



**PANDEMIC SCIENCES  
INSTITUTE (PSI)**

Forging a safer world through science

# **Epidemiology of the NHS COVID-19 contact tracing app.**

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**Pathogen sequencing - Mathematical modelling - Statistical modelling - Communication**



**Mark Briers**  
Turing



**Chris Holmes**  
Turing



**Daphne Tsallis**  
Zuhlke



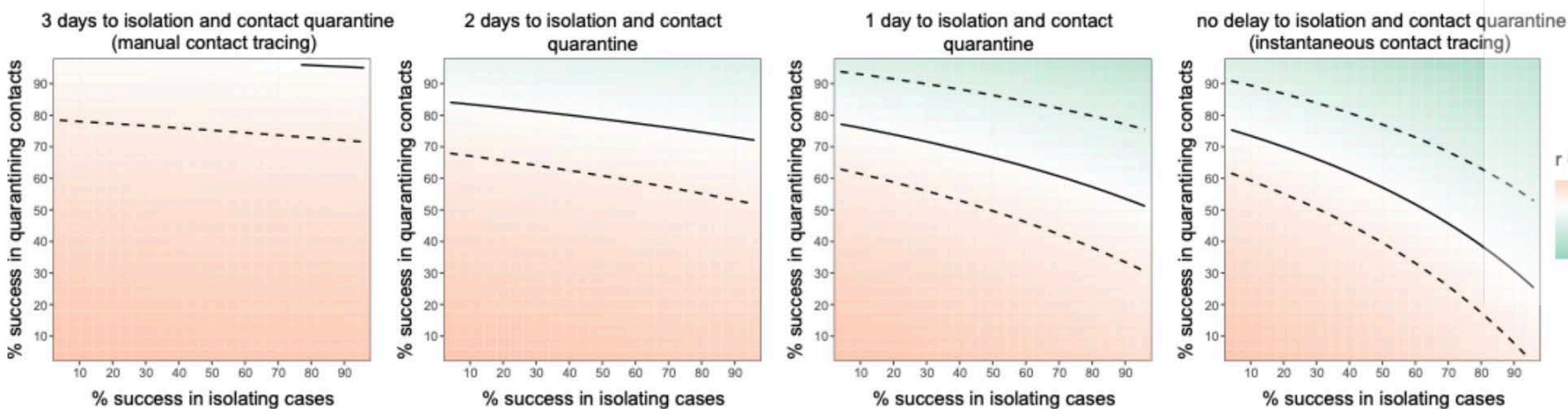
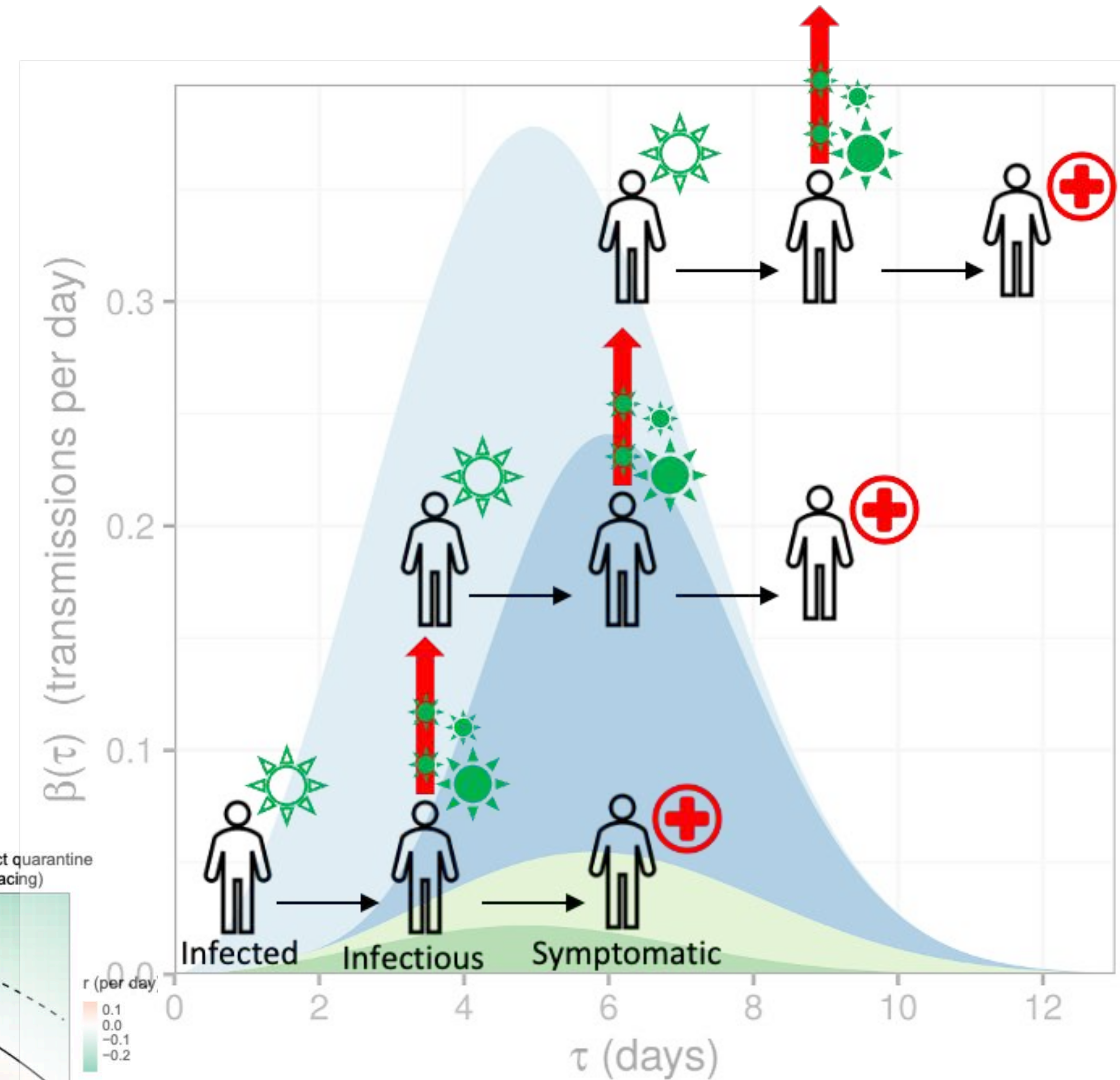
**Luke Milsom**  
Oxford Economics

# Transmission dynamics COVID-19 and contact tracing

The average time it takes for an individual to show symptoms = 5 - 6 days.

The average time from infection to onward transmission = 5 - 6 days.

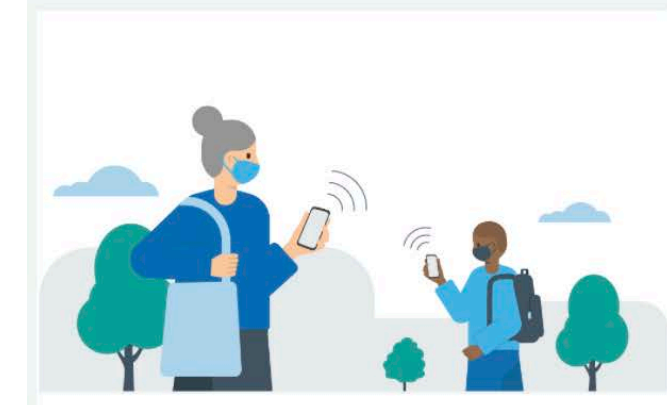
Predicted effects very sensitive to delays in testing and contact tracing.



