UMC Utrecht

# Modelling Contact Tracing for COVID-19

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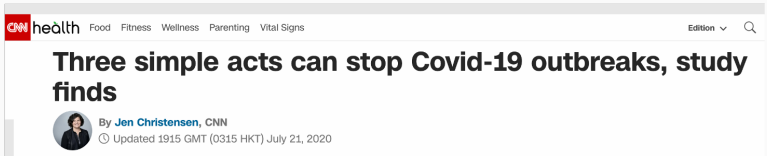
ZonMw

coresma

# Modelling projects COVID-19

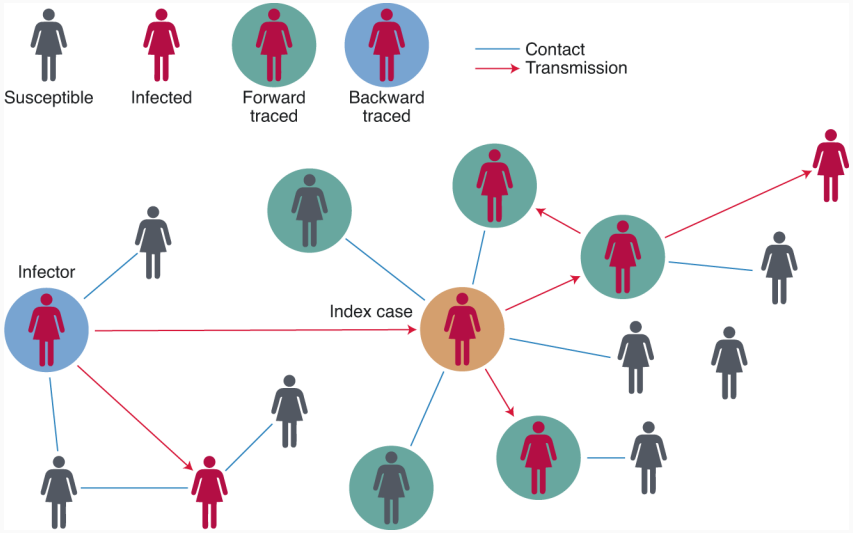
## Projects

- Impact of awareness and hygiene measures on epidemic (Teslya et al 2020)
- Effectiveness of contact tracing (Kretzschmar et al 2020; 2021)
- Impact of school based interventions (Rozhnova et al 2021)
- Impact of interventions in hospitals (Pham et al; submitted)
- Lockdown fatigue and vaccination (Teslya et al; submitted)
- NPI and vaccination in Portugal (Viana et al; submitted)

# Contact Tracing

Make use of the contact network to find infections.




- used for many infectious diseases
- forward/backward tracing
- one step/multistep tracing

Review paper:

Müller & Kretzschmar. Contact tracing: Old Models and New Challenges. Inf Dis Modelling 2021

