

# Challenges in estimating parameters and characterizing transmission dynamics from incomplete epidemic data

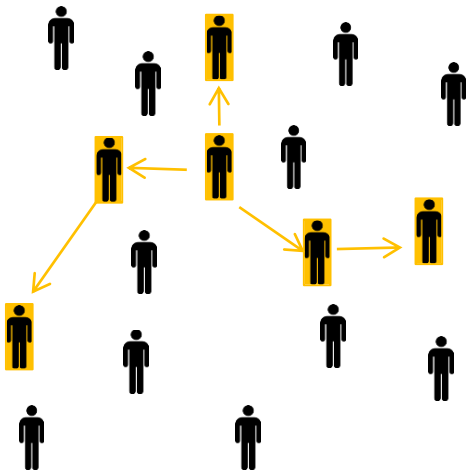
**Simon Cauchemez**

Mathematical Modelling of Infectious Diseases Unit

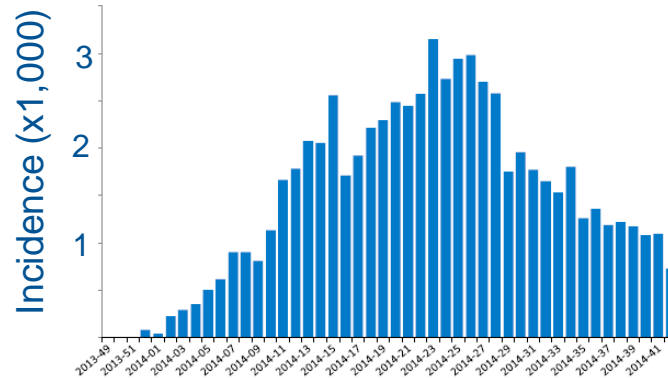
Institut Pasteur, Paris

# The multiple scales of spread

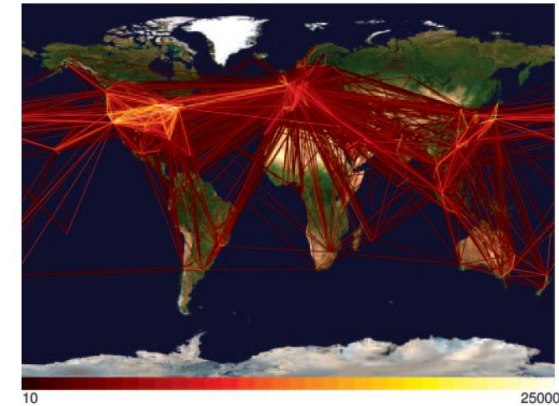
## Local



## Regional / national



## International



- Analysis of detailed outbreak data is critical to estimate transmission parameters of infectious diseases
- But burdened by a number of challenges: missing data, measurement errors, censoring...
- Bayesian data augmentation have played a key role to address these challenges and maximize insight

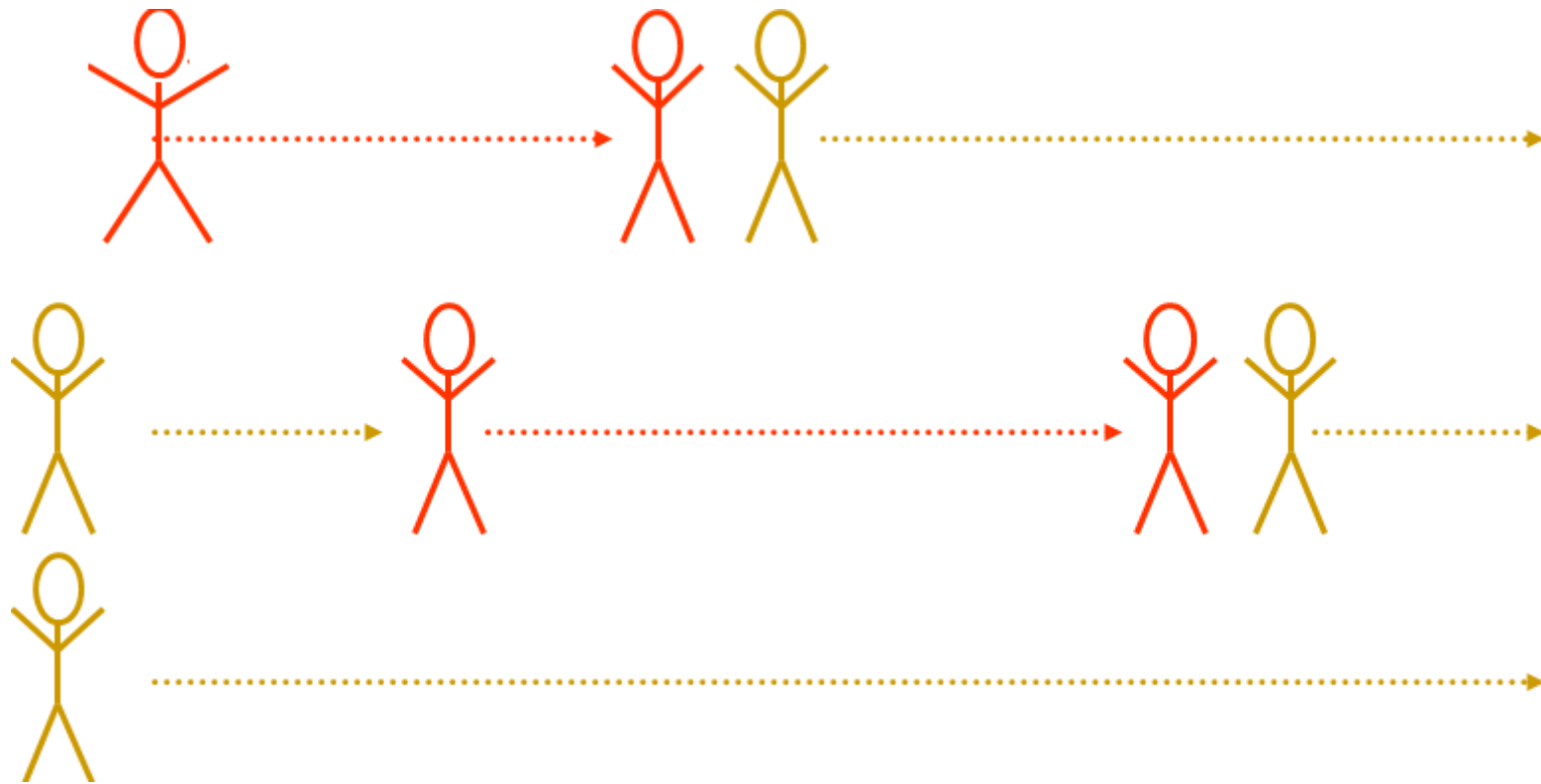
# Studying transmission from incomplete data

- Household transmission studies.
- Progressively adding more complexity to the analysis:
  - Missing data issues.
  - Complex social structures.
  - Space.
  - Repeated measurements.
- Different pathogens:
  - Seasonal and pandemic influenza;
  - Chikungunya and dengue.
- Future directions.

# Study of influenza transmission in French households

[Cauchemez et al, Stat Med, 2004; Ferguson et al, Nature 2005]

Follow-up of symptoms in 334 households for 15 days after onset in a confirmed index case



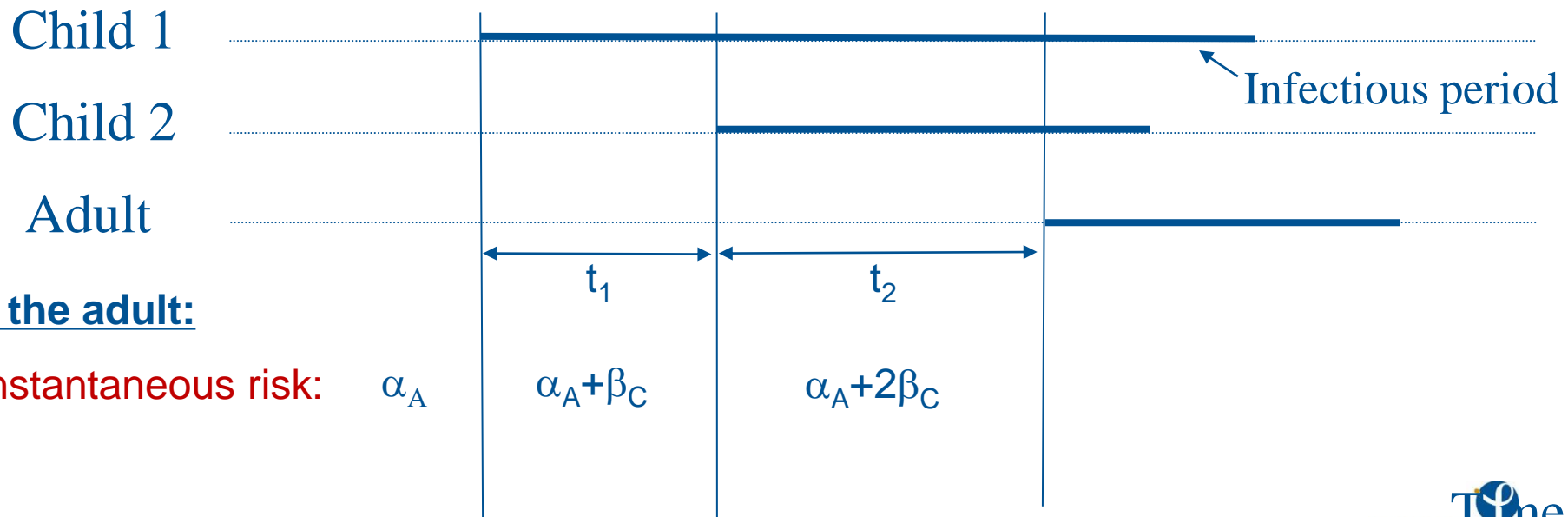
# Transmission model and likelihood-based inference from complete data

