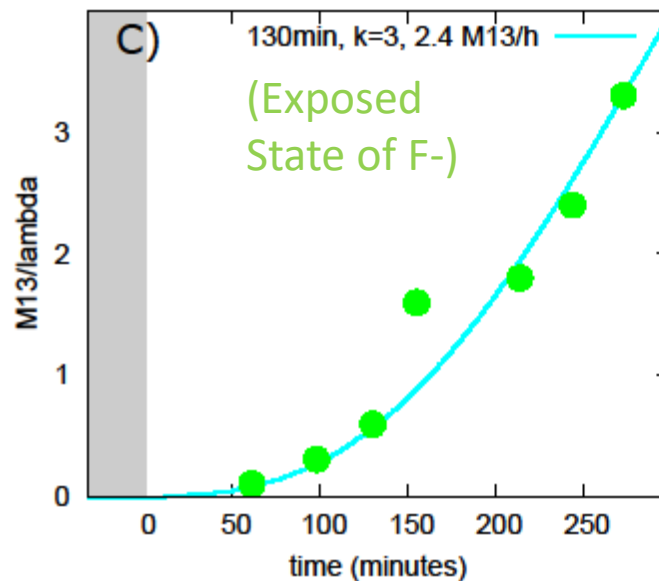
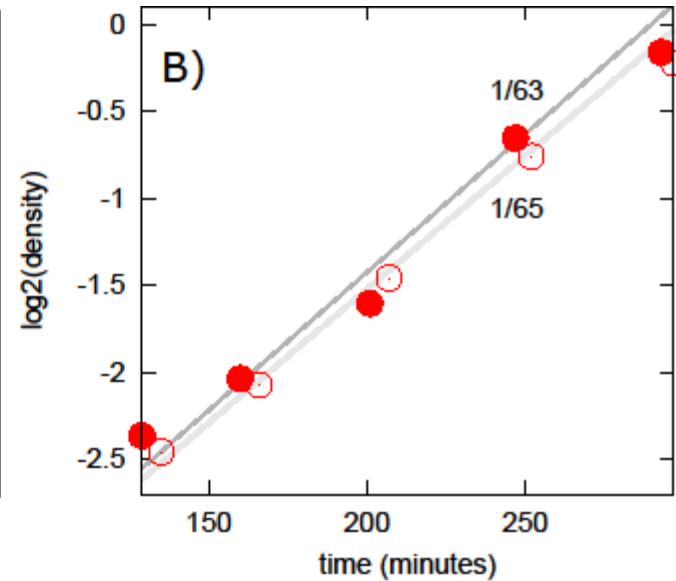
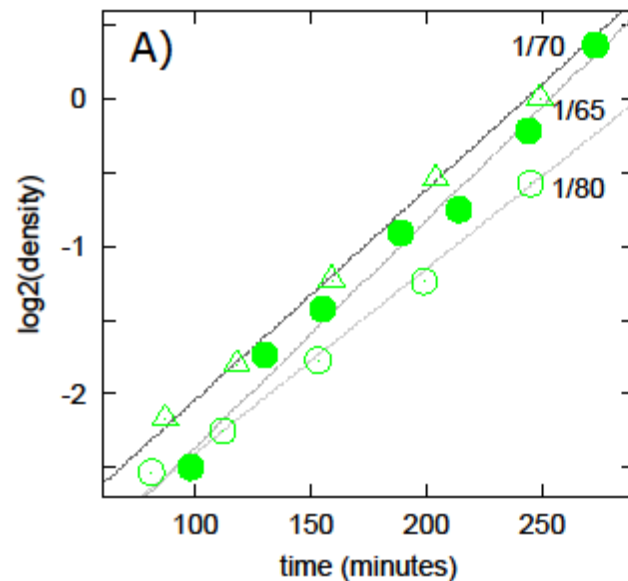
**Colony Level Correction**