# Contact tracing model for COVID-19

# Publications contact tracing

frontiers in Physics

ORIGINAL RESEARCH
published: 10 February 2021
doi: 10.3389/fphy.2020.622485

Check for updates

## Isolation and Contact Tracing Can Tip the Scale to Containment of COVID-19 in Populations With Social Distancing

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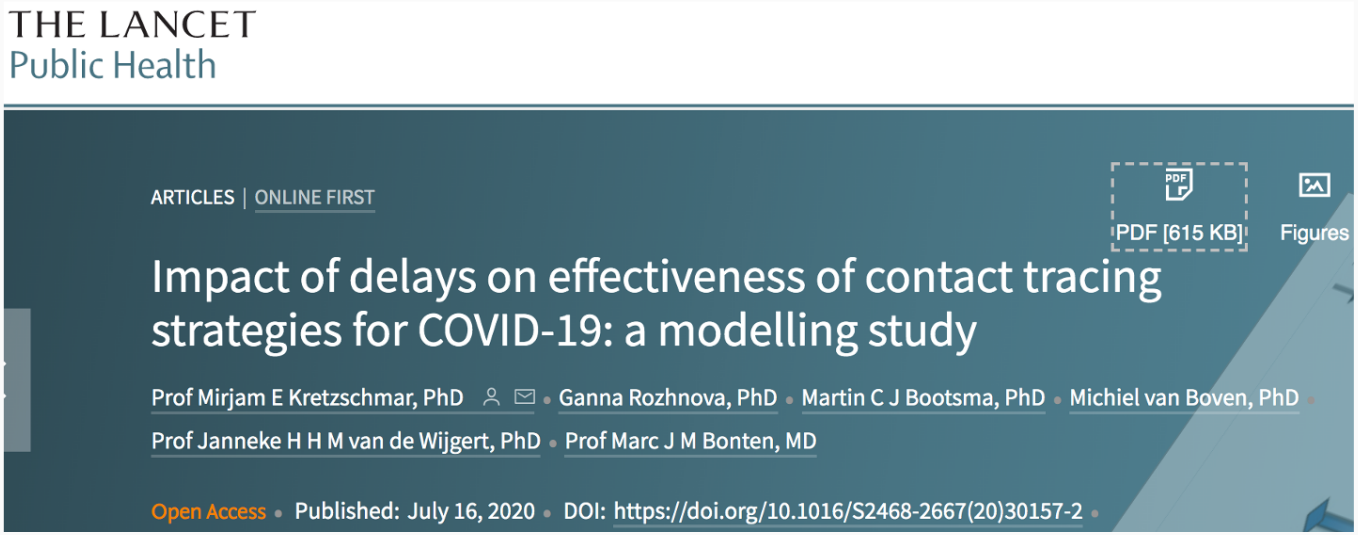

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Figures

## Impact of delays on effectiveness of contact tracing strategies for COVID-19: a modelling study

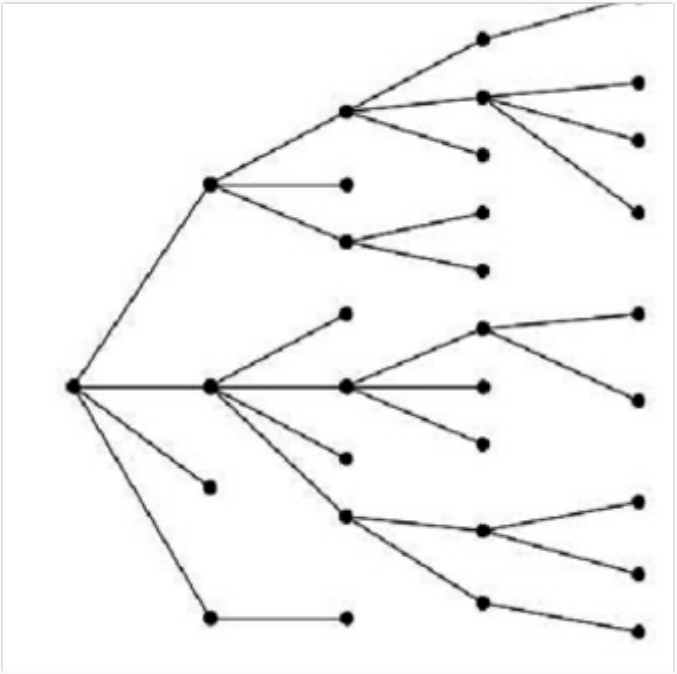
Prof Mirjam E Kretzschmar, PhD • Ganna Rozhnova, PhD • Martin C J Bootsma, PhD • Michiel van Boven, PhD • Prof Janneke H H M van de Wijgert, PhD • Prof Marc J M Bonten, MD

Open Access • Published: July 16, 2020 • DOI: https://doi.org/10.1016/S2468-2667(20)30157-2 •