Model for the hazard of infection of individual  $s$  at time  $t$  in the household:

$$\lambda_s(t) = \alpha_s + \sum_{i \in I(t)} \beta_i$$

Hazard of infection outside household

Force of infection exerted by infectious household members



**For the adult:**

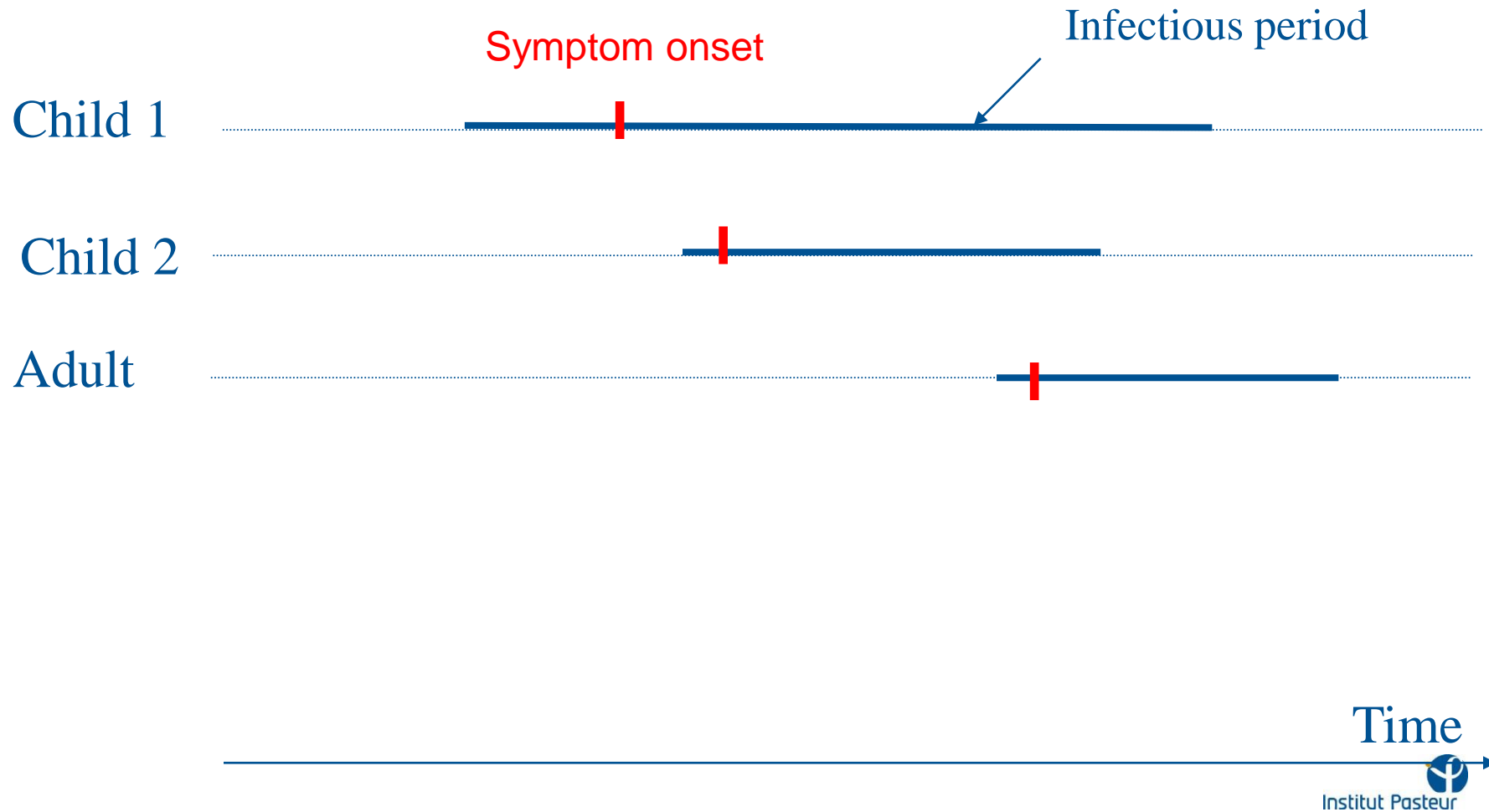
➤ Instantaneous risk:  $\alpha_A$

$\alpha_A + \beta_C$

$\alpha_A + 2\beta_C$

# Inference from incomplete data (1)

- Infectious periods are unknown – we just observe dates of symptom onset;
- Explore trajectories consistent with data on symptoms onset.



# Inference from incomplete data (2)

- Notations:

- $Y$ : observed data – dates of symptom onset
- $Z$ : “missing” (augmented) data – dates when infectivity starts and when it ends;
- $\theta$ : parameters

- Three-level hierarchical model:

$$P(Y, Z, \theta) = P(Y | Z) P(Z | \theta) P(\theta)$$

Observation level: ensures that augmented data consistent with observed data

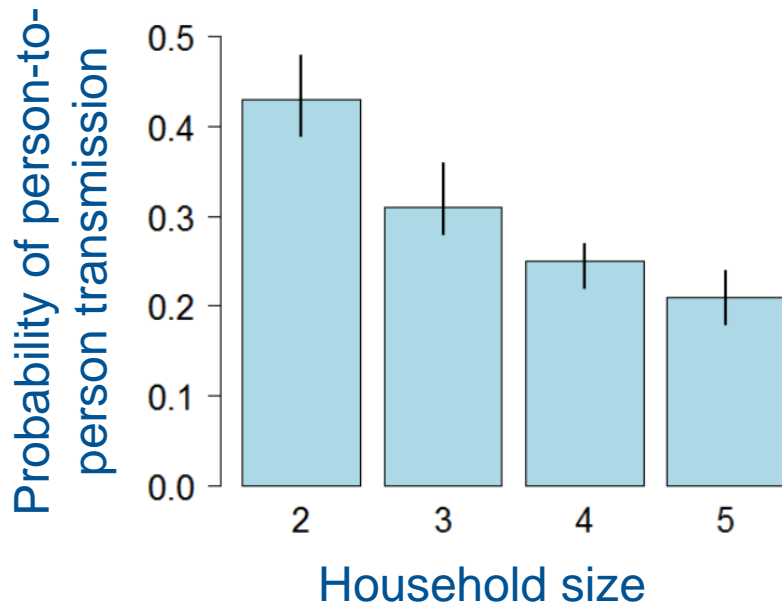
Prior level

Transmission level: describes the latent transmission process

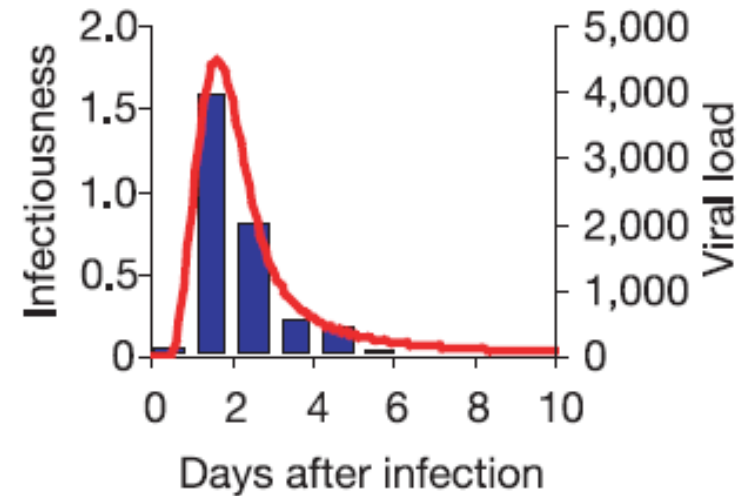
- Joint posterior distribution of augmented data and parameters explored via MCMC.

# Transmission of seasonal influenza in French households [Cauchemez et al, Stat Med, 2004; Ferguson et al, Nature 2005]

## Household structure and transmission



## Key transmission parameters: the generation time



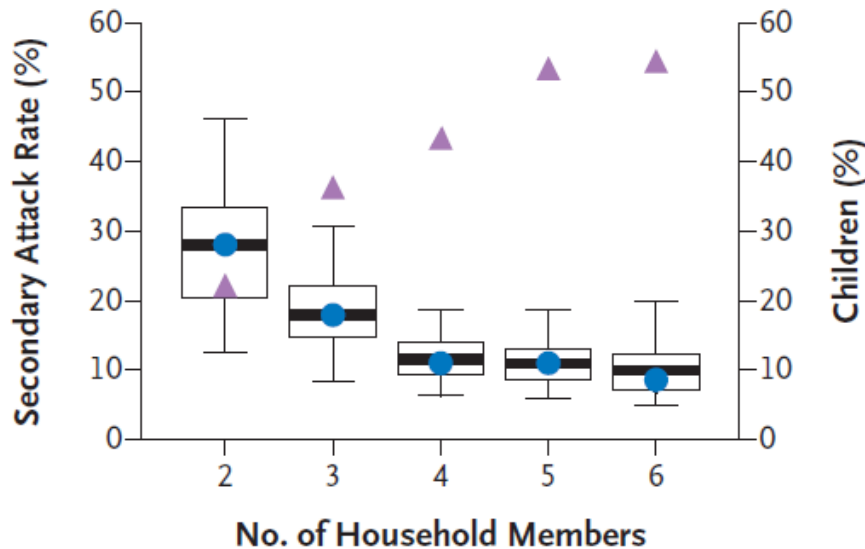
- Substantially shorter than initially thought (2.6 vs 4.1 days)
- Important implications for control



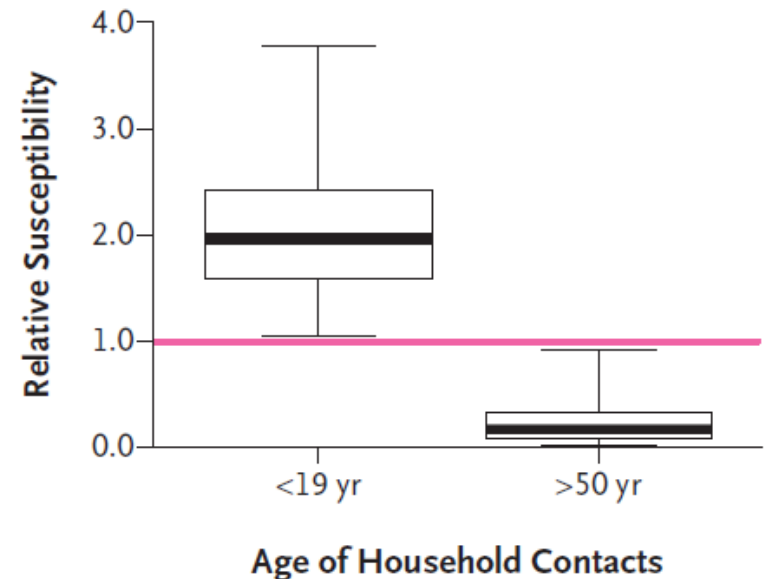
# Household studies for early assessment during the 2009 H1N1 pandemic [Cauchemez et al, NEJM 2009]