# Sept 2020 - UK



## What the app does



Trace



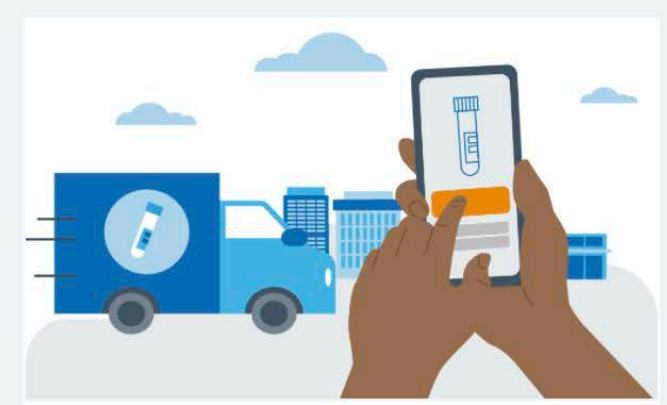
Alert



Check-in



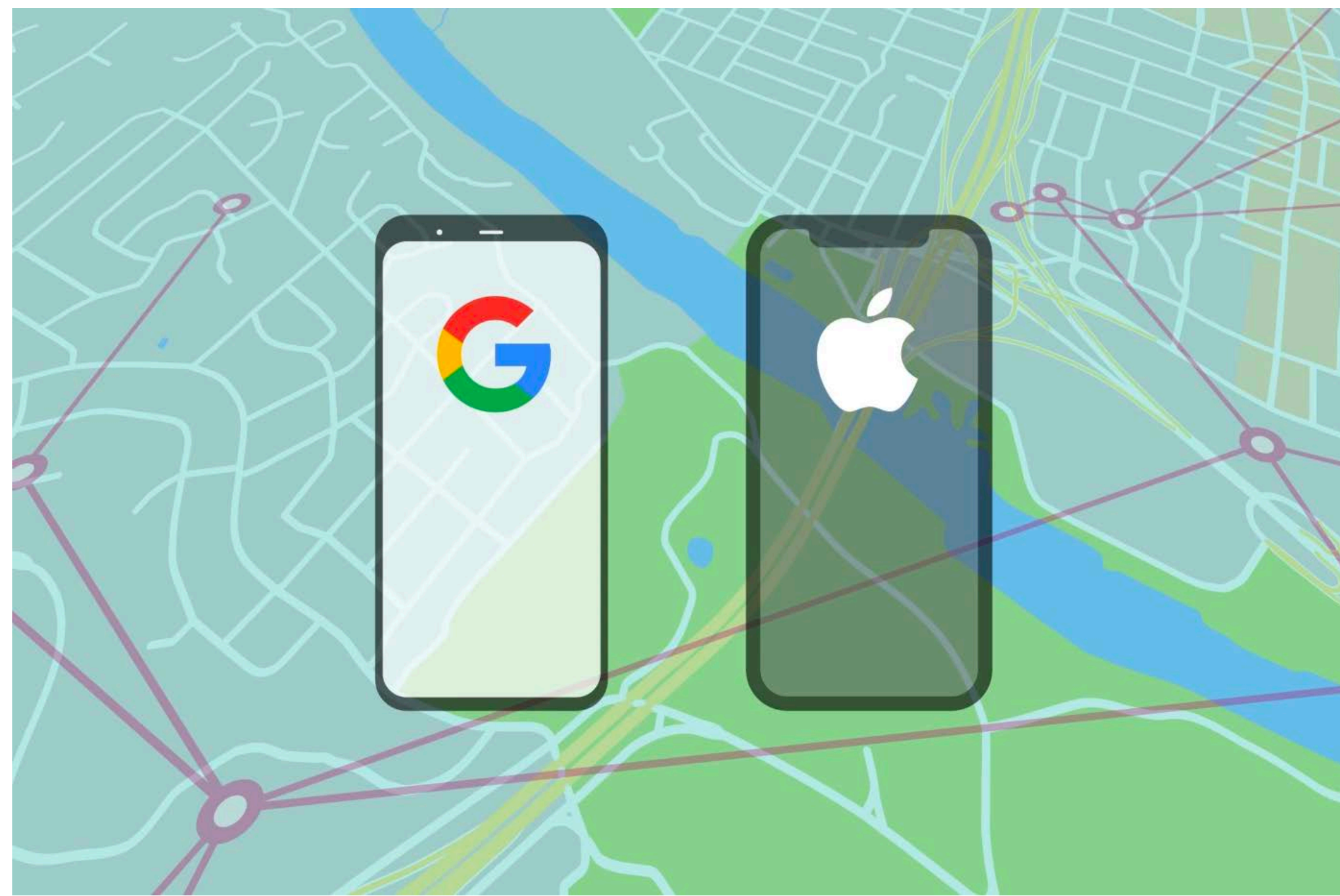
Symptoms

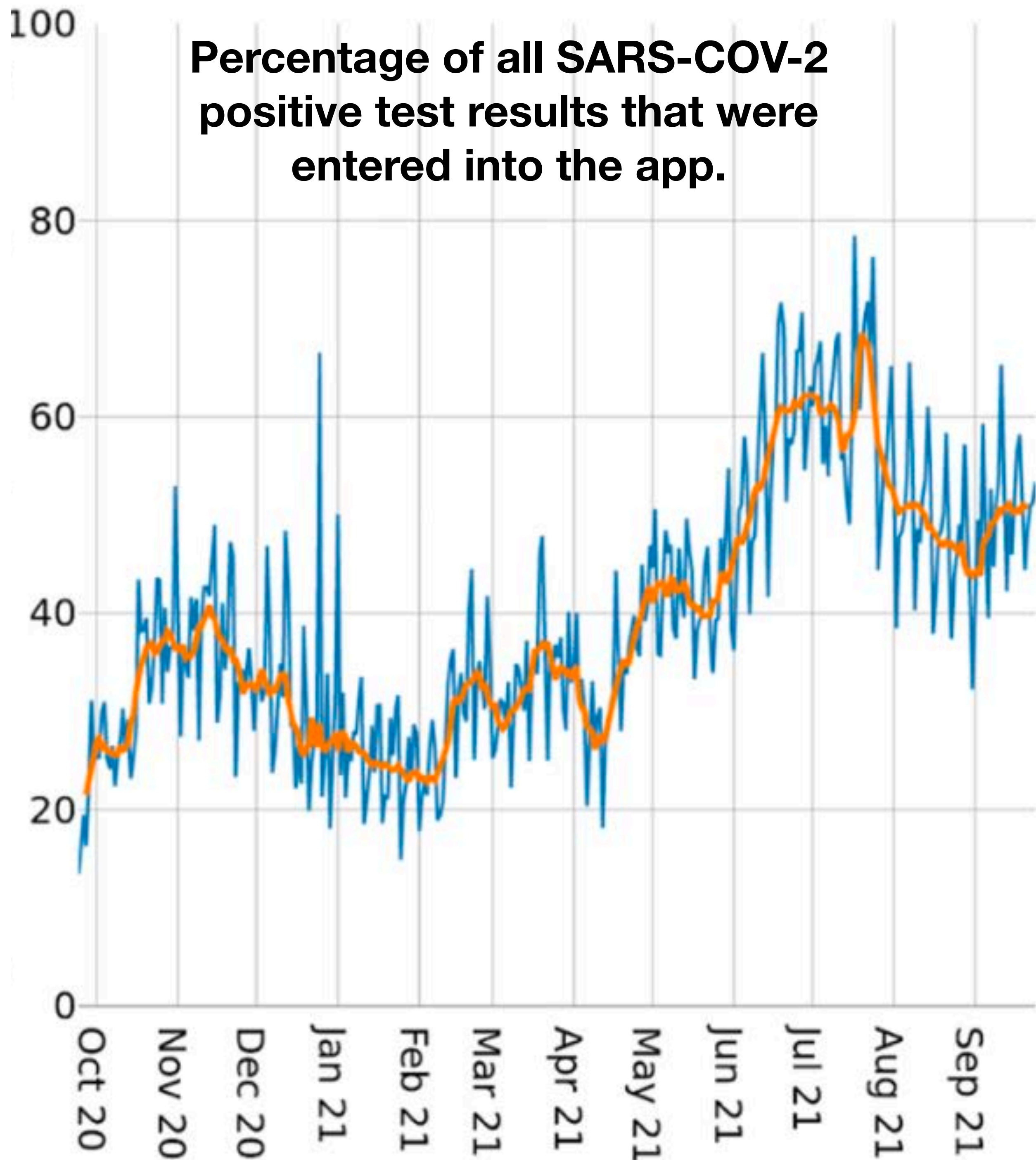


Test



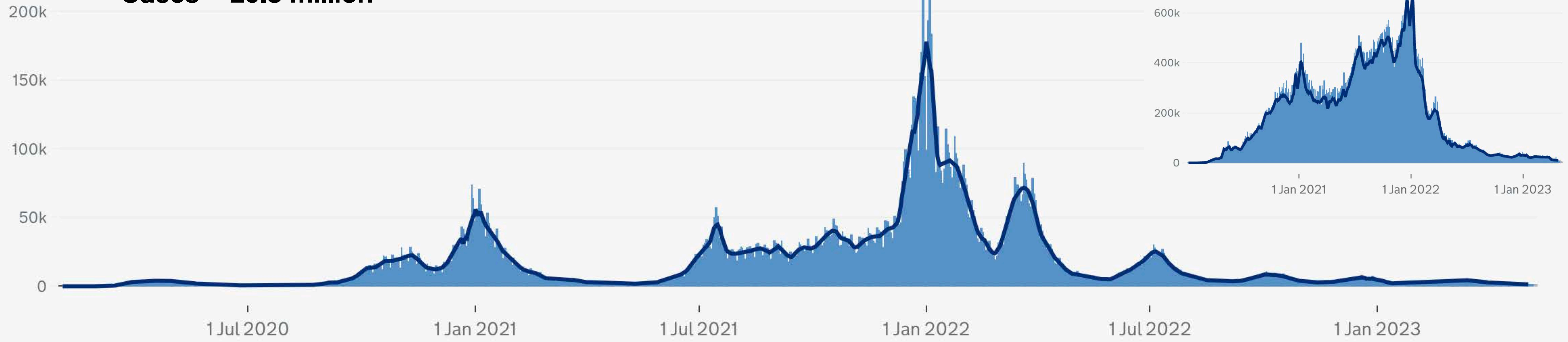
Isolate



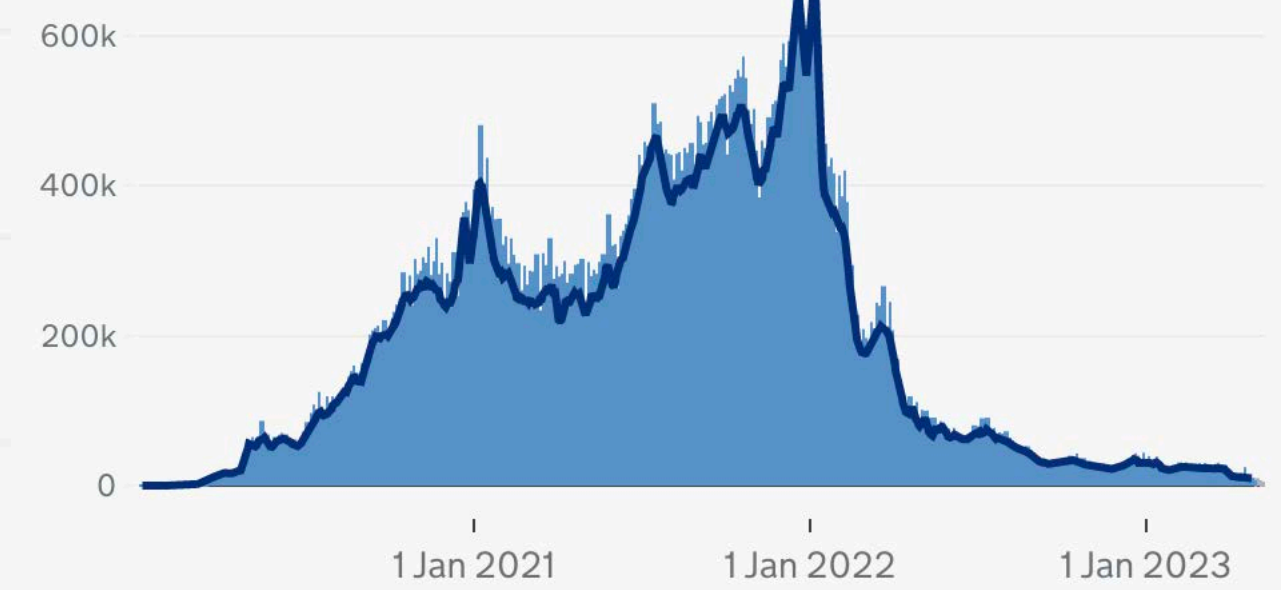


UK had centralised provision and recording of SARS-COV-2 testing

**Cases ~ 20.8 million**

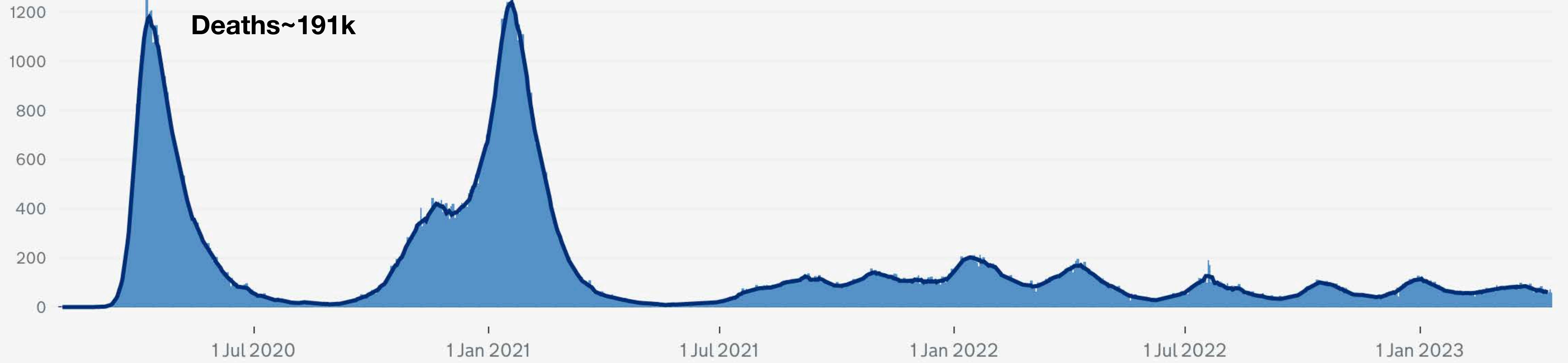