$$v_{abs} = v_0 \cdot \left( \frac{v + v^L}{v_0} \right)^{1/3}$$

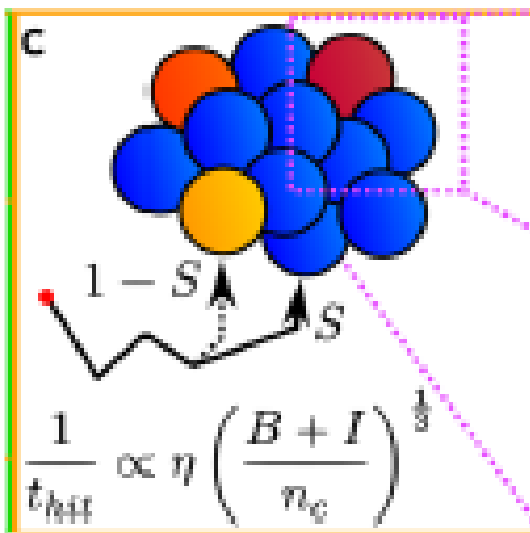
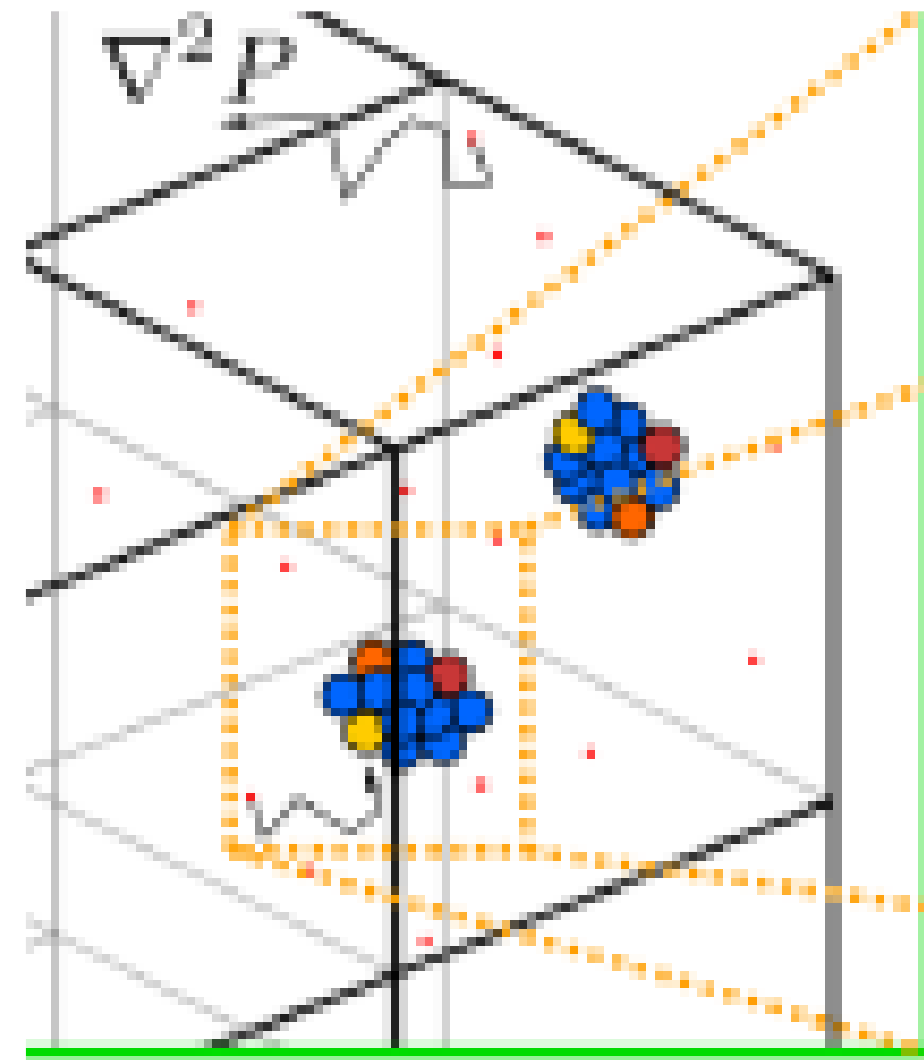
$$v_{avai} = v_{abs} \cdot \exp \left( - \frac{\frac{v^L}{v_0}}{4 \cdot \left( \frac{v + v^L}{v_0} \right)^{2/3}} \right)$$

$$f_{abs} = f_0 \cdot \left( \frac{f + f^L + f^*}{f_0} \right)^{1/3}$$

$$f_{avai} = f_{abs} \cdot \exp \left( - \frac{\frac{(f^L + f^*)}{v_0}}{4 \cdot \left( \frac{f + f^L + f^*}{v_0} \right)^{2/3}} \right)$$







$$v_{abs} = v_0 \cdot \left( \frac{v + v^L}{v_0} \right)^{1/3}$$

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$$f_{avai} = f_{abs} \cdot \exp \left( - \frac{\frac{f^L + f^*}{v_0}}{4 \cdot \left( \frac{f + f^L + f^*}{v_0} \right)^{2/3}} \right)$$