Collaboration with CDC – Follow-up of 216 households for 7 days

Transmission risks within households

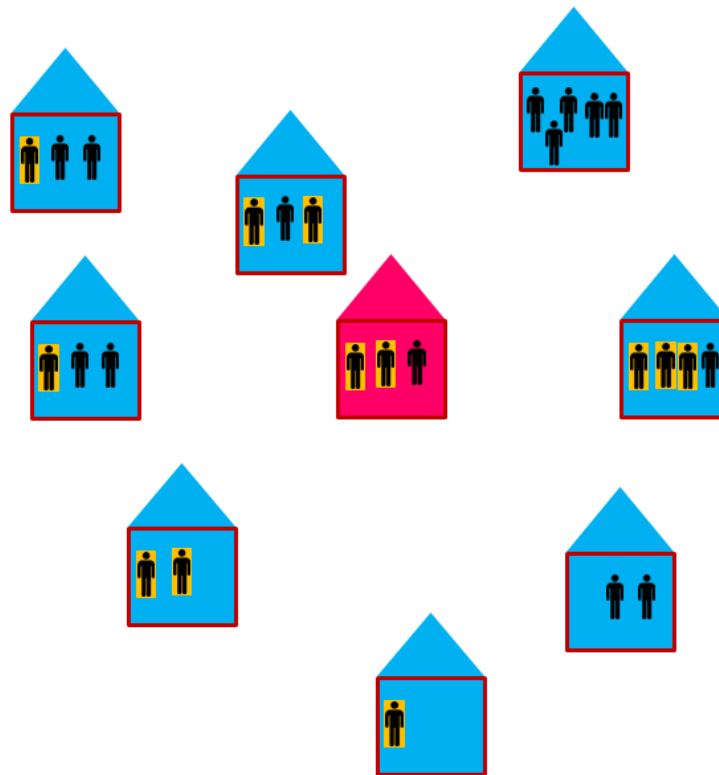


Children twice more susceptible than adults



# Need for more developments

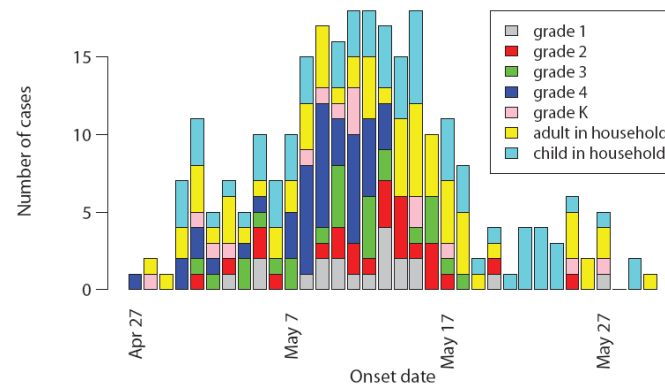
**Households are not isolated  
from the rest of the world!**



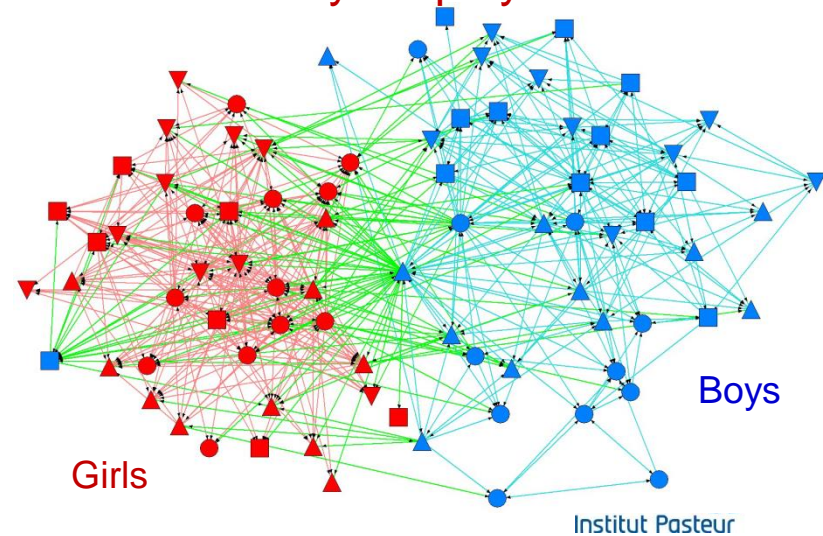
# Transmission in other settings: A school outbreak of pandemic influenza in 2009 [Cauchemez et al, PNAS, 2011]

- Demographic & clinical information collected on students and their family members – 2 phone interviews:
  - 370 students,
  - 899 household members.
- Surveys in school for 4<sup>th</sup> graders:
  - Activities,
  - Seating charts,
  - Playmates.

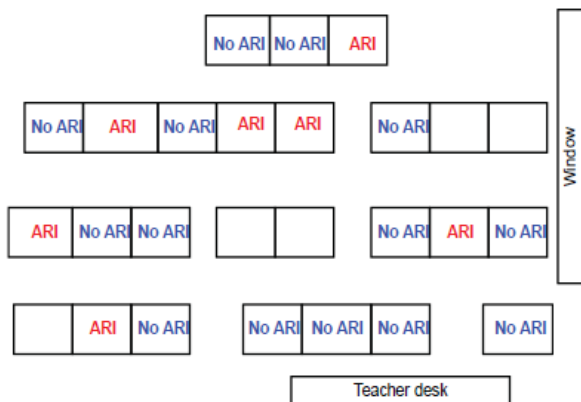
## Epidemic curve



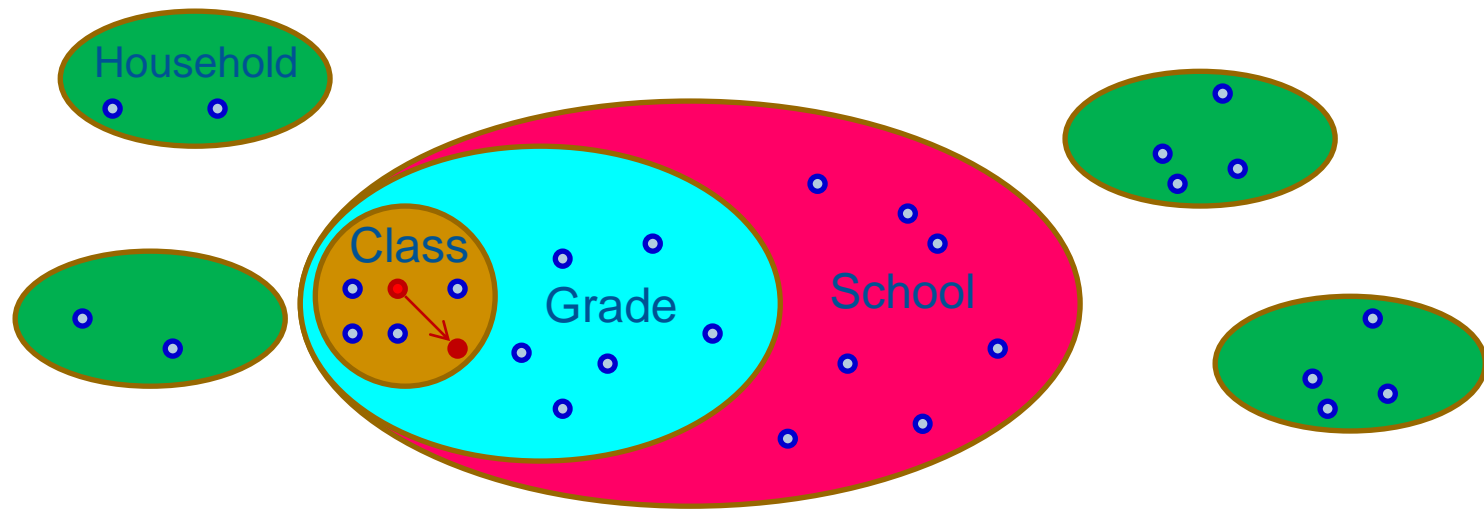
## Social networks - Who are your playmates?