**Tests ~ 543 million**

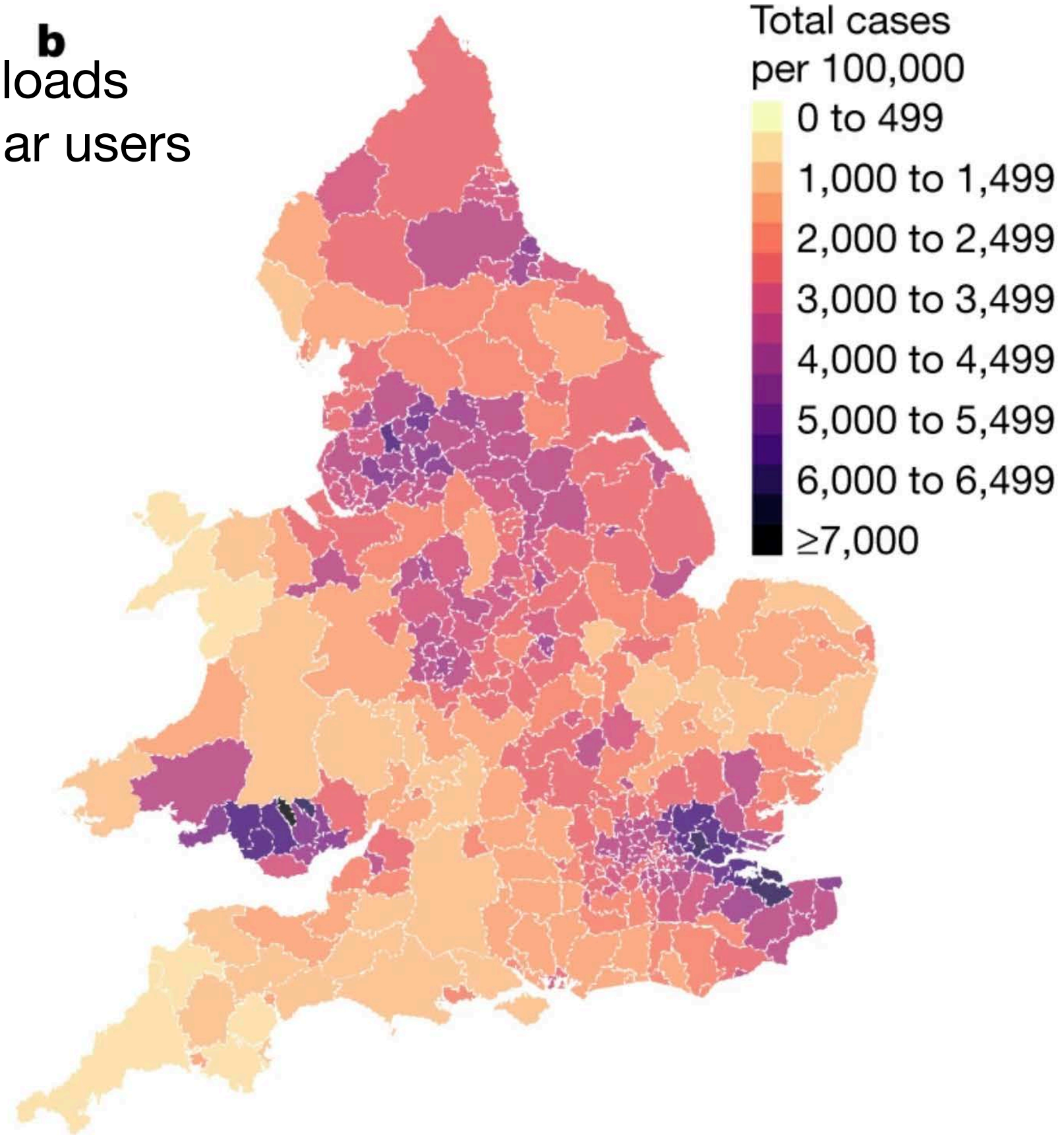
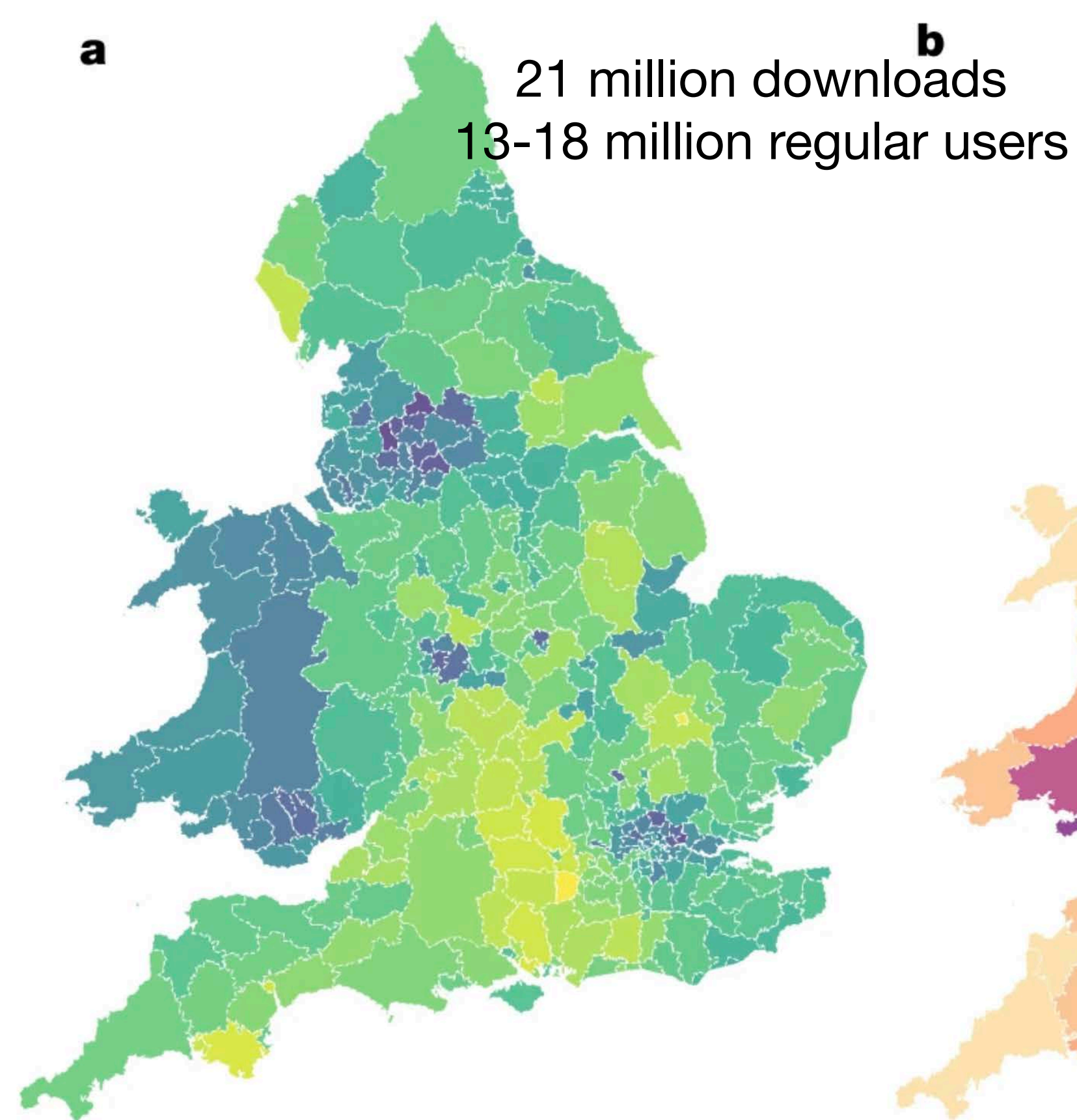


■ Most recent 5 days (incomplete) ■ Number of cases — Cases (7-day average)

**Deaths ~ 191k**



■ Number of deaths — (7-day average)



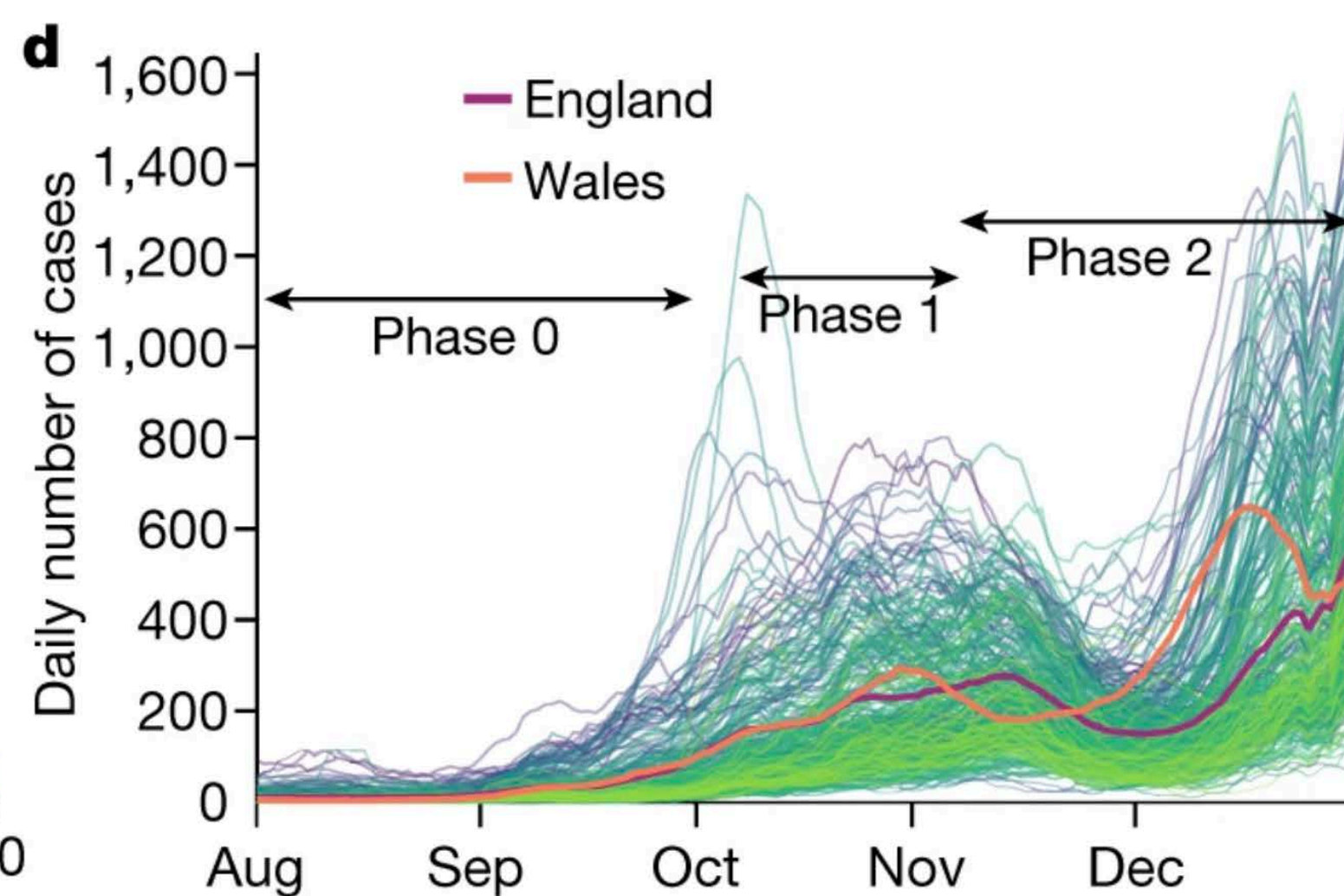
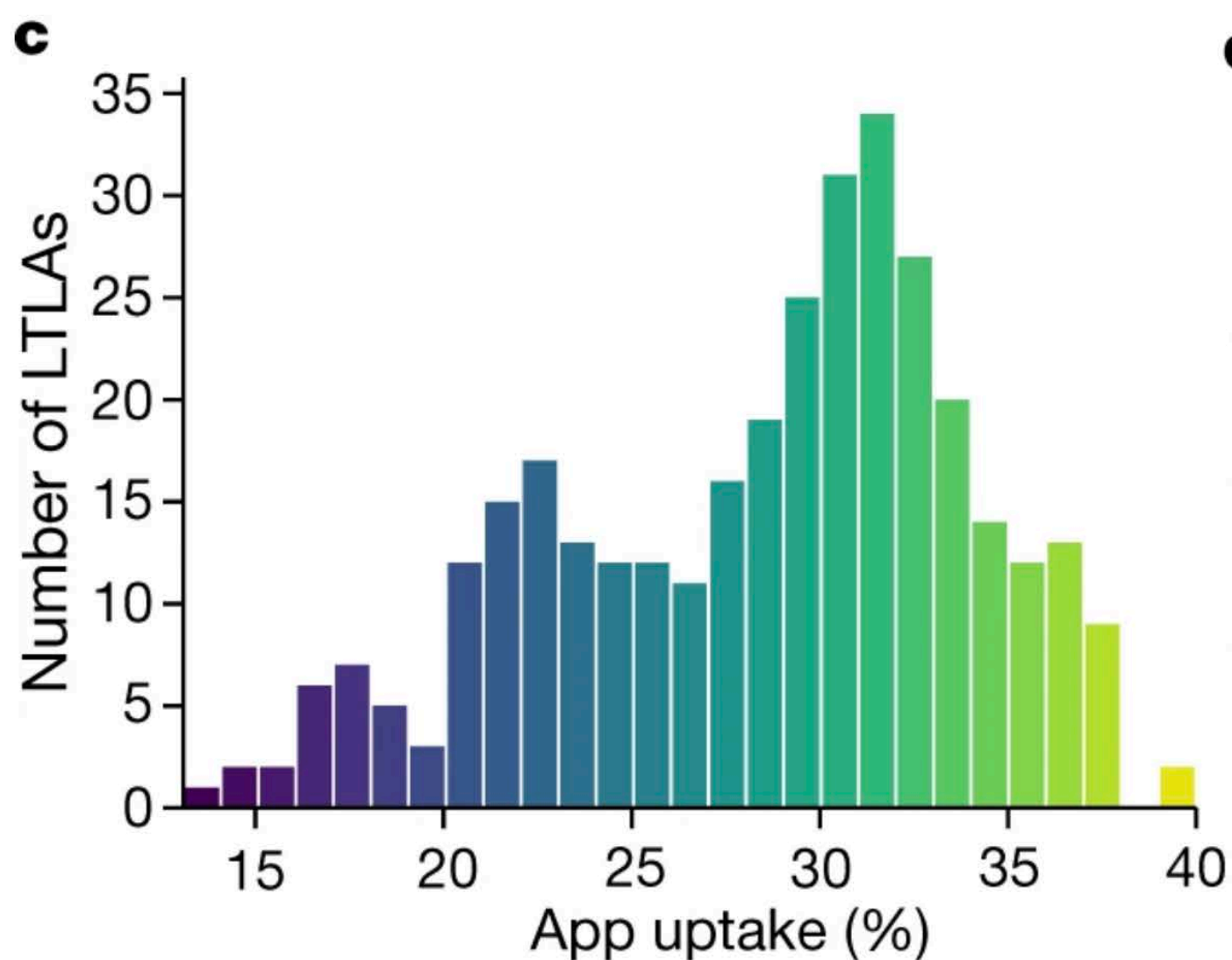
**Does having increased uptake of the app lead to fewer infections?**