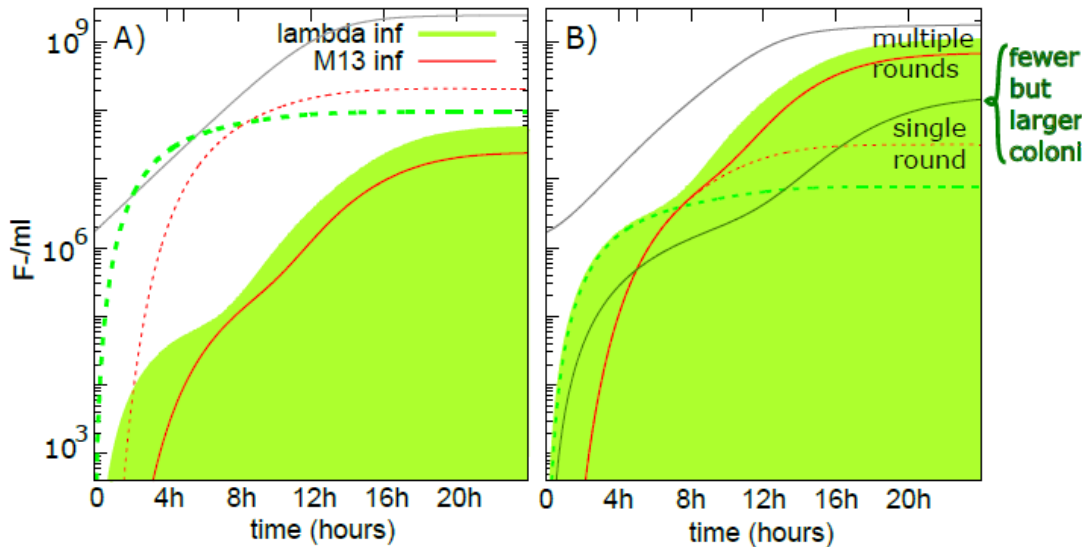
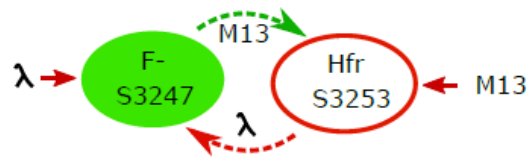
# Model & model parameters:

$$\begin{aligned} \frac{df}{dt} &= \Gamma_f \cdot f \cdot C - \eta_\lambda \cdot P_\lambda \cdot f_{avai} + \Gamma_{cure} \cdot f^* \cdot C \\ \frac{df_1}{dt} &= \eta_\lambda \cdot P_\lambda \cdot f_{avai} - f_1 \cdot \frac{n_m}{\tau_m} + \Gamma_f \cdot f_1 \cdot C \\ \frac{df_i}{dt} &= f_{i-1} \cdot \frac{k_m}{\tau_m} - f_i \cdot \frac{k_m}{\tau_m} + \Gamma_f \cdot f_i \cdot C, \quad i = 2, 3, \dots \\ \frac{df^*}{dt} &= f_n \cdot \frac{k_m}{\tau_m} + \Gamma_f \cdot f^* \cdot C - \Gamma_{cure} \cdot f^* \cdot C \\ \frac{dP_m}{dt} &= \Omega_m \cdot f^* \cdot C - \eta_m \cdot P_m \cdot v_{abs} - Loss_m \cdot P_m \\ \frac{dv}{dt} &= \Gamma \cdot v \cdot C - \eta_m \cdot P_m \cdot v_{avai} \\ \frac{dv_1}{dt} &= \eta_m \cdot P_m \cdot v_{avai} - v_1 \frac{k_\lambda}{\tau_\lambda} \\ \frac{dv_i}{dt} &= v_{i-1} \cdot \frac{k_\lambda}{\tau_\lambda} - v_i \cdot \frac{k_\lambda}{\tau_\lambda} \quad \text{for } i = 2, 3, \dots, n_\lambda \\ \frac{dP_\lambda}{dt} &= \beta \cdot C \cdot v_{n_\lambda} \frac{k_\lambda}{\tau_\lambda} - \eta_\lambda \cdot P_\lambda \cdot f_{abs} - Loss \cdot P_\lambda \\ v_{abs} &= v_0 \cdot \left( \frac{v + v^L}{v_0} \right)^{1/3} \\ v_{avai} &= v_{abs} \cdot \exp \left( - \frac{\frac{v^L}{v_0}}{4 \cdot \left( \frac{v + v^L}{v_0} \right)^{2/3}} \right) \\ f_{abs} &= f_0 \cdot \left( \frac{f + f^L + f^*}{f_0} \right)^{1/3} \\ f_{avai} &= f_{abs} \cdot \exp \left( - \frac{\frac{(f^L + f^*)}{v_0}}{4 \cdot \left( \frac{f + f^L + f^*}{v_0} \right)^{2/3}} \right) \end{aligned}$$