## Seating charts

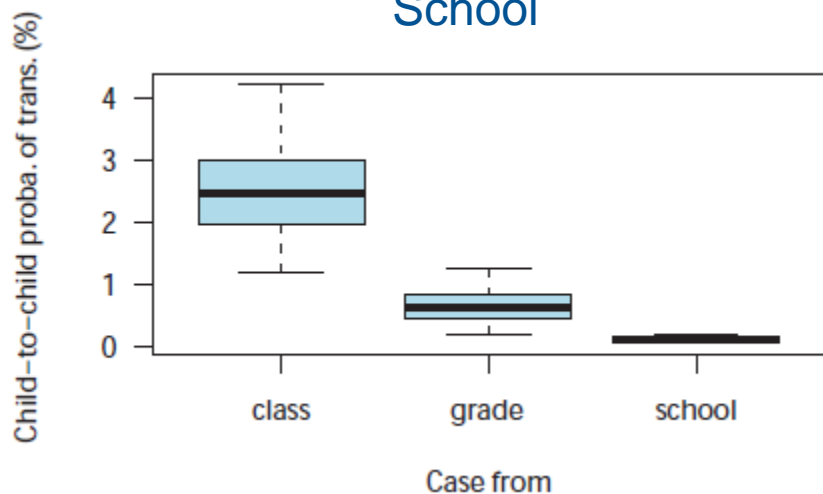


# Statistical model

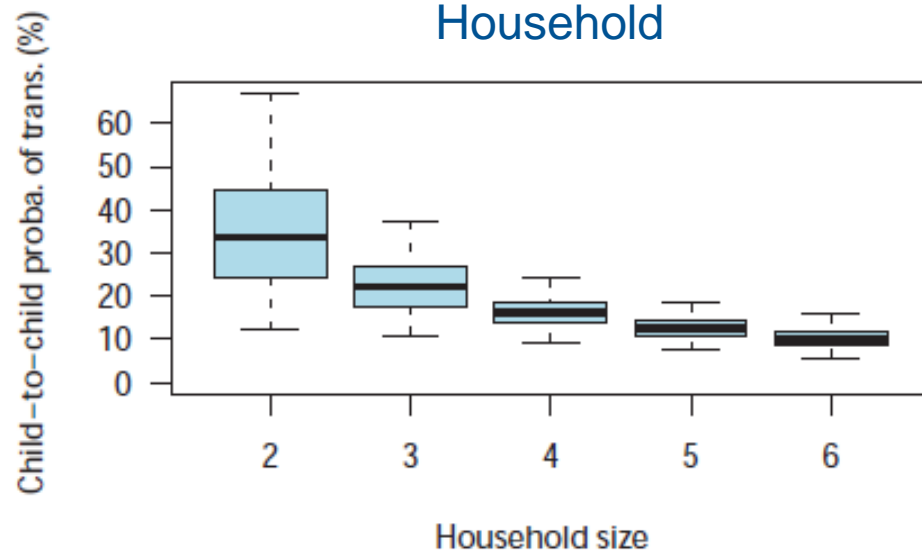


# Transmission rates in the school and in the household

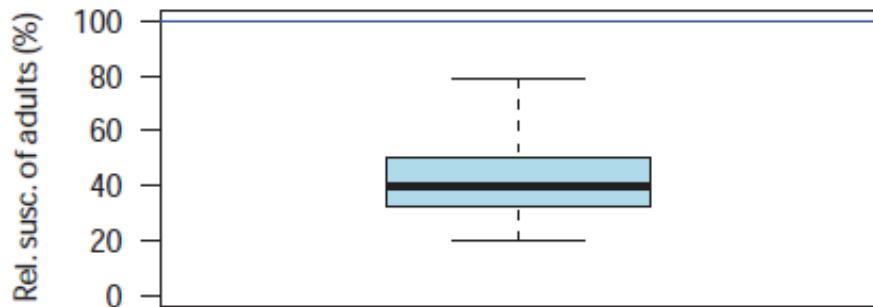
## School



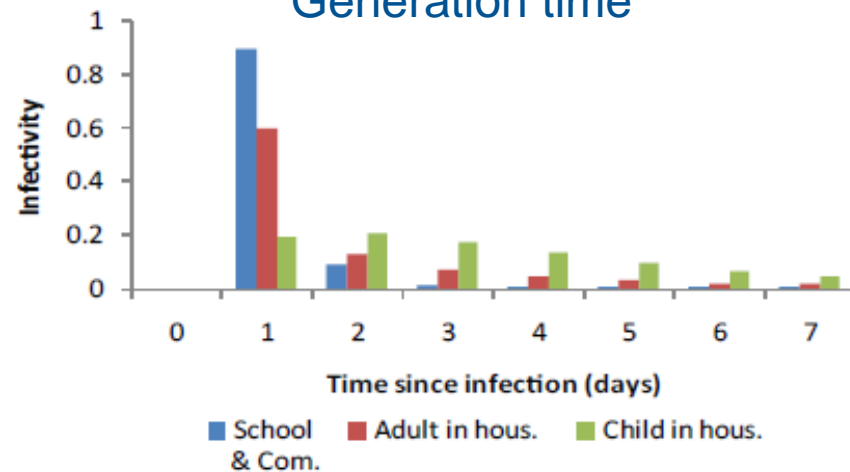
## Household



## Age dependent susceptibility

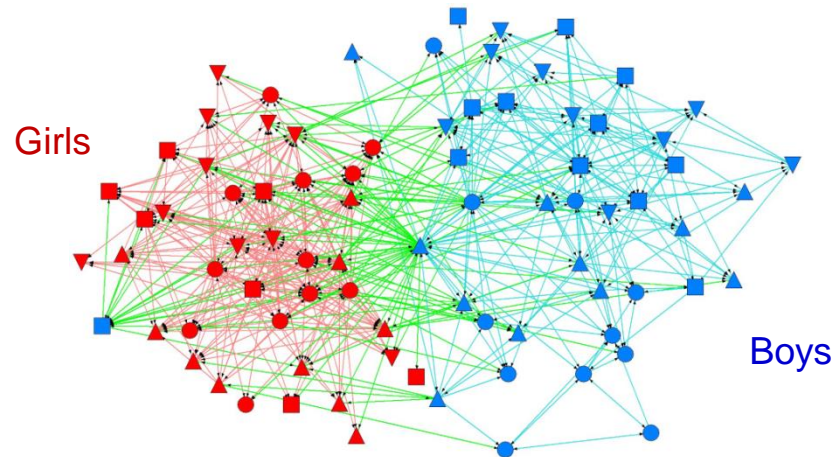


## Generation time



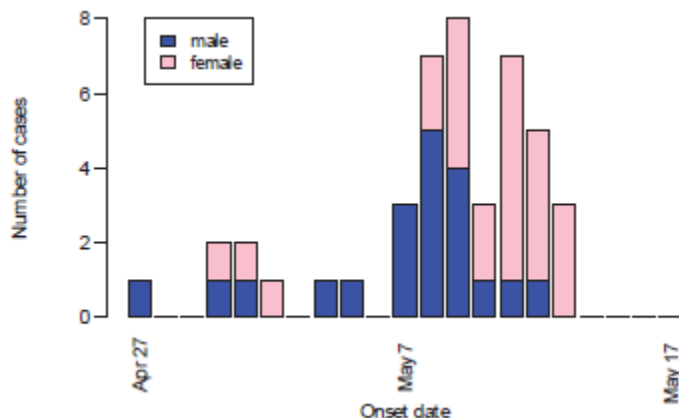
# Gender-related mixing & transmission patterns

Social networks: Students are 4 times more likely to play with students of the same gender

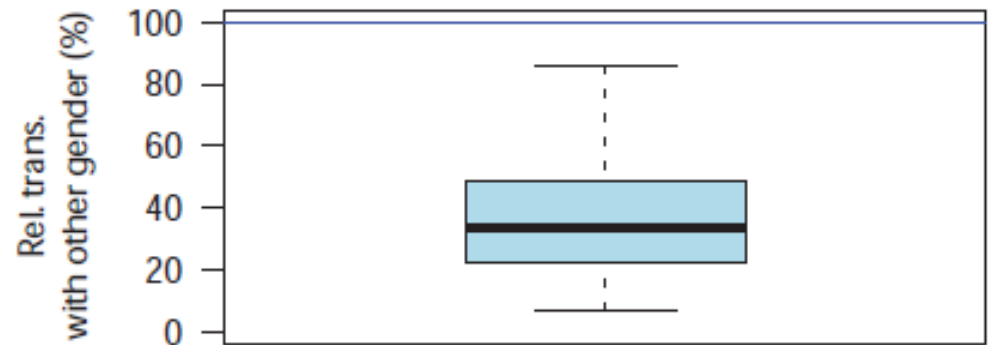


Evidence that this aspect of mixing patterns affected the transmission dynamics

i) Boys had onset before girls! ( $p=0.023$ )



ii) Bayes Factor for model with gender-effect: 8.0

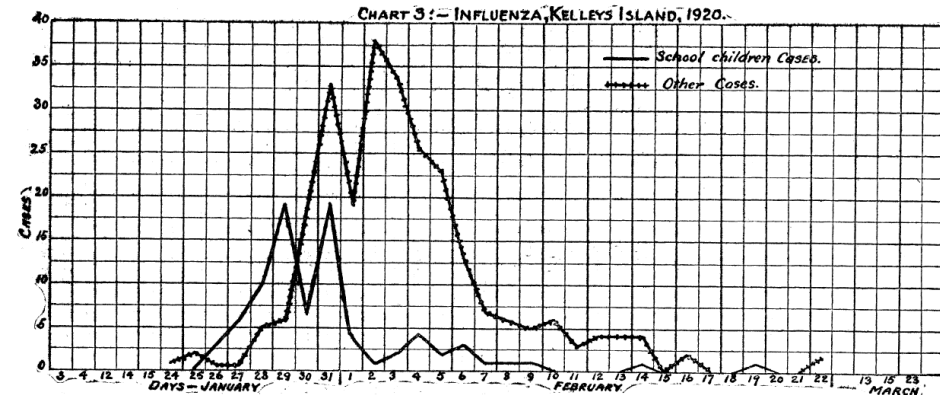


# Was influenza transmission different 100 years ago?

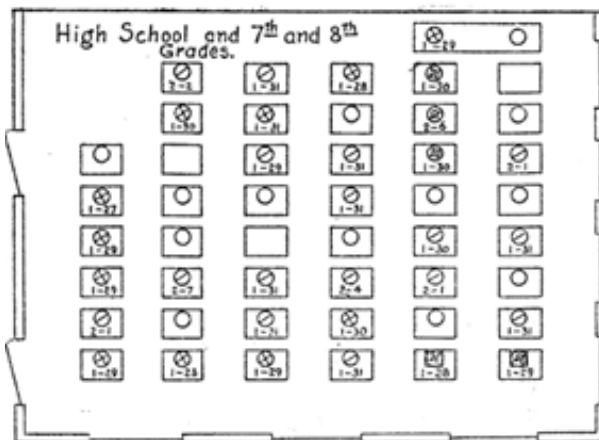
## Pandemic flu in Kelly Island, 1920 (C. Armstrong)

- Isolated island, 689 inhabitants;
- Epidemic period: 24 Jan – 16 Feb 1920.
- Investigation begins 19 Feb 1920.
- Demographic, clinical and contact information collected on the 689 inhabitants of the island.

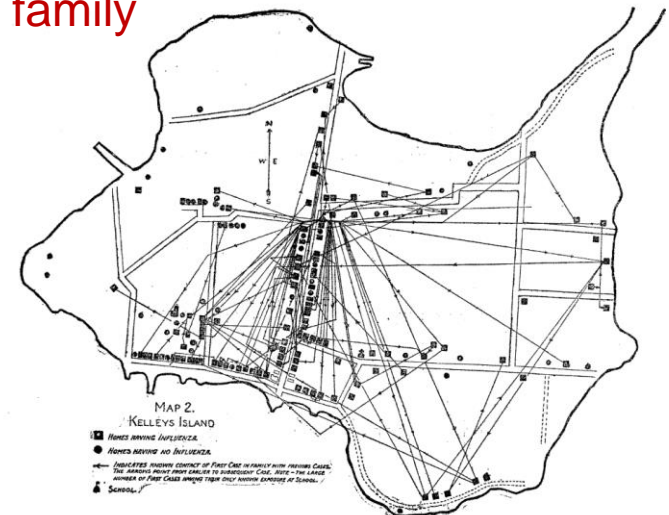
### Epidemic curves



### Seating charts



### Known contact for first case in family





# Additional difficulty: Individual records have been destroyed

- No individual level records available, even after Armstrong's daughter examined his personal effects.
- However, some person specific, and a lot of marginal data available in the paper
  - Epidemic curves for different types of cases e.g. students/others, first case in HH...
  - Whether first case in each HH is a student,
  - Know contact for first case in family,
  - Age and sex distribution of cases,
  - Generation times in HH,
  - General census info on HH structure...

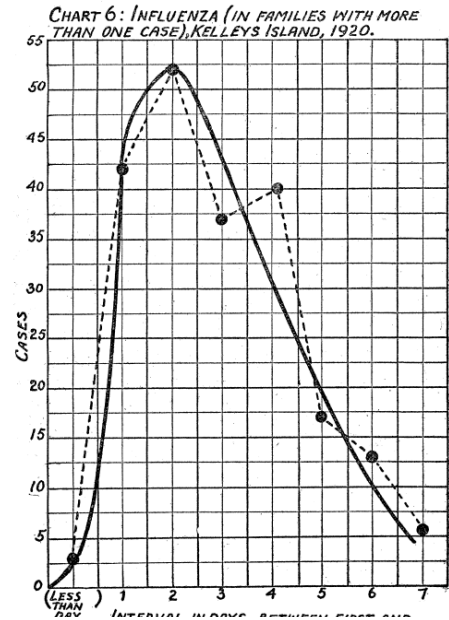
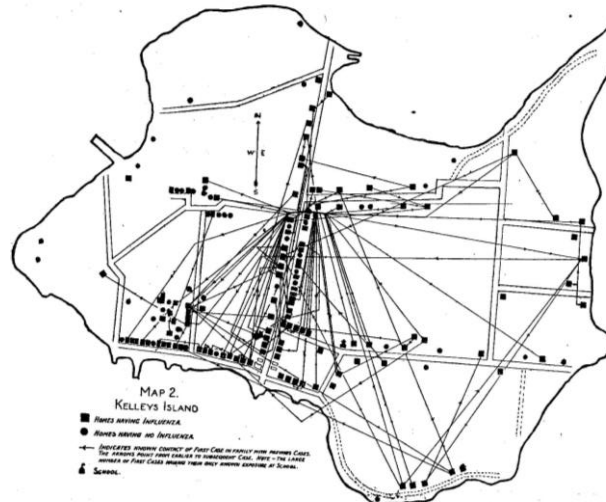


TABLE XIII.—Summary of 27 known contacts followed by influenza, Kelleys Island, 1920.