Uptake is heterogeneous across country. We compared 338 lower tier local health authorities in England & Wales.

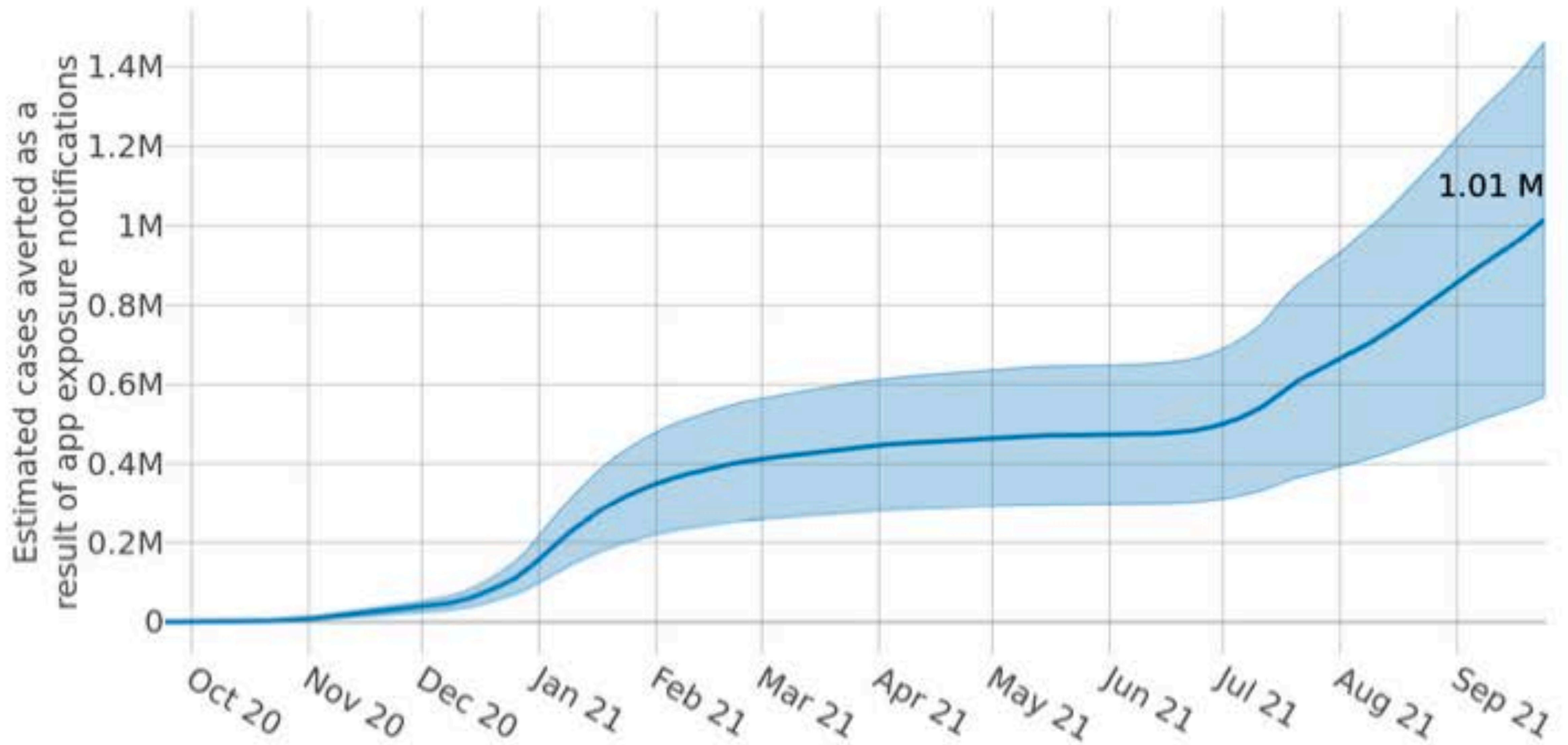
Modelling: ~300,000 cases prevented.  
Causal inference ~ 600,000 cases prevented.

Modelling: ~ 0.79% reduction in cases per 1% population using app.  
Causal inference: ~ 2.26% reduction in cases per 1% population using app.

Phase 1 / Phase 2 change: epidemiological effect matched changes in operational sensitivity.



# Modelling estimate of cases prevented (direct effects + transmission chains)





# Theoretical basis for digital contact tracing

1. BLE attenuation as a measure of proximity
2. Proximity as a proxy for transmission risk:

Closer proximity = higher risk

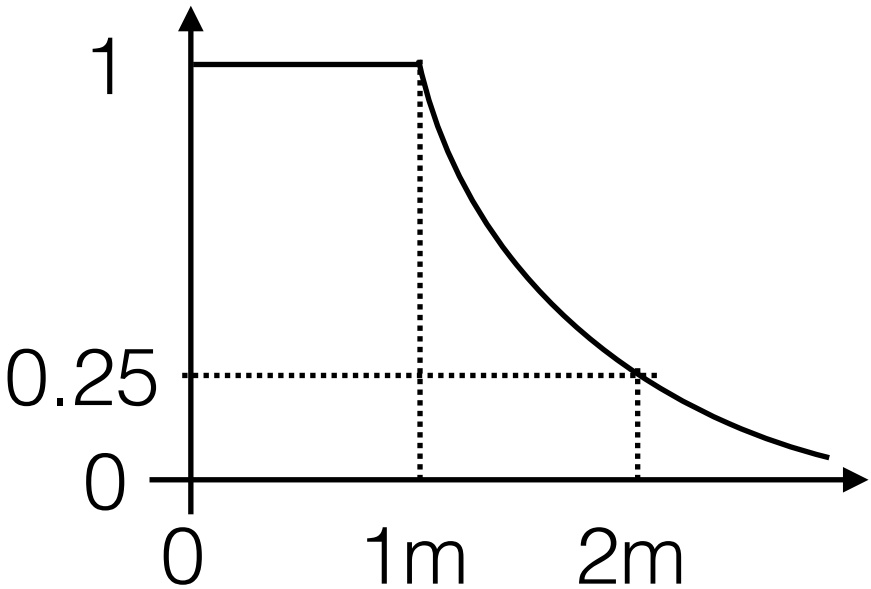
In practice, many doubts have been expressed publicly on both these points, e.g.

1. BLE attenuation is a very noisy measure of proximity
2. Increasing understanding on the airborne transmission of SARS-CoV-2 and other viruses (including flu?)

Transmission risk is not necessarily related to distance for airborne diseases



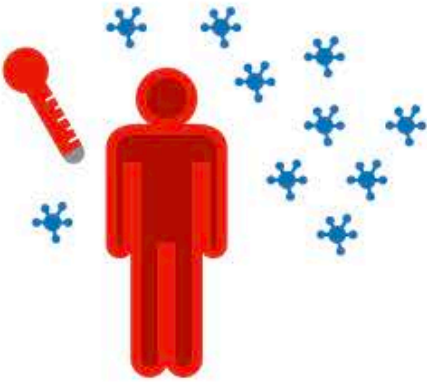
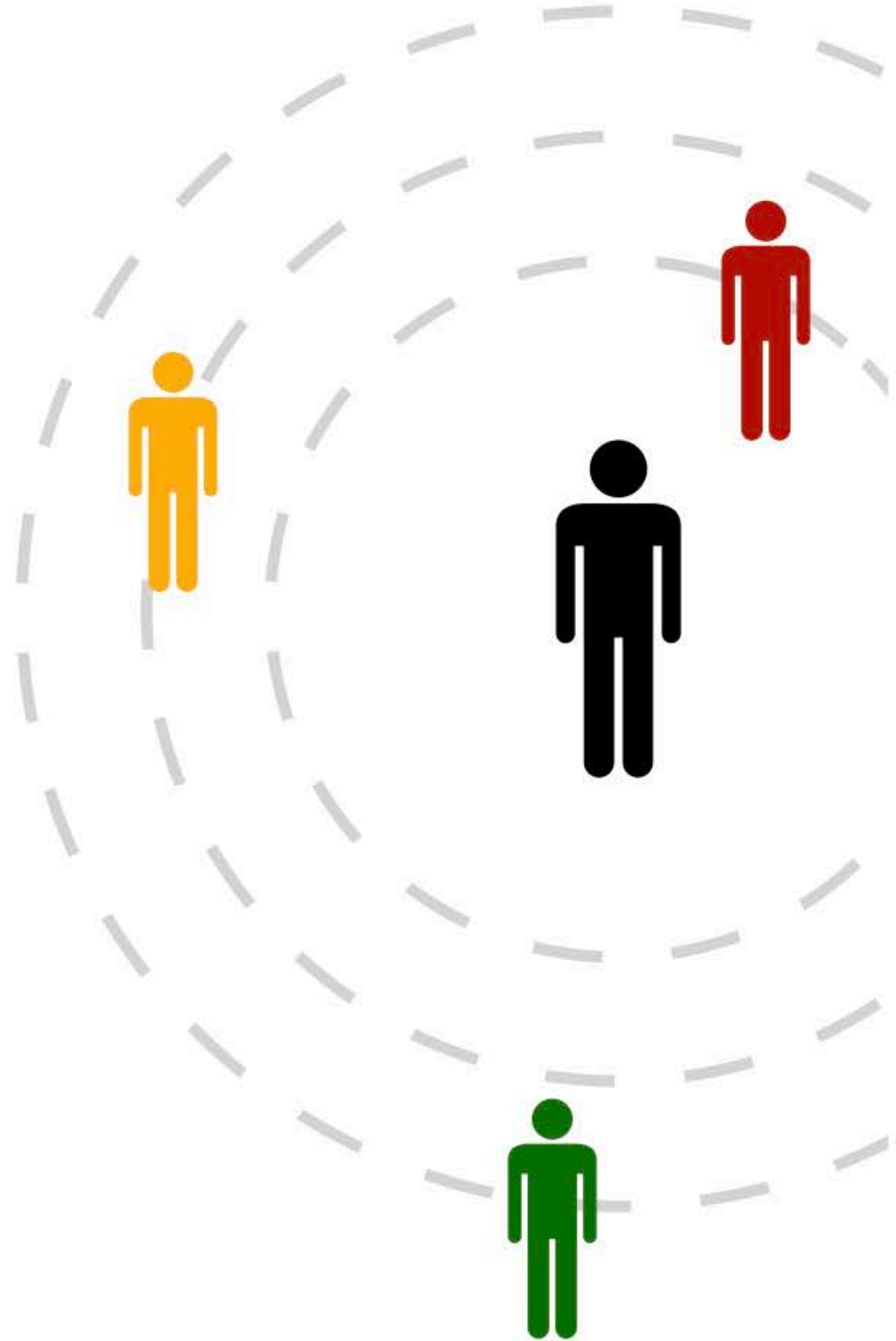
# NHS COVID-19 app risk calculation, in separate 30-minute windows:



0-30 mins

2.5 if exposure in [-2, +3] days w.r.t. index's symptoms, 1 if in [+4, +9], 0 otherwise

**Risk = *proximity* × *duration* × *infectiousness***



Fraser, Ferretti, Bonsall, Hinch, Finkelstein, github 2020

Example data for contacts  $C_1$ ,  $C_2$ ,  $C_3$  notified of risky exposure.