Parameter	and its meaning	Value	Source
$\Gamma_f$	Growth rate (F <sup>-</sup> )	$\ln(2)/(72\text{min})$	Figure 4A
$\Gamma_{cure}$	Loss of infectivity	$0.8 \cdot \Gamma_f$	Fit to Fig. 2B
$\Gamma$	Growth rate (Hfr)	$\ln(2)/(64\text{min})$	Figure 4B
$K$	carrying capacity	$3.1 \cdot 10^9/\text{ml}$	saturated broth culture
$f_0$	initial F <sup>-</sup>	$1.6 \cdot 10^5/\text{ml}$	Measured
$v_0$	initial Hfr	$1.6 \cdot 10^6/\text{ml}$	Measured
$\eta_\lambda$	adsorption of $\lambda$	$0.65/\text{min}/(10^9/\text{ml})$	From ref. [15]
$\eta_m$	adsorption of M13	$0.09/\text{min}/(10^9/\text{ml})$	From ref. [16]
$Loss_\lambda$	Loss of $\lambda$ phage	$1/(650\text{min})$	Loss from 0.9mm with $6.2\mu\text{m}^2/\text{s}$ diffusion
$Loss_m$	Loss of M13 phage	$1/(650\text{min})$	Estimated as $Loss_\lambda$
$\Omega_m$	Production of M13	$0.040/\text{min} \times 0.5$	Figure 4C
$\tau_m$	Latency time (M13)	130min	Figure 4C
$k_m$	Latency form factor	3	Figure 4C
$\beta$	Burst of $\lambda$	70	Figure 4D
$\tau_\lambda$	Latency time ( $\lambda$ )	150min	Figure 4D
$k_\lambda$	Latency form factor	10	Figure 4D

Need to consider colony level heterogeneity to reproduce Data with reasonable parameters (weakens phage to travel)

# Model Simulations:

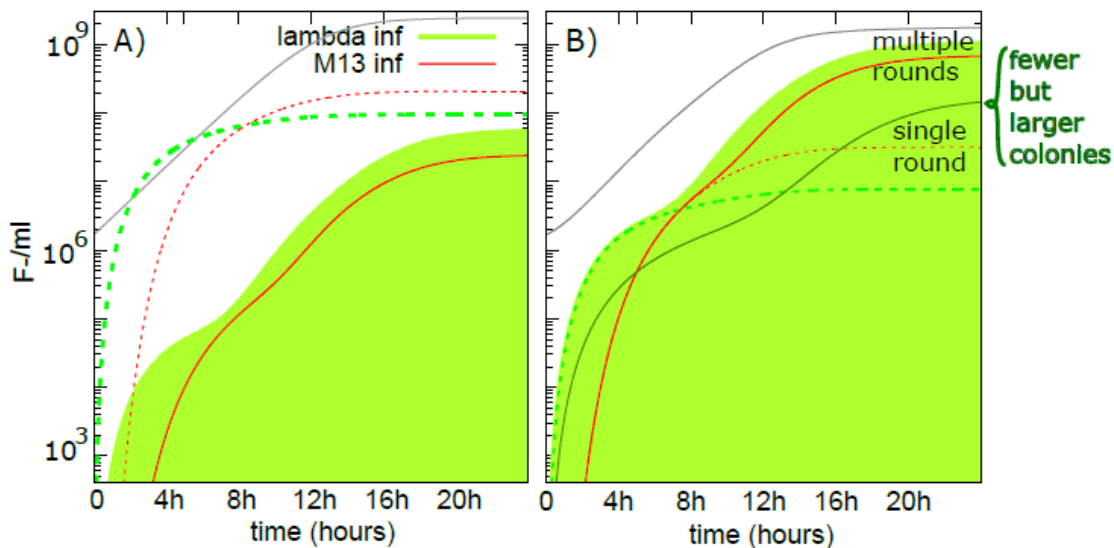
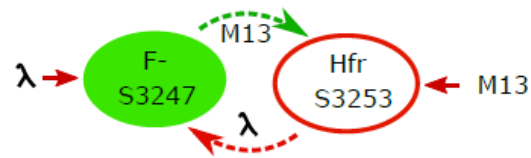