Home No.	Age.	Sex.	Date of exposure.		Date of onset.	Interval in days.	Day of illness of the case to which exposed.	Nature of contact.
			From—	To—				
2	46	F.	Jan. 28	Jan. 29	Feb. 1	4	1st.....	Visiting cases.
20	42	M.	Jan. 29	Jan. 29	Jan. 31	2-3	1st.....	Associated with ill persons at a dance.
21	66	F.	Feb. 2	.....	Feb. 4	2	2d, 3d, and 4th.	Visiting cases.
33	21	M.	Feb. 1	.....	Feb. 2	1	1st, 2d, and 5th.	Do.
35	70	F.	Jan. 31	Feb. 3	Feb. 3	0-3	1st, 2d, and 3d.	Caring for cases.
37	28	M.	Feb. 2	.....	Feb. 3	1	2d.....	Visiting cases.
41	24	F.	Jan. 29	Jan. 31	Jan. 31	2	1st.....	Associated with ill persons at a dance.
42	26	F.	Jan. 29	Jan. 30	Jan. 30	1	1st.....	Gave vitamin lessons to ill boy.
43	81	F.	Jan. 29	Jan. 29	Jan. 30	1	1st.....	Kissed and visited with ill nephew.
44	54	M.	Jan. 29	Jan. 29	Jan. 29	0-2	1st.....	Visiting cases.
45	19	M.	Jan. 29	.....	Feb. 2	4	1st and 2d.	Do.
46	22	F.	Jan. 29	.....	Feb. 1	3	1st.....	Associated with ill at a dance.
48	56	F.	Jan. 29	.....	Jan. 31	2	1st.....	Do.
51	36	M.	Jan. 31	Feb. 2	Feb. 3	1-3	1st, 2d, and 3d.	Visiting and caring for cases.
56	58	F.	Feb. 4	.....	Feb. 7	3	1st, 2d, and 3d.	Caring for cases.
76	34	M.	Jan. 29	.....	Feb. 1	3	1st and 2d.	Visiting cases.
79	52	F.	Jan. 30	.....	Jan. 31	1	1st, 2d, and 3d.	Caring for cases.
81	35	F.	Jan. 24	Jan. 27	Jan. 27	3	1st.....	Visiting cases.
82	34	M.	Jan. 18	Jan. 29	Jan. 31	2-3	1st.....	Visited and had refreshments at home of ill.
101	28	F.	Feb. 2	.....	Feb. 3	1	1st.....	Visited cases.
104	60	F.	Feb. 5	.....	Feb. 7	2	8th and 7th.	Do.
121	24	F.	Jan. 30	Feb. 1	Feb. 3	2-3	1st and 2d.	Caring for cases.
147	35	F.	Jan. 30	Feb. 3	Feb. 3	4-4	1st, 2d, 3d, and 4th.	Do.
152	37	F.	Feb. 3	.....	Feb. 4	1	1st, 2d, and 3d.	Visiting cases.
154	24	F.	Jan. 31	.....	Feb. 1	0-1	1st.....	Husband returned from mainland ill.
156	25	M.	Feb. 14	Feb. 16	Feb. 16	0-2	1st, 2d, and 3d.	Caring for cases.
160	43	F.	Feb. 2	.....	Feb. 3	1	2d.....	Visiting cases.





# Additional difficulty : Individual records have been destroyed (2)

**Solution:** Multiple imputation of assignments of reported cases to HHs that fulfill marginal constraints

**Method 1:** Exhaustive deterministic search of assignment space

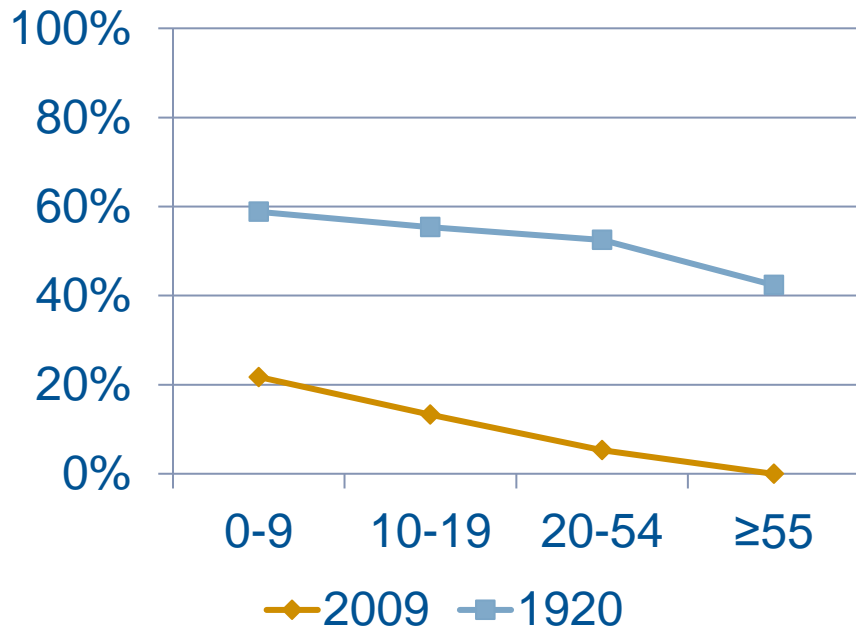
- Unknown if there are contradictory constraints (full search needed to be sure)
- Even with efficient constraint propagation, no valid assignment of even 1/3 of households after >400,000,000 assignments considered (>4 days compute time),

**Method 2:** Probabilistic search

- Ensuring good match of marginal distributions.
- MCMC and data augmentation.
- Convergence in <5 minutes (~5000 iterations).

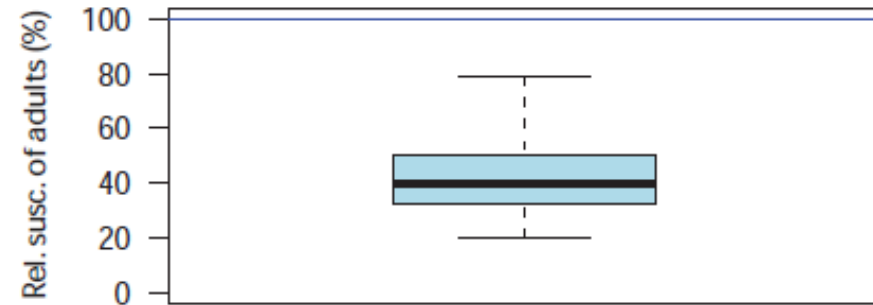
# Attack rates by age group

Attack rate by age group



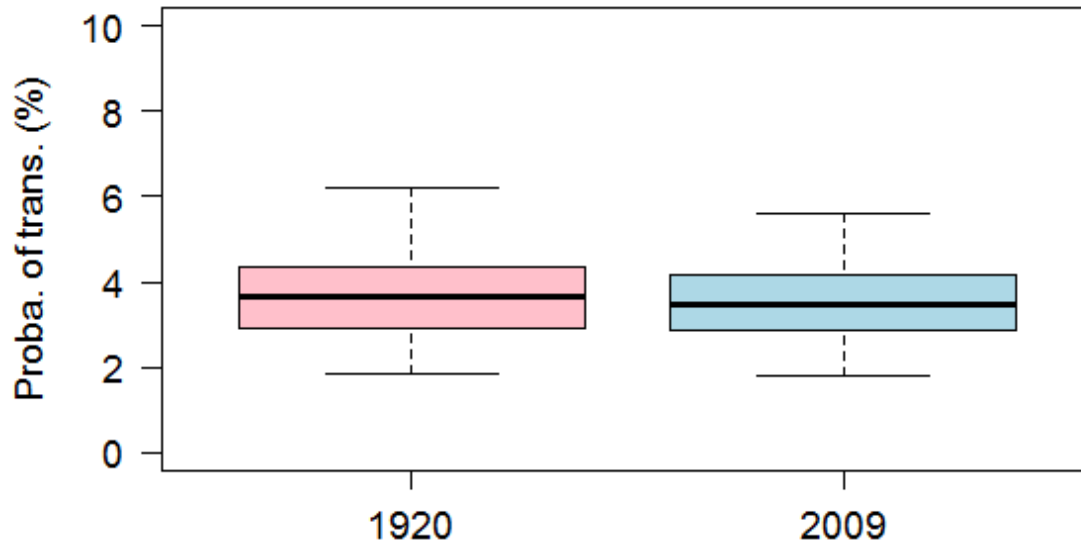
**2009**

Age dependent susceptibility

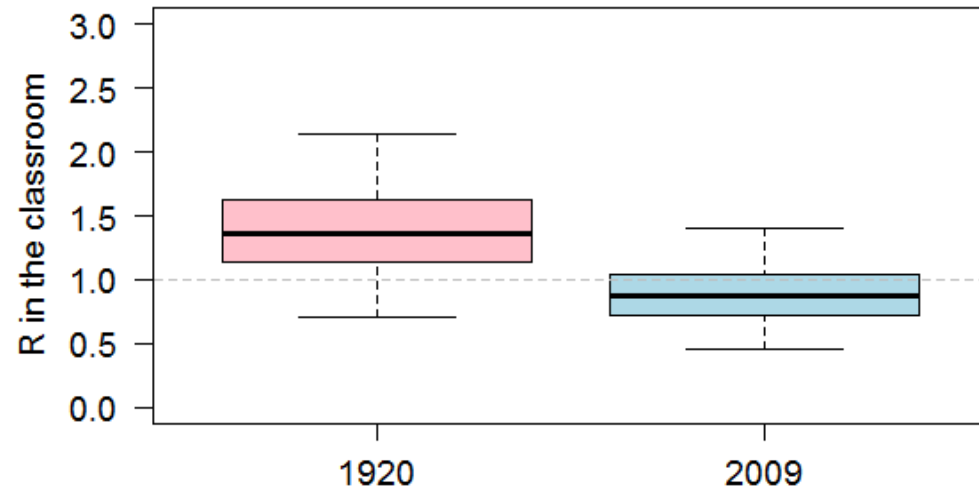


# Probability of transmission in the class

Same probability of transmission...