No data about the associated index cases except their binary infectiousness level: contacts and indices are decoupled.)

Data for each window over the threshold:

Exposed contact	Exposure window	Risk score / threshold	Proximity score	Duration / minutes	Index infectiousness	Exposure date
$C_1$	1	2	0.25	30	1	1/1/2022
$C_1$	2	8	1	30	1	1/1/2022
$C_1$	3	4	1	15	1	1/1/2022
$C_2$	1	7	1	30	2.5	2/1/2022
$C_3$	1	2	0.25	30	1	1/12/2021
$C_3$	2	1.33	0.25	20	1	2/12/2021

Outcome data for each contact:

Exposed contact	Reported positive
$C_1$	TRUE
$C_2$	FALSE
$C_3$	FALSE

Reported positive means via voluntary testing, entered in the app in the window [notification, 14 days since exposure]. Under-ascertainment.

We have this for *7 million* notified contacts, *23 million hours* of risky exposure.

Are contacts' outcomes predicted by their exposure data?

Exposed contact	Exposure window	Risk score / threshold	Proximity score	Duration / minutes	Index infectiousness	Exposure date
C <sub>1</sub>	1	2	0.25	30	1	1/1/2022
C <sub>1</sub>	2	8	1	30	1	1/1/2022
C <sub>1</sub>	3	4	1	15	1	1/1/2022
C <sub>2</sub>	1	7	1	30	2.5	2/1/2022
C <sub>3</sub>	1	2	0.25	30	1	1/12/2021
C <sub>3</sub>	2	1.33	0.25	20	1	2/12/2021

Exposed contact	Reported positive
C <sub>1</sub>	TRUE
C <sub>2</sub>	FALSE
C <sub>3</sub>	FALSE

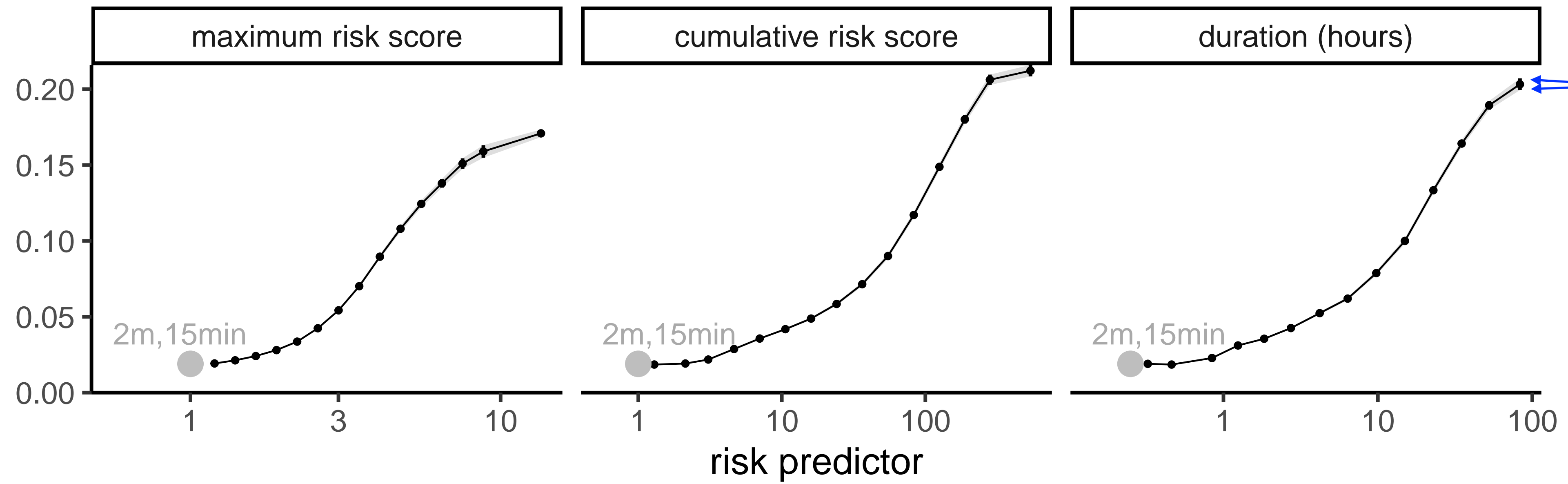
Summarise each contact's measurements into summary metrics. e.g. here,  
 Max risk score = 8,  
 Cumulative risk score = 14,  
 Cumulative duration = 75 mins

Exposed contact	Exposure window	Risk score / threshold	Proximity score	Duration / minutes	Index infectiousness	Exposure date
C <sub>1</sub>	1	2	0.25	30	1	1/1/2022
C <sub>1</sub>	2	8	1	30	1	1/1/2022
C <sub>1</sub>	3	4	1	15	1	1/1/2022
C <sub>2</sub>	1	7	1	30	2.5	2/1/2022
C <sub>3</sub>	1	2	0.25	30	1	1/12/2021
C <sub>3</sub>	2	1.33	0.25	20	1	2/12/2021

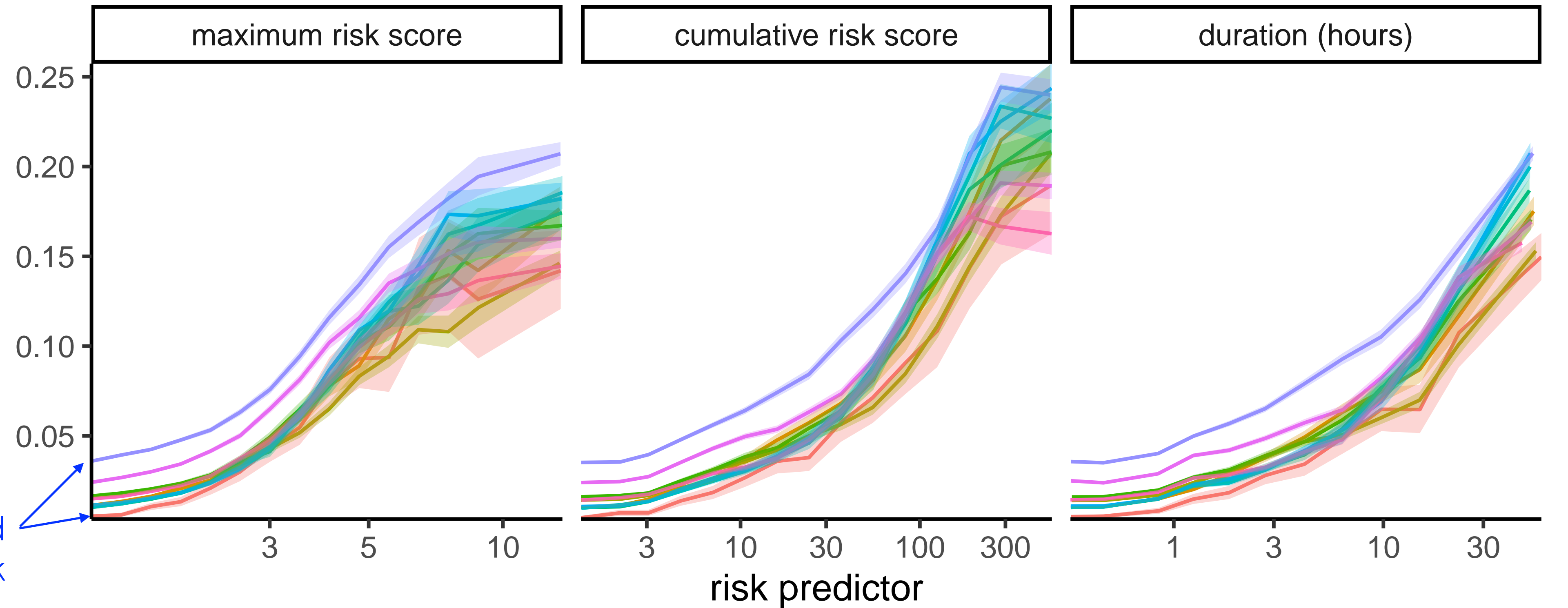
Exposed contact	Reported positive
C <sub>1</sub>	TRUE
C <sub>2</sub>	FALSE
C <sub>3</sub>	FALSE

Then group/bin contacts by their metric value, and calculate the fraction reporting a positive test = “observed probability of infection”.