Parameter	and its meaning	Value	Source
$\Gamma_f$	Growth rate ( $F^-$ )	$\ln(2)/(72\text{min})$	Figure 4A
$\Gamma_{cure}$	Loss of infectivity	$0.8 \cdot \Gamma_f$	Fit to Fig. 2B
$\Gamma$	Growth rate (Hfr)	$\ln(2)/(64\text{min})$	Figure 4B
$K$	carrying capacity	$3.1 \cdot 10^9 / \text{ml}$	saturated broth culture
$f_0$	initial $F^-$	$1.6 \cdot 10^5 / \text{ml}$	Measured
$v_0$	initial Hfr	$1.6 \cdot 10^6 / \text{ml}$	Measured
$\eta_\lambda$	adsorption of $\lambda$	$0.65 / \text{min} / (10^9 / \text{ml})$	From ref. [15]
$\eta_m$	adsorption of M13	$0.09 / \text{min} / (10^9 / \text{ml})$	From ref. [16]
$Loss_\lambda$	Loss of $\lambda$ phage	$1 / (650\text{min})$	Loss from 0.9mm with $6.2 \mu\text{m}^2 / \text{s}$ diffusion
$Loss_m$	Loss of M13 phage	$1 / (650\text{min})$	Estimated as $Loss_\lambda$
$\Omega_m$	Production of M13	$0.040 / \text{min} \times 0.5$	Figure 4C
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$\beta$	Burst of $\lambda$	70	Figure 4D
$\tau_\lambda$	Latency time ( $\lambda$ )	150min	Figure 4D
$k_\lambda$	Latency form factor	10	Figure 4D

Reproducing data of (adjust Gamma\_cure)

Single round experiment,  
With 1000 fold larger MOI  
(don't fit dotted red line,  
KS5 failure).

# Model $\leftrightarrow$ Experiment: Social Heterogeneity & Herd immunity...



Bact. Density	$\lambda$ -form PFU per spot	Ratio data	Ratio model
$\times 0.1$	$3.7 \times 10^5$ , $1.2 \times 10^5$	9	12
$\times 1$	$4.1 \times 10^4$ , $1.4 \times 10^4$	1	1
$\times 10$	$1.4 \times 10^4$ , $4.6 \times 10^3$	0.3	0.7
	M13-form PFU per spot		
$\times 0.1$	$1.0 \times 10^7$ , $3.3 \times 10^6$	18	25
$\times 1$	$3.7 \times 10^5$ , $3.7 \times 10^5$	1	1
$\times 10$	$4.1 \times 10^4$ , $4.1 \times 10^4$	0.1	0.3
Immune Strain (50%)	$\lambda$ -form PFU per spot		
none	$4.1 \times 10^4$ , $4.1 \times 10^4$ , $4.1 \times 10^4$	1	1
F <sup>-</sup>	$3.3 \times 10^6$ , $1.1 \times 10^6$ , $1.1 \times 10^6$	45	50
Hfr	$1.2 \times 10^5$ , $4.1 \times 10^4$ , $1.2 \times 10^5$	2.3	3.3
	M13-form PFU per spot		
none	$3.7 \times 10^5$ , $1.0 \times 10^5$	1	1
F <sup>-</sup>	$1.0 \times 10^7$ , $1.0 \times 10^7$	63	40
Hfr	$1.1 \times 10^6$ , $1.0 \times 10^5$	2	5

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- **Sine Svenningsen**
- **Isabella Østerlund**

## A Synthetic Biology System for Vector-Borne Diseases

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