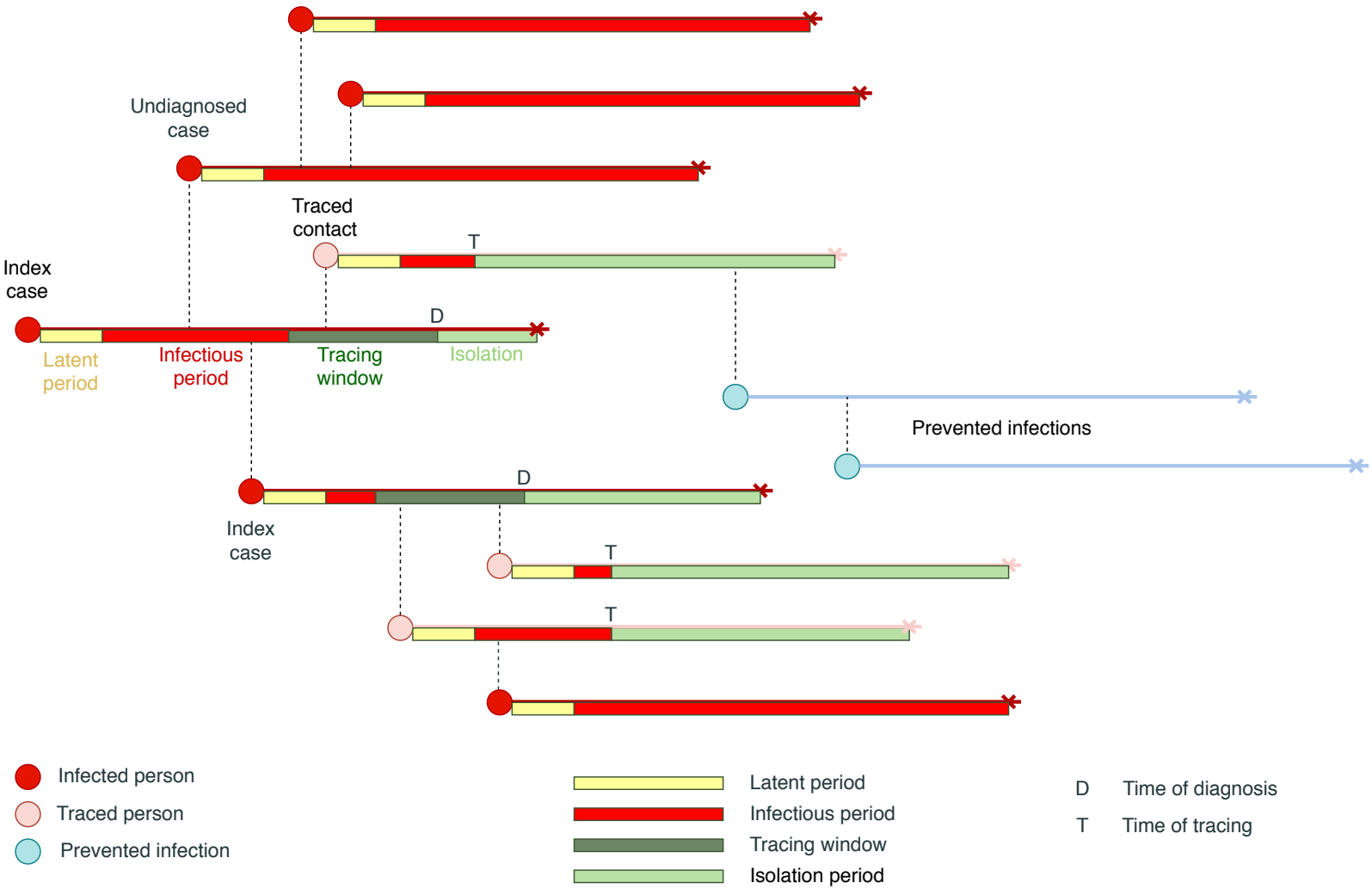
# Questions for COVID-19

- Can contact tracing control the epidemic?
- How fast does contact tracing have to be to control epidemic?
- How do conventional CT and digital app based CT compare?