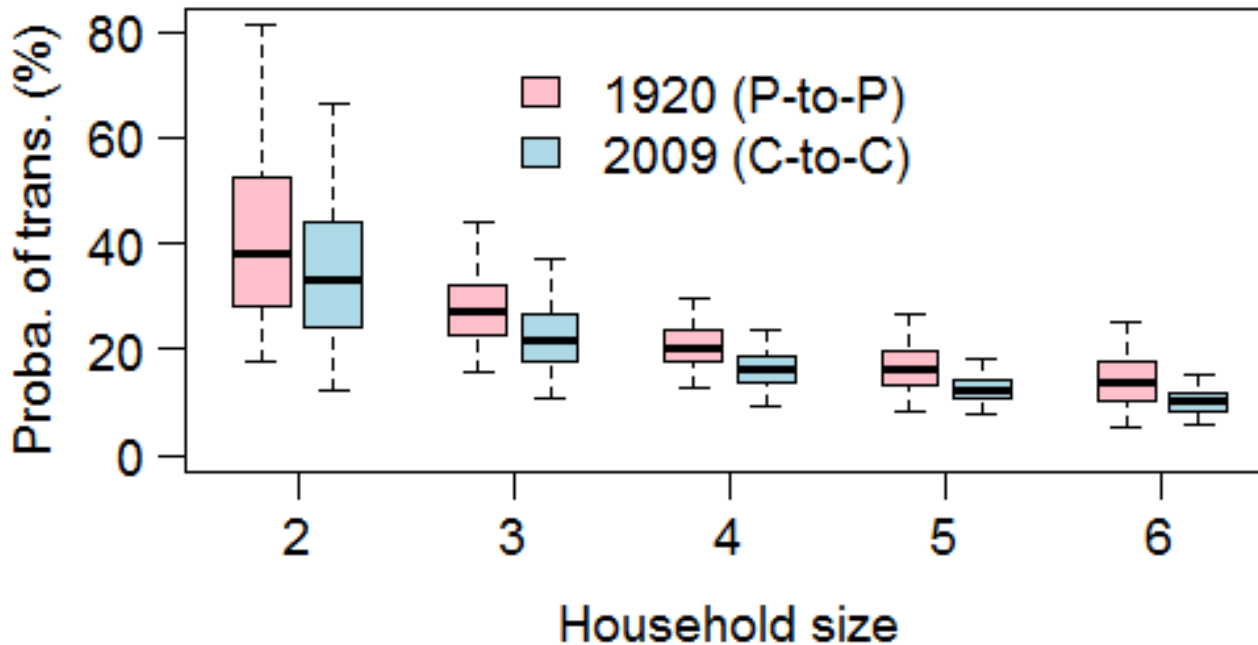


... but more children per class



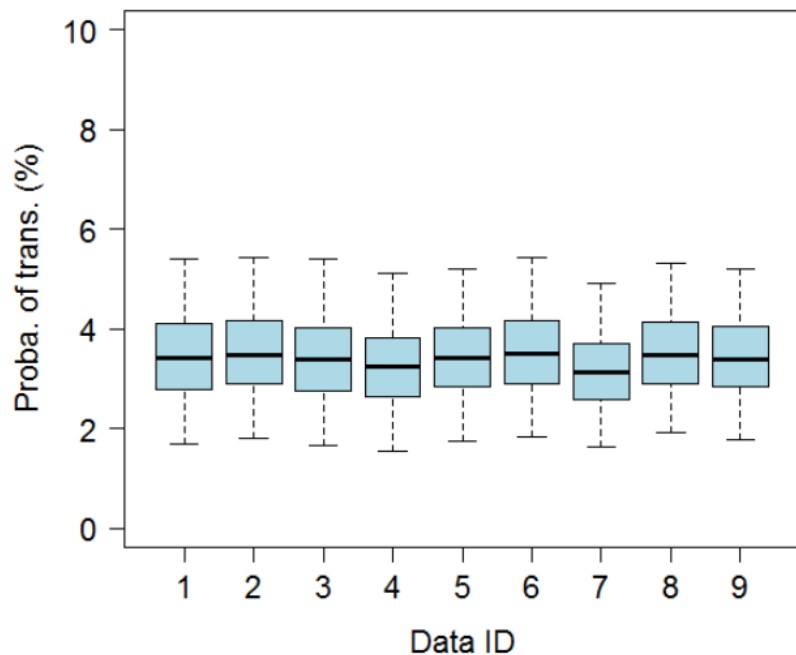
	Average number of children per class
1920	39
2009	25

# Probability of transmission in the household

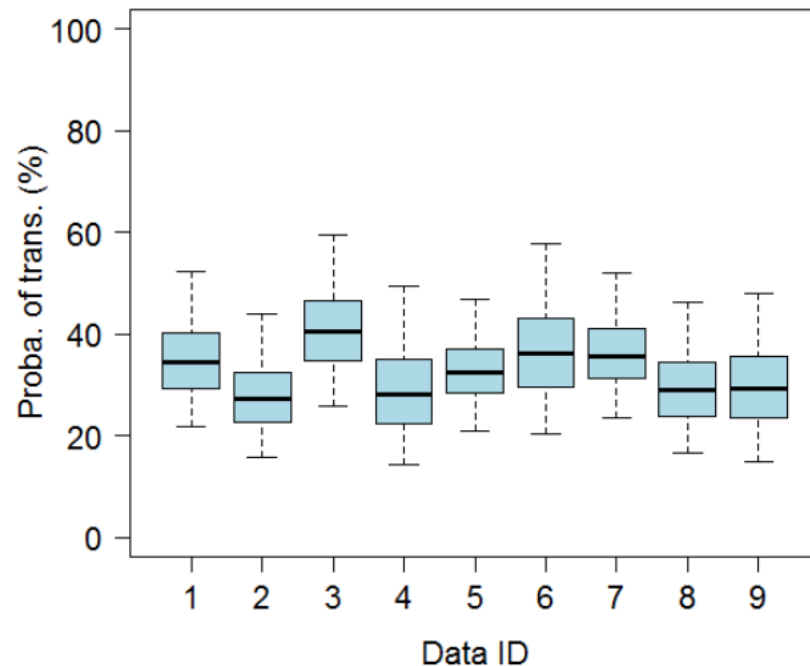


# Sensitivity analysis: reconstruction of individuals records

## Person-to-person transmission in the school

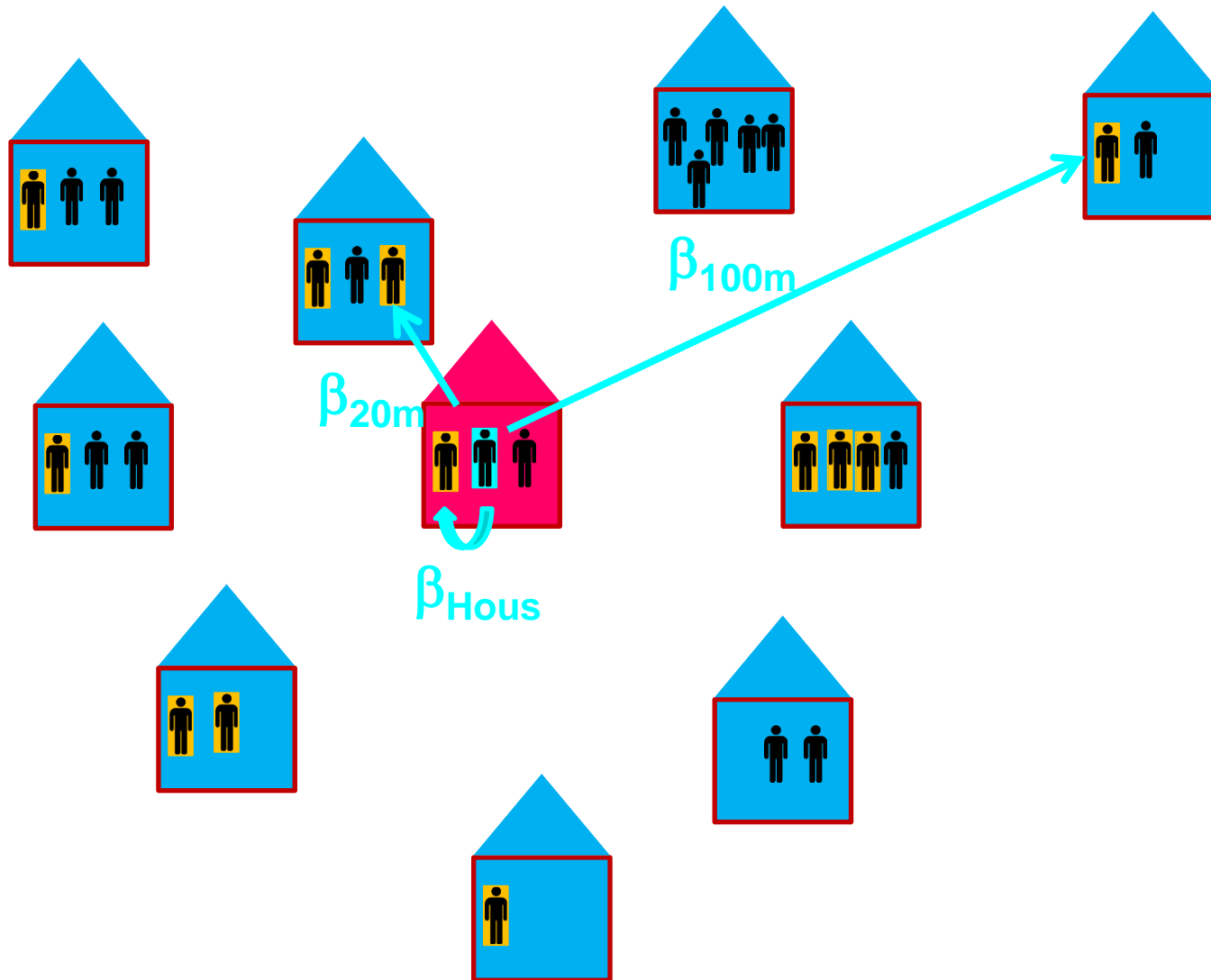


## Person-to-person transmission in a household of size 3



# Spread of chikungunya in a village in Bangladesh

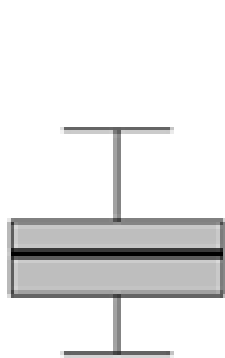
[Salje et al, PNAS, 2016]



# Transmission rates in households and as a function of distance

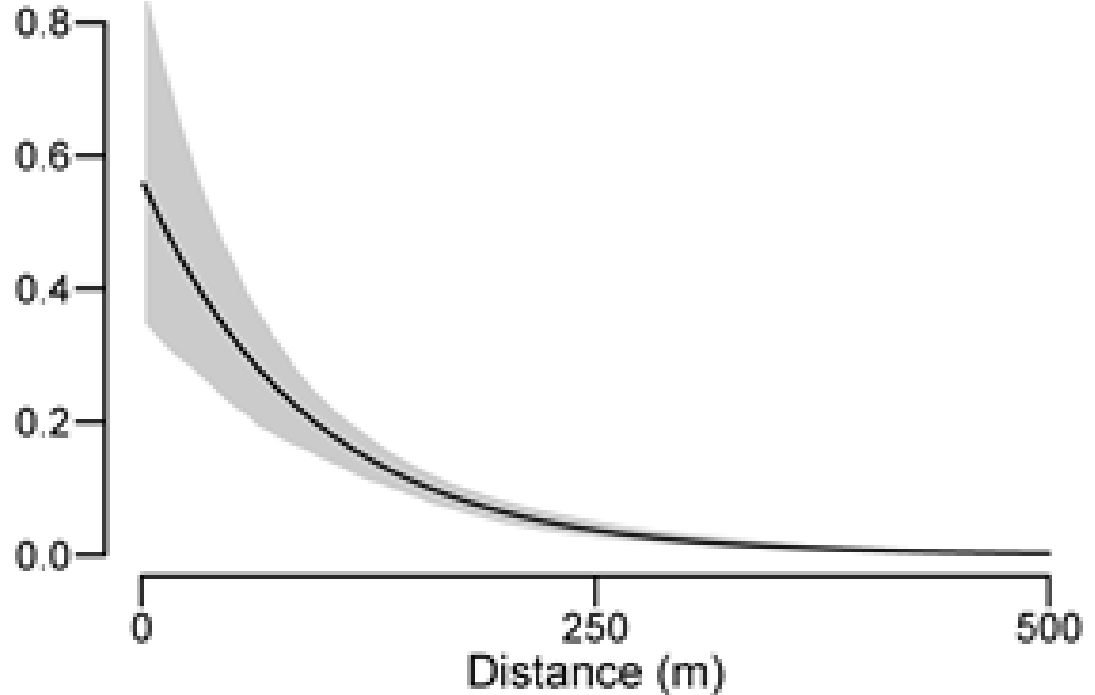
**Household transmission rate**

Probability of household transmission (%)