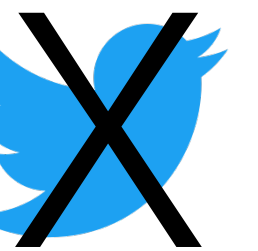
Observed probability of infection



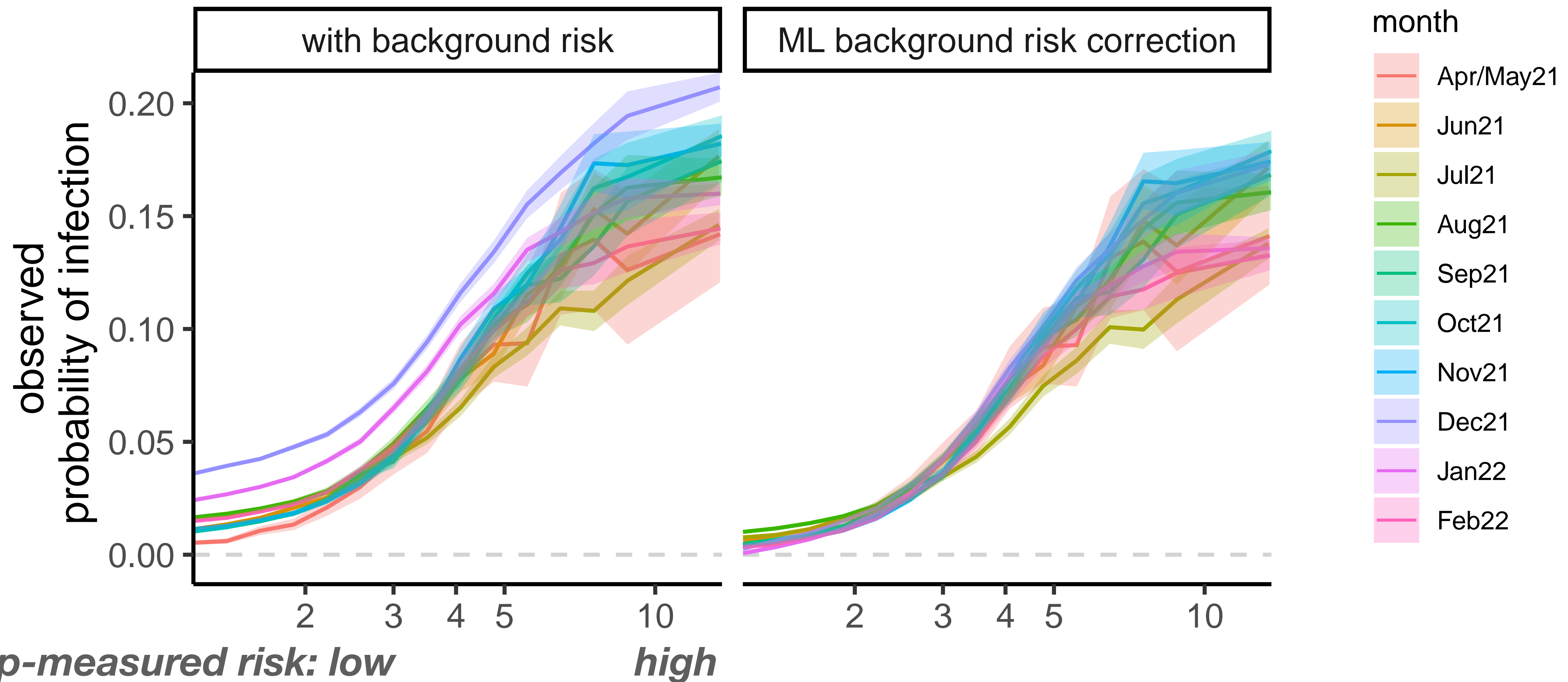
Observed probability of infection



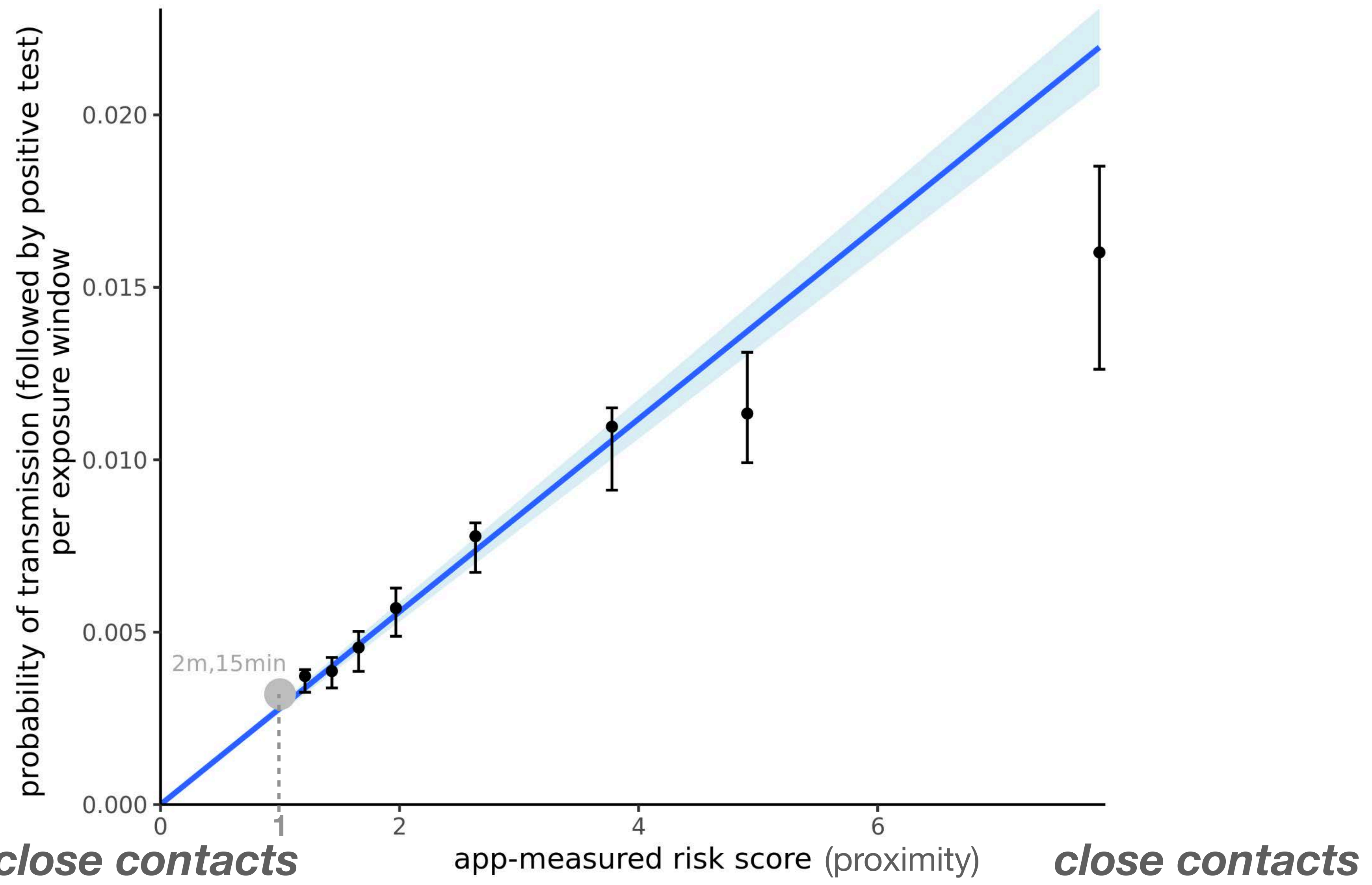
background risk



# Empirical risk of infection/transmission versus app “risk score” from riskiest window



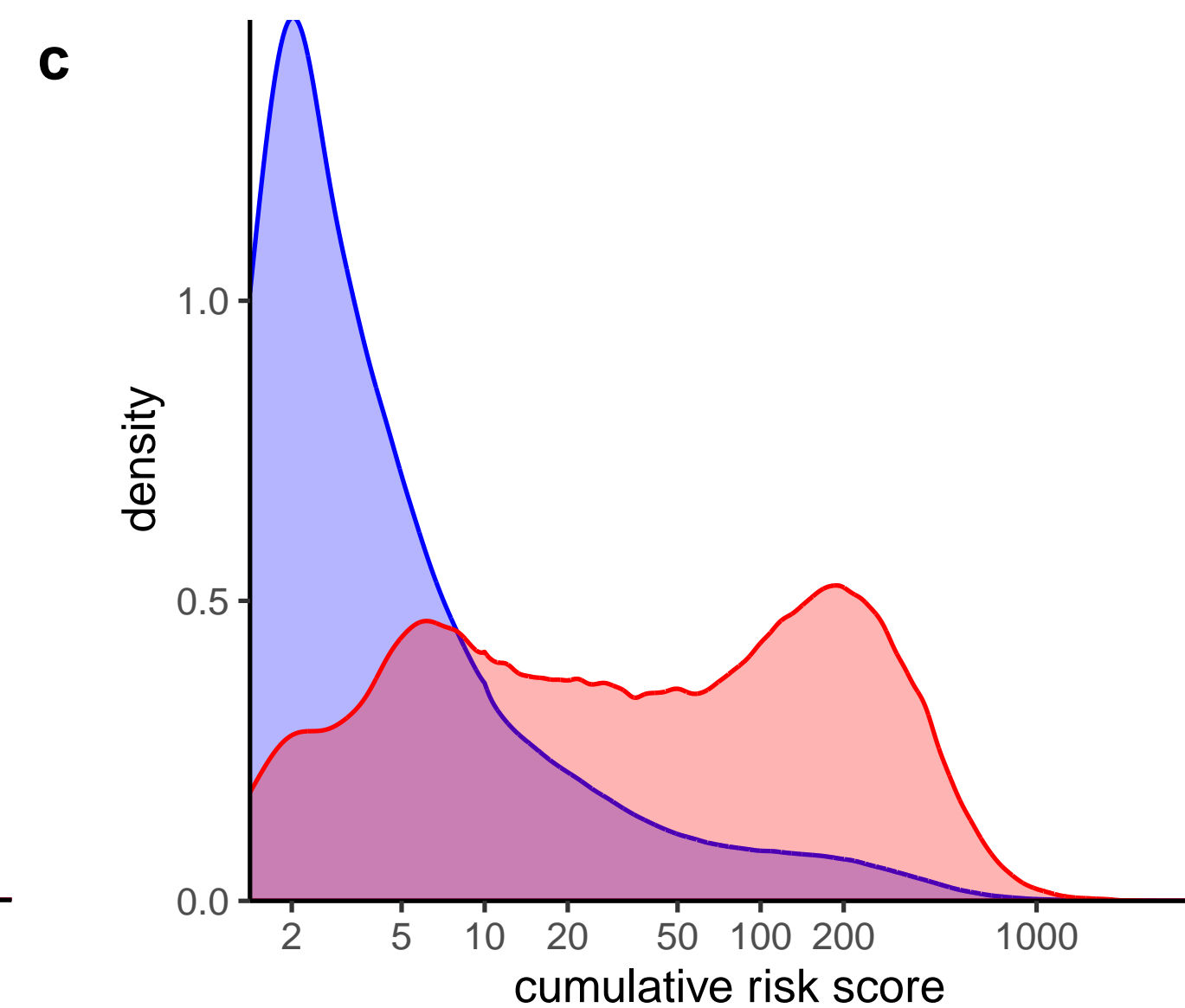
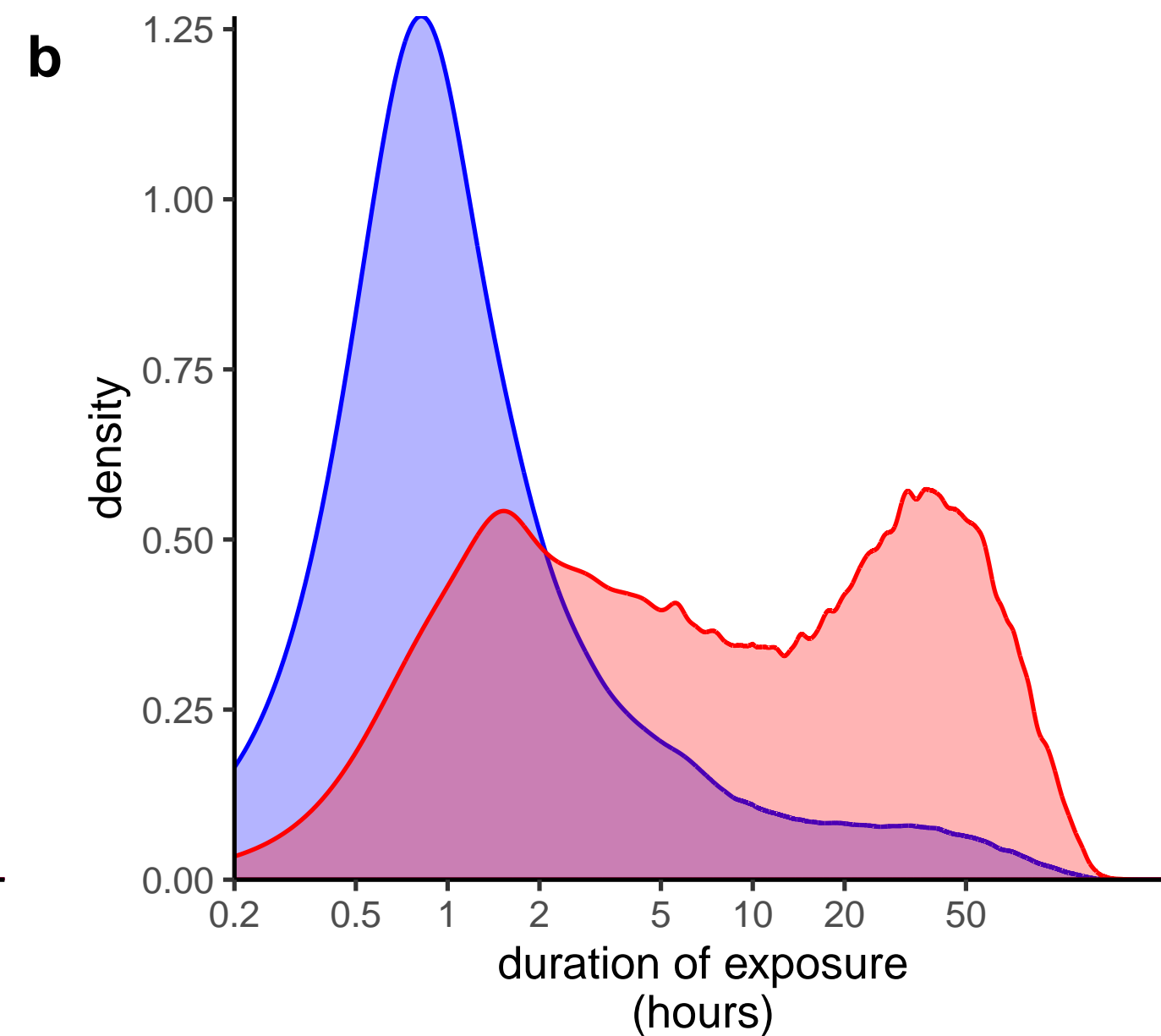
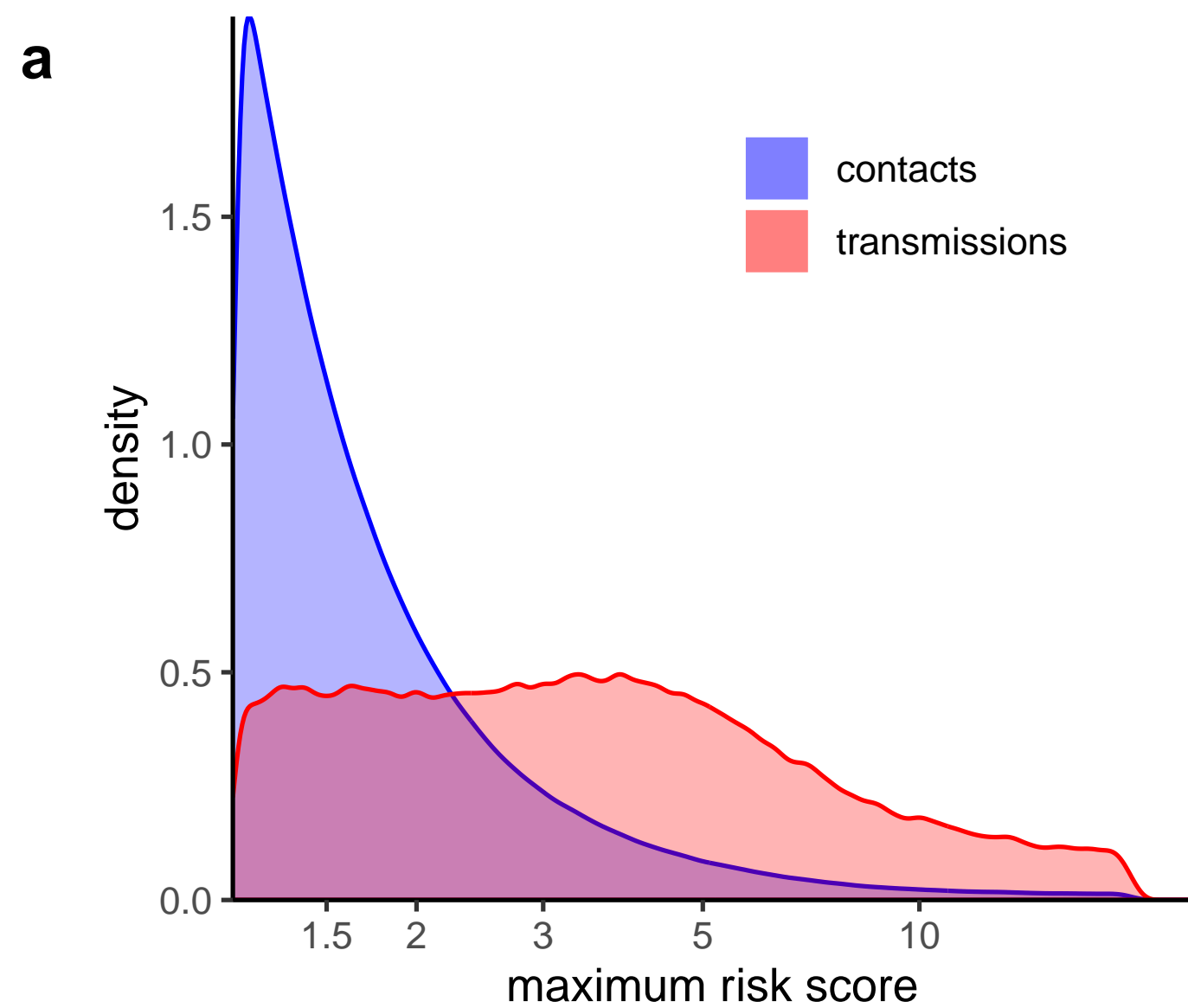
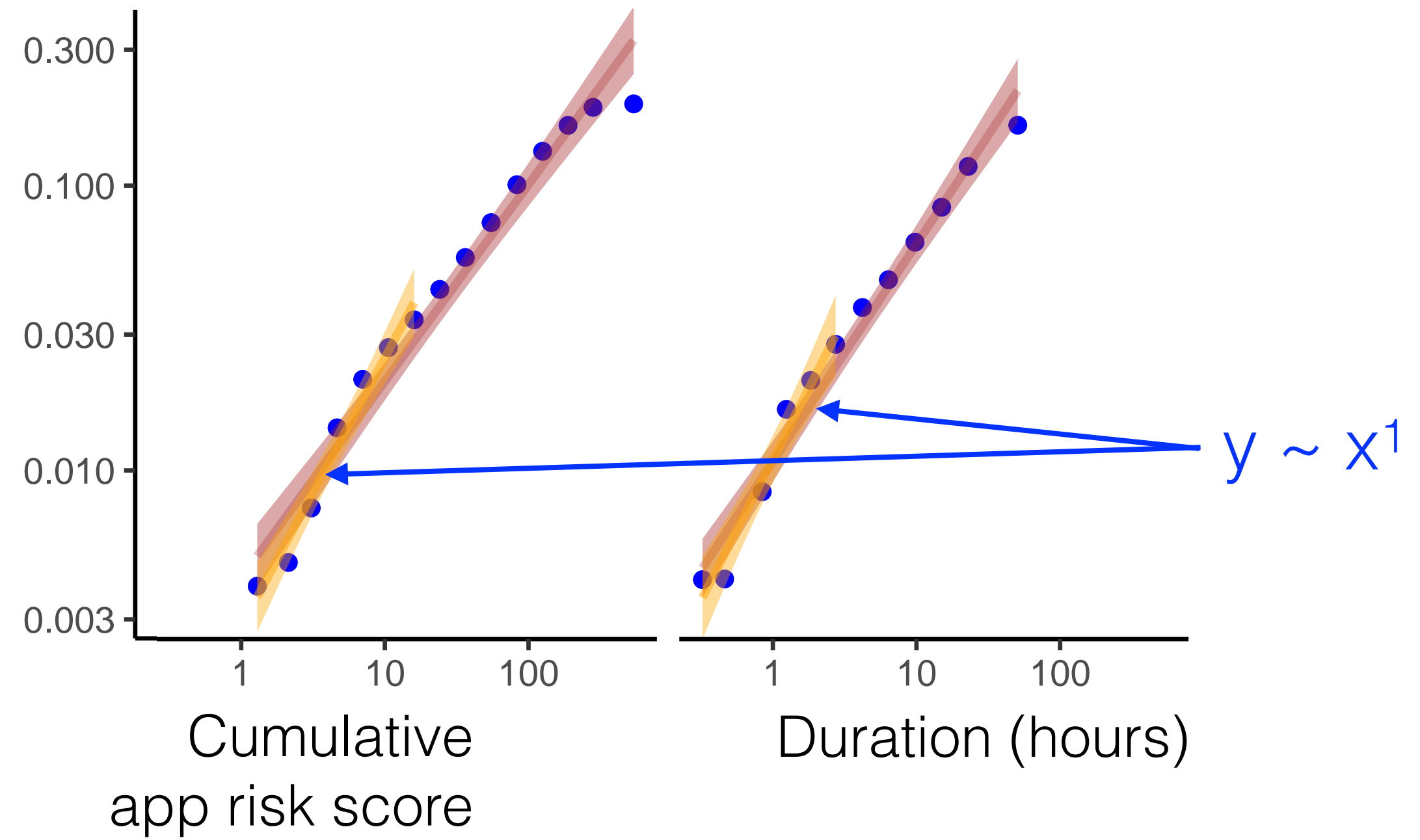