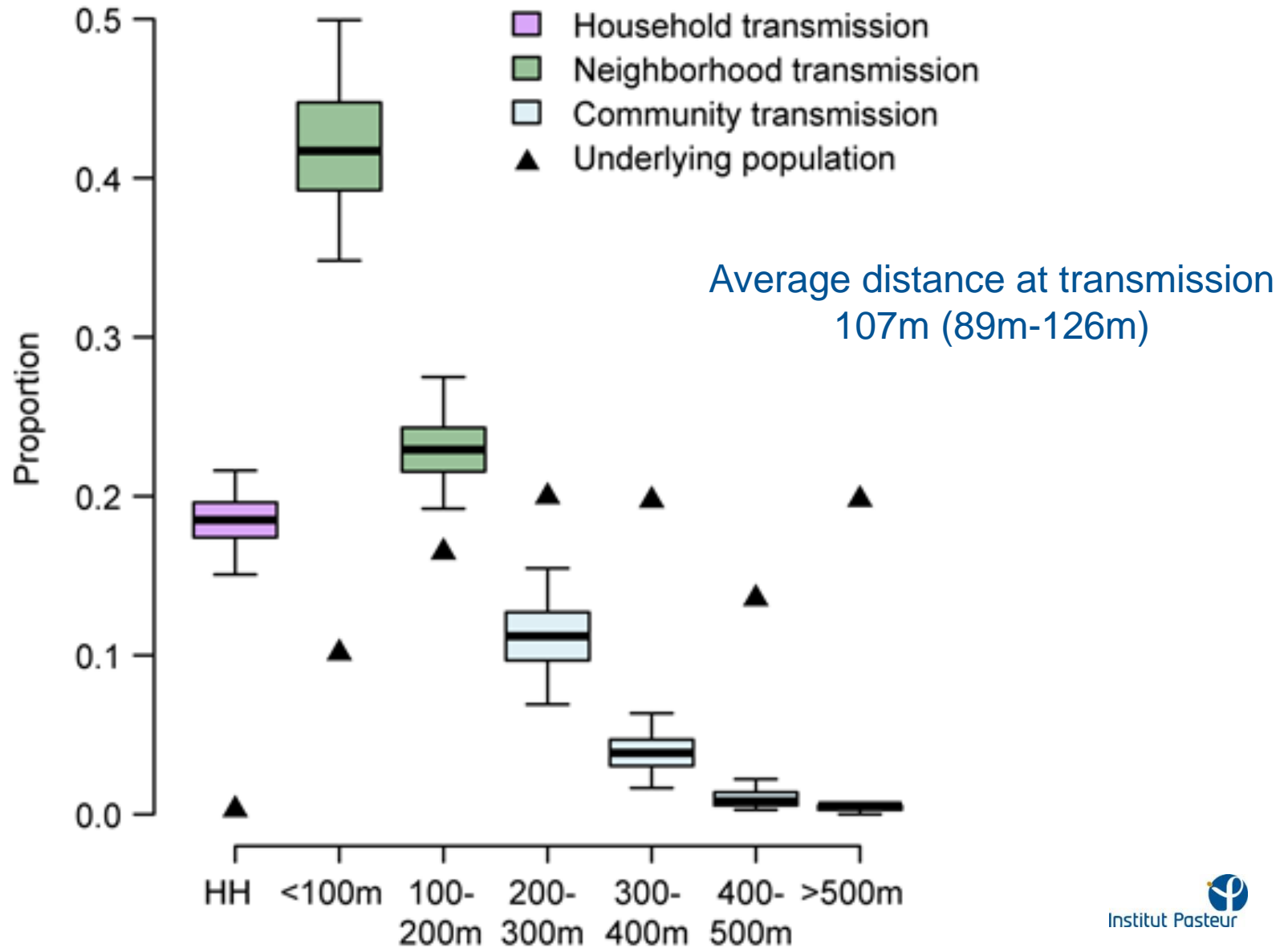


**Transmission rate as a function of distance**

Probability of community transmission (%)