# Risk of transmission from single exposure window





Estimate & subtract the background risk, attributing remaining positive tests in each bin to the recorded exposures: “transmissions”

Observed probability of transmission



# Classification of exposures



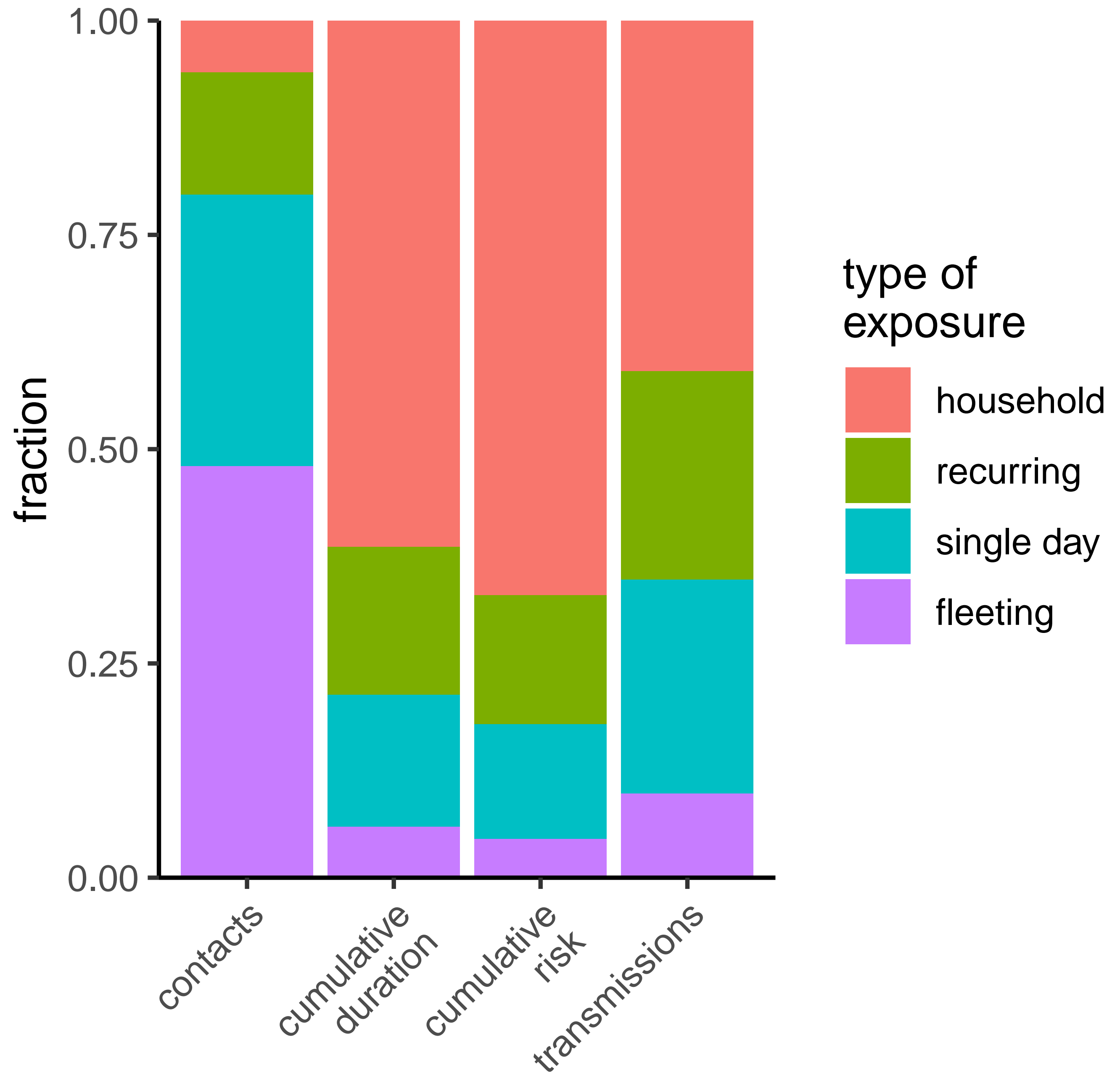
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Using extra information available due to linkage between exposures:  
days of exposure & total duration of exposure during each day

Classification:

- **Household:** >8 hours in the same day; i.e. living together/sharing bedroom
- **Recurring:** non-household, >30 mins total, on multiple day; may be workplaces, friends/relatives or regular activities
- **One-day:** non-household, >30 mins total, on a single day
- **Fleeting:** <30 mins





# Precision epidemiology: disentangling the contributions to $R_t$



$$R_t = \text{number of contacts} \times \text{probability of transmission (secondary attack rate)}$$

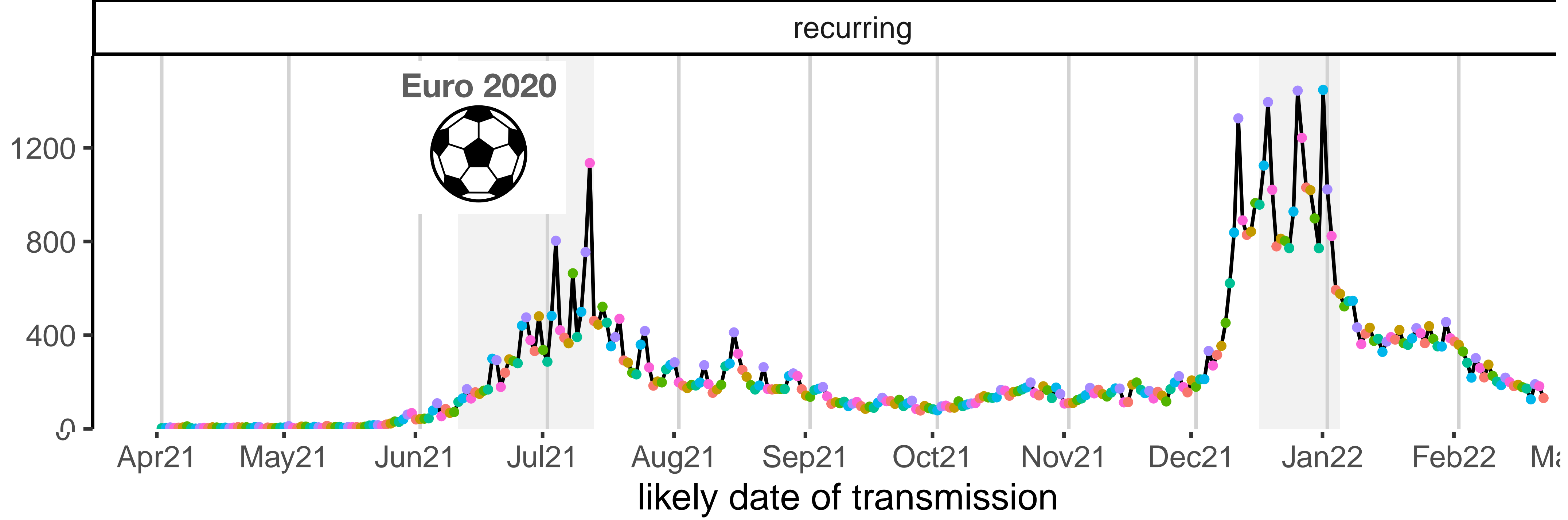
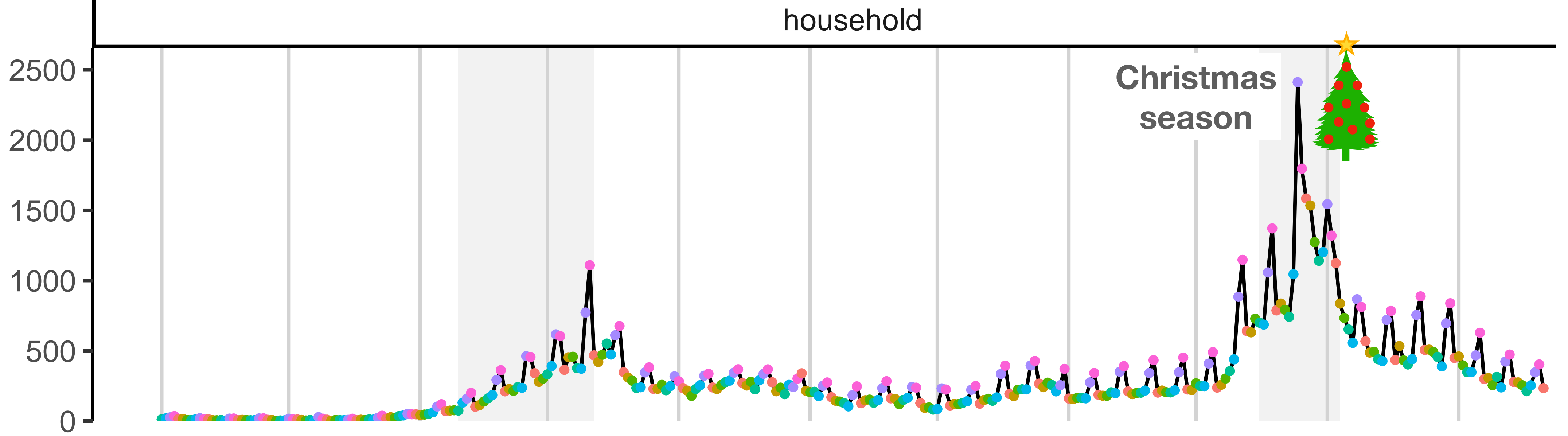
proximity x duration  
and other physical, biological,  
immunological & behavioural components





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**Transmissions detected by the app**



weekday

- Mon
- Tue
- Wed
- Thu
- Fri
- Sat
- Sun





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Transmissions detected by the app

single day

Christmas  
season

fleeting

Euro 2020



weekday

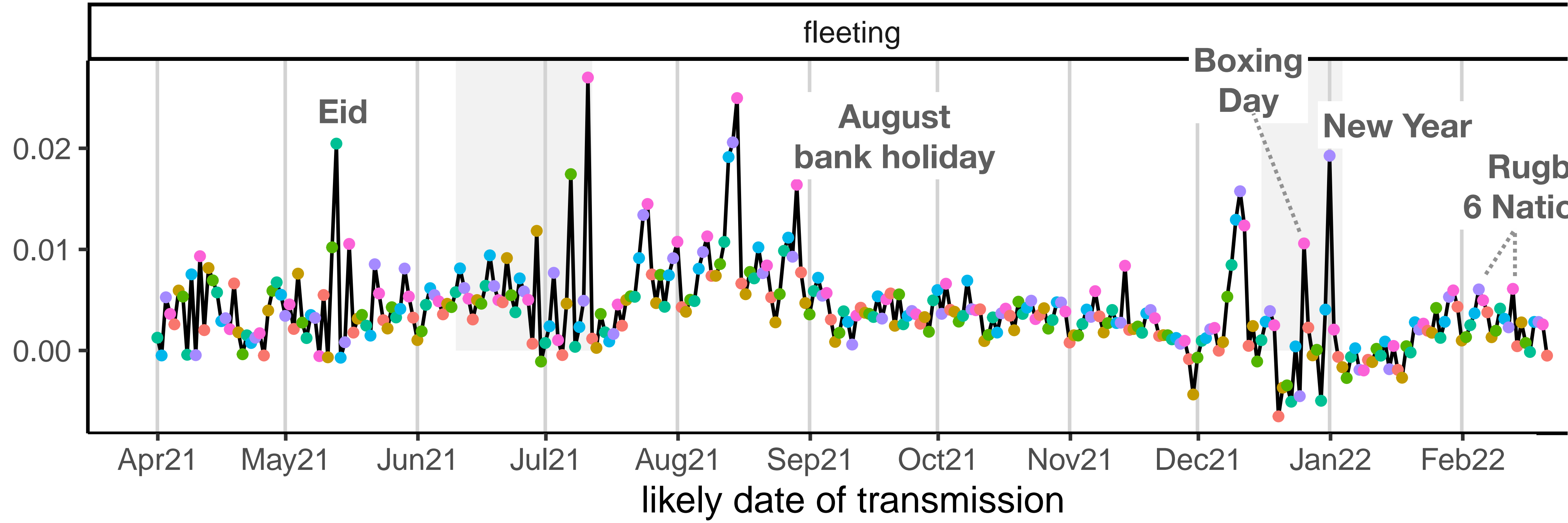
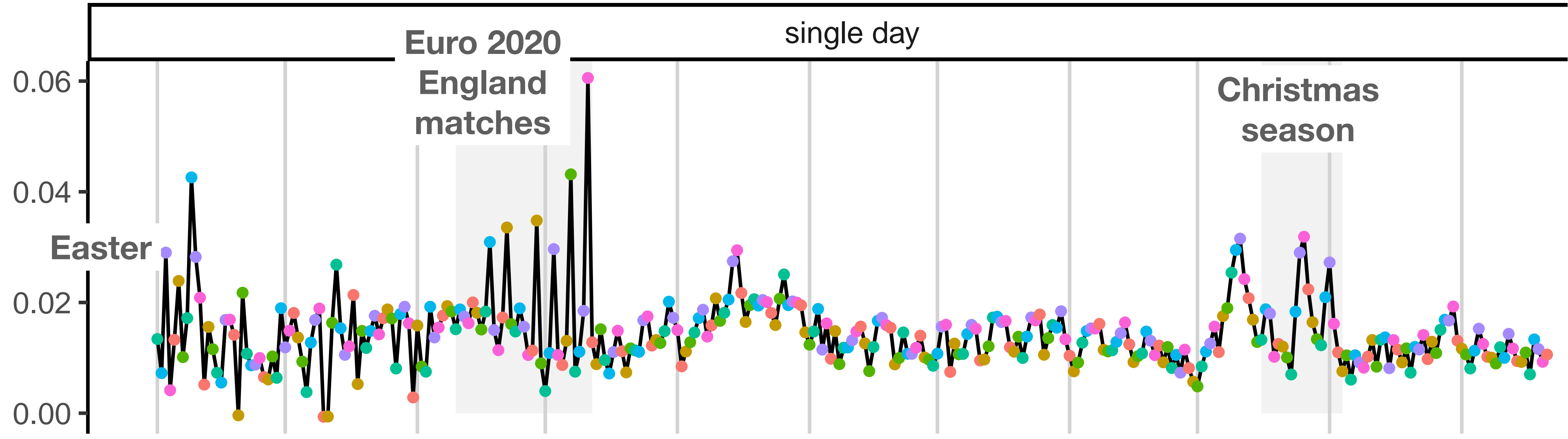
- Mon
- Tue
- Wed
- Thu
- Fri
- Sat
- Sun

Apr21 May21 Jun21 Jul21 Aug21 Sep21 Oct21 Nov21 Dec21 Jan22 Feb22 M

likely date of transmission



SAR observed by the app



- weekday
- Mon
  - Tue
  - Wed
  - Thu
  - Fri
  - Sat
  - Sun



# Summary

- Digital contact tracing is feasible & offers something unique and additional;.
- Effectiveness analysis points to substantial effect, both realised and potential (more targeted than lockdowns).
- It requires close integration with government services, and so is very political.
- Networked intervention that results in continuous direct exchange of data between neighbouring phones requires strong oversight & governance.
- Quantitative insights into transmission, 1.1% transmission per hour, 40% in households, drivers of  $R_t$ .
- Types of insights could be generated for other pathogens and disease X within weeks.



# Thank you!



# Thanks to NHS App team.