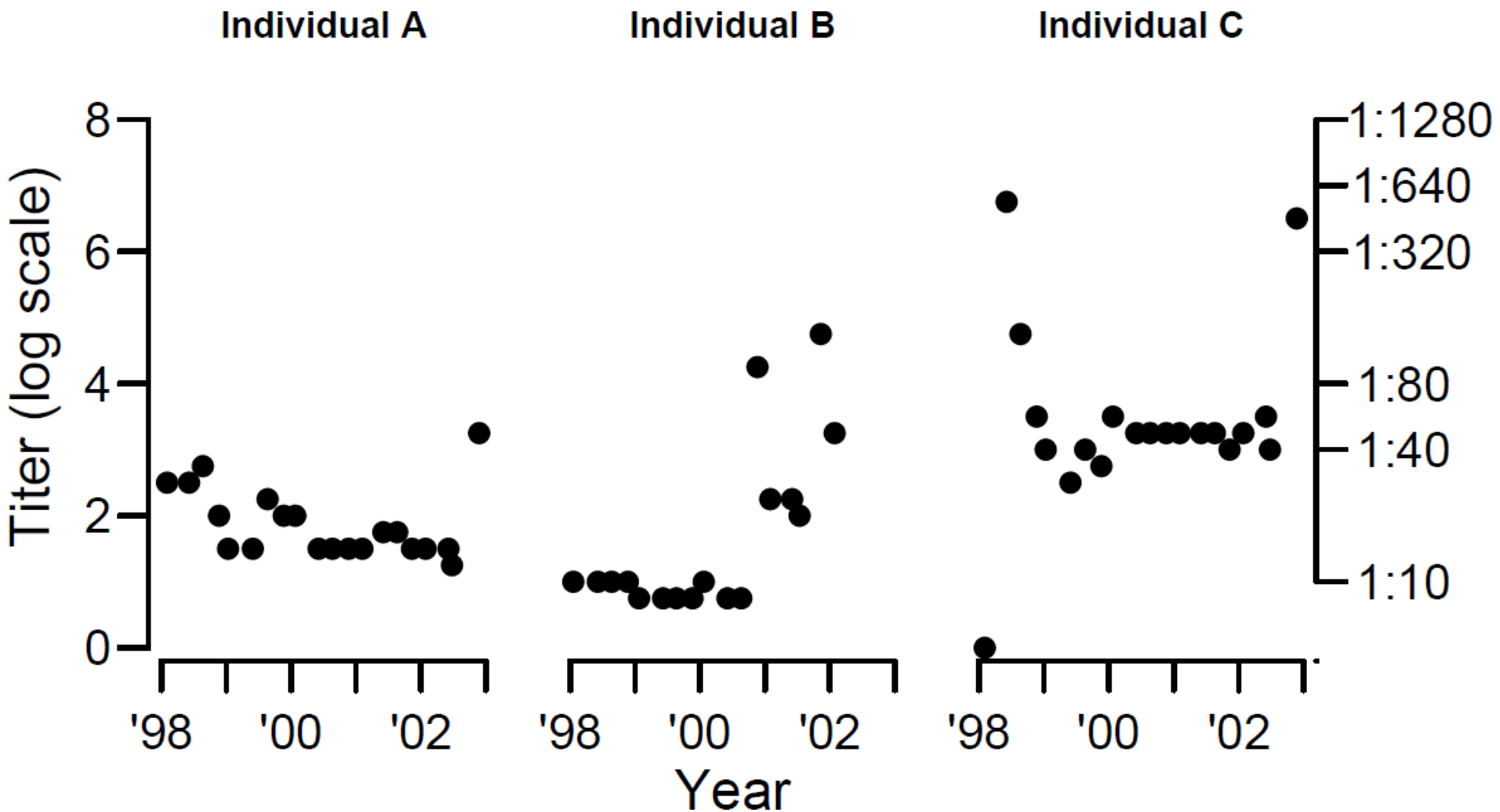


# Where does transmission occur?





# Characterizing infection burden and antibody dynamics from repeated measurements [Salje et al, Nature 2018]

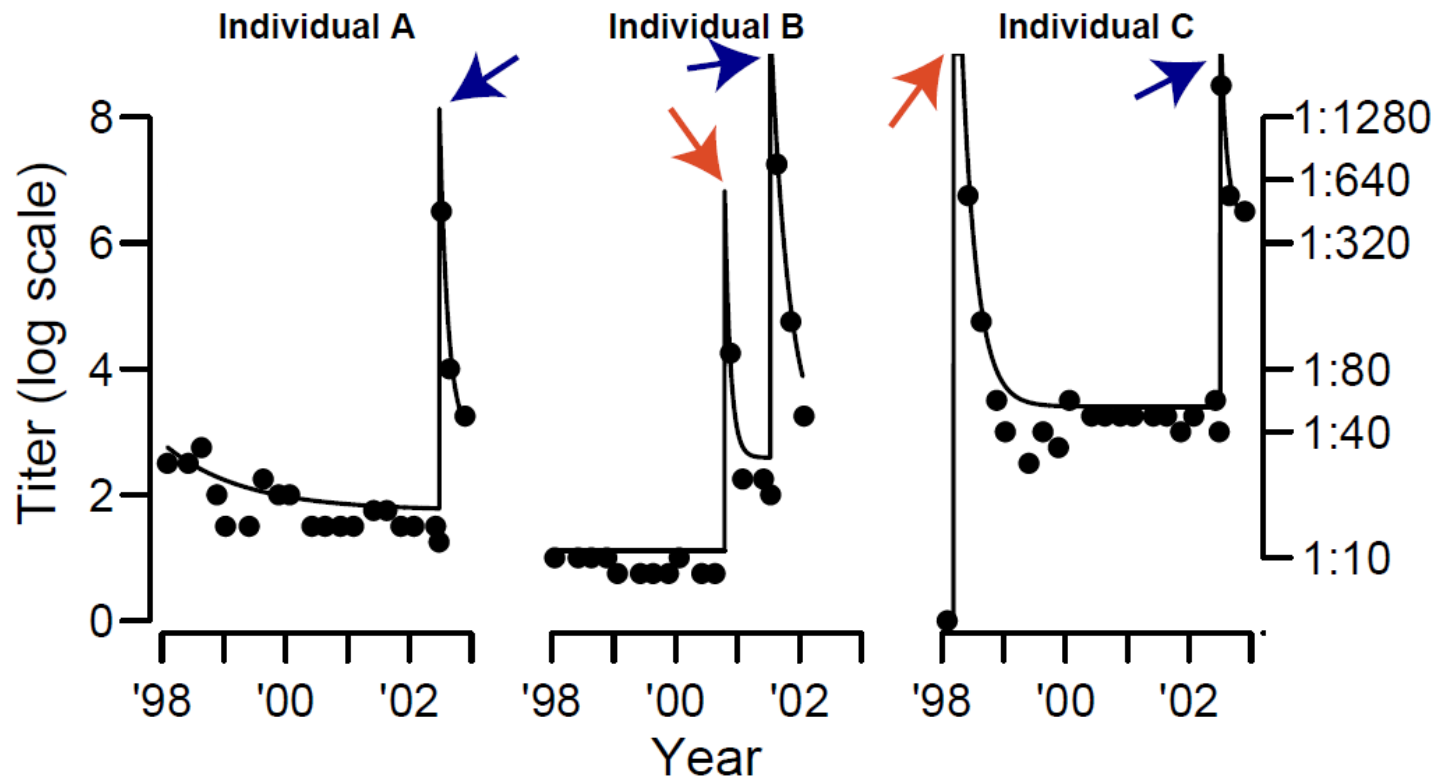


Dengue antibody titers measured every 3 months in >3000 Thai children

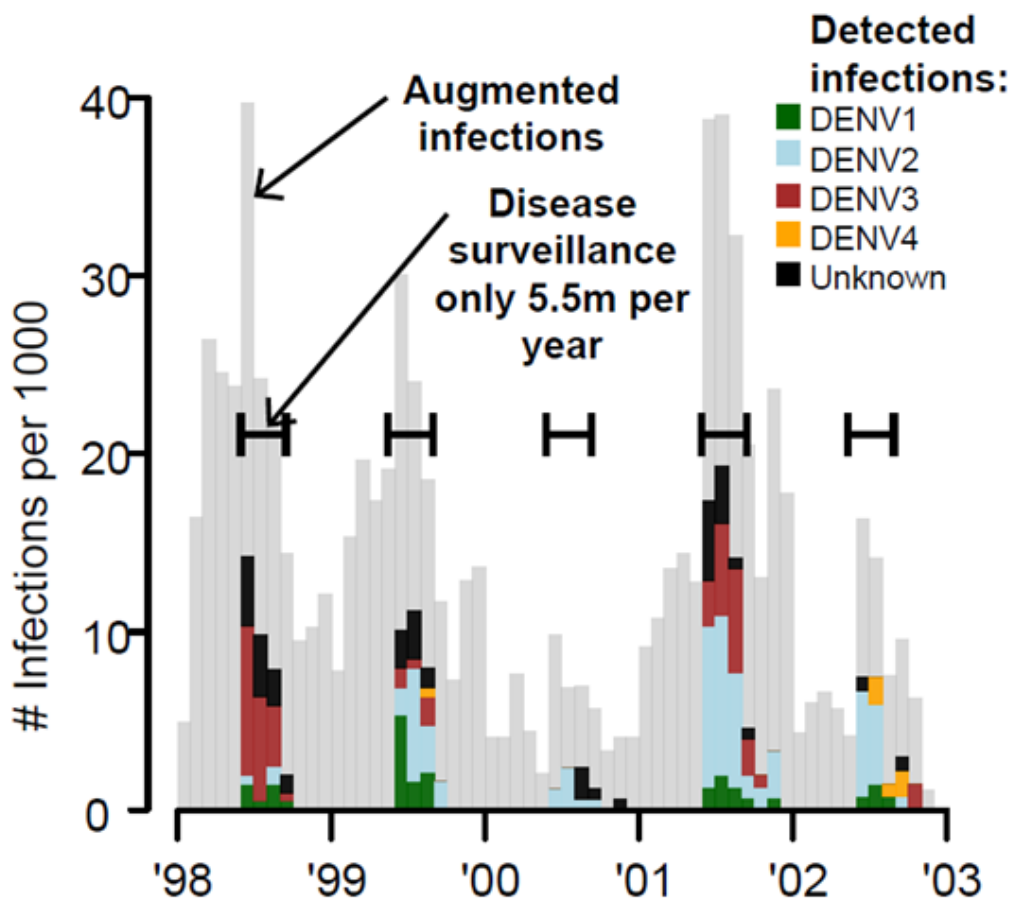


# Methods

- Bayesian hierarchical model characterizing antibody titers in individuals:
  - A model describing the history of infection.
  - A model describing antibody titer dynamics given history of infection.
  - A model describing measurement errors.
- Reversible jump MCMC used for inference.

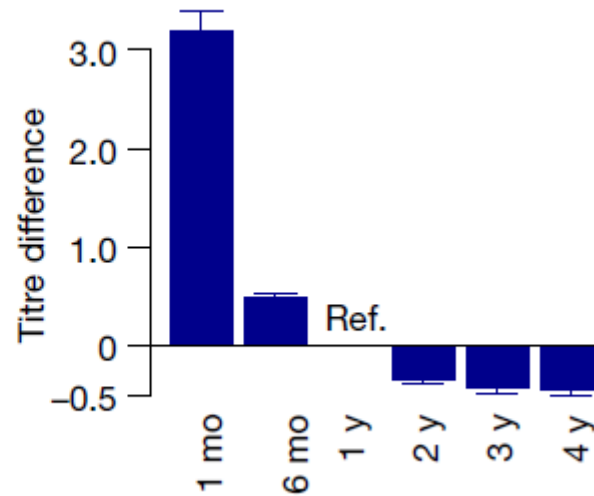
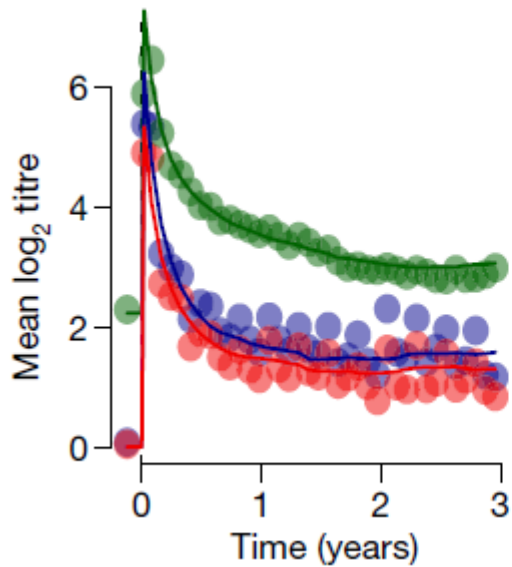


# Characterizing subclinical infections



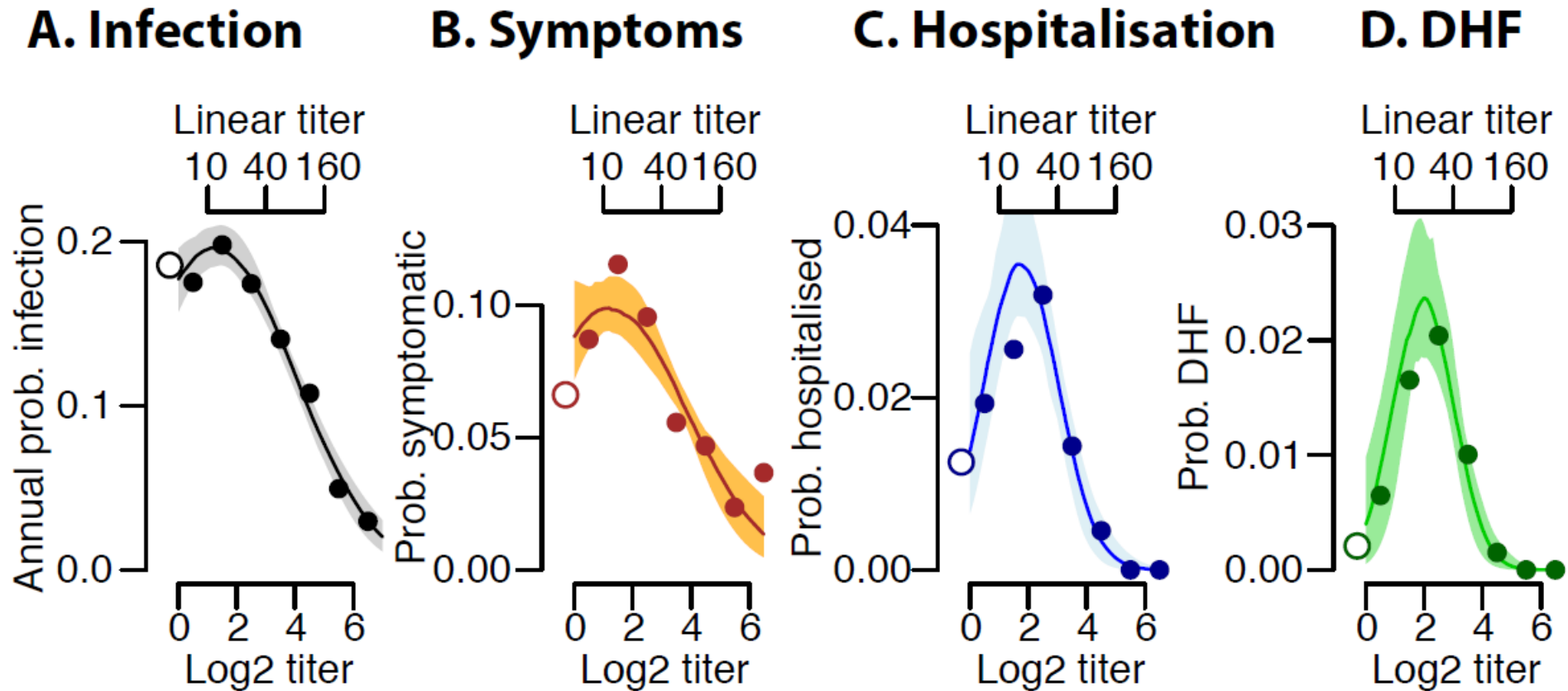
- 65% of infections subclinical.
- 34% of subclinical infections due to serotype 4 while serotype 4 only represents 3% of symptomatic infections.
- Lower risk to develop symptoms for serotype 4.

# Antibody titer dynamics



- Primary infection, infecting serotype
- Primary infection, non-infecting serotype
- Post-primary infection

# Correlates of protection and of severity



# Conclusions

- Household transmission studies:
  - Within household transmission vs community transmission.
  - Many other insights...
    - ✓ Flu in France, US...
- Progressively added more features to these analyses:
  - Missing data problems
    - ✓ Lost individual records.
  - More complex social structures & space
    - ✓ School settings.
    - ✓ Community outbreaks.
  - Repeated measurements
    - ✓ Dengue cohort.
- Striking similarities in some of the fundamental parameters that govern spread.
- But nonetheless, transmission rates are highly variable:
  - Social structures, contact networks, distance;
  - Spatial heterogeneities.
- Further developments:
  - Inclusion of contact data;
  - Model comparison.

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- **CDC (USA):** L. Finelly, D. Swerdlow, C. Reed, A. Bhattarai.
- **Pennsylvania Department of Health (USA):** S. Ostroff
- **ICDDR,B (Bangladesh):** Emily Gurley, KK Paul.
- **Stanford University (USA):** SP Luby.
- **WHO:** M. Van Kerkhove.
- **Johns Hopkins University (USA):** J. Lessler.
- **University of Florida (USA):** D. Cummings.
- **INSERM (France):** F. Carrat, P.Y. Boëlle, G. Thomas, A.J. Valleron.
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# Thank you!