Approach:
Stochastic branching process
$R_0$ and $R_e$ can be calculated explicitly
Doubling time and exponential growth rate can be calculated



# Schematic view of contact tracing



# Model description contacts

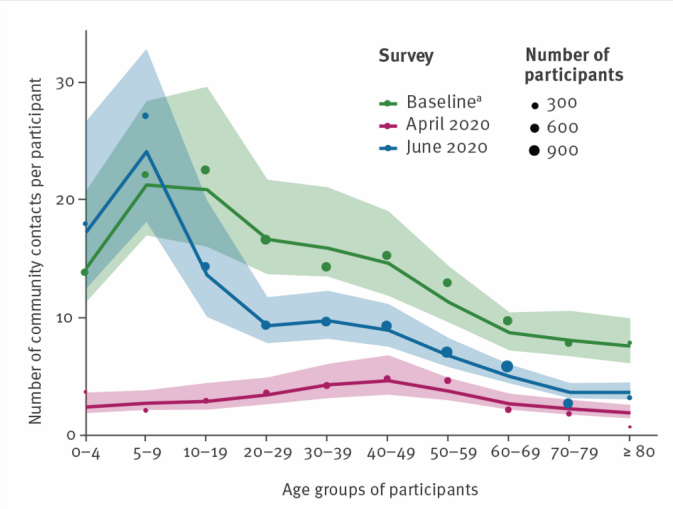
Model defined in timesteps of 1 day, $\tau$ day since infection

Contacts:

- Close contacts (household) per day: Poisson distributed, mean $\mu_1(\tau)$
- Casual contacts per day: Negative binomial distribution, mean $\mu_2(\tau)$
- Fit to Polymod data or other available contact data
- Social distancing: means reduced by factors $r_h$ and $r_c$, for close and casual contacts

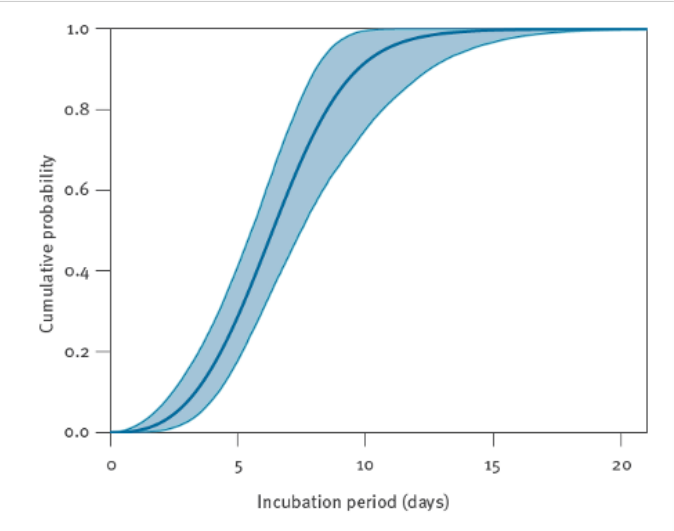
Contact data:

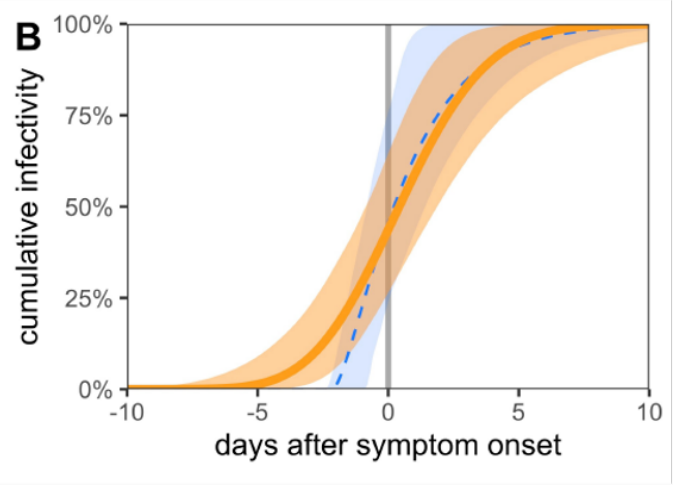
- Without social distancing based on Polymod (Mossong et al. 2008)
- With social distancing based on Backer et al. 2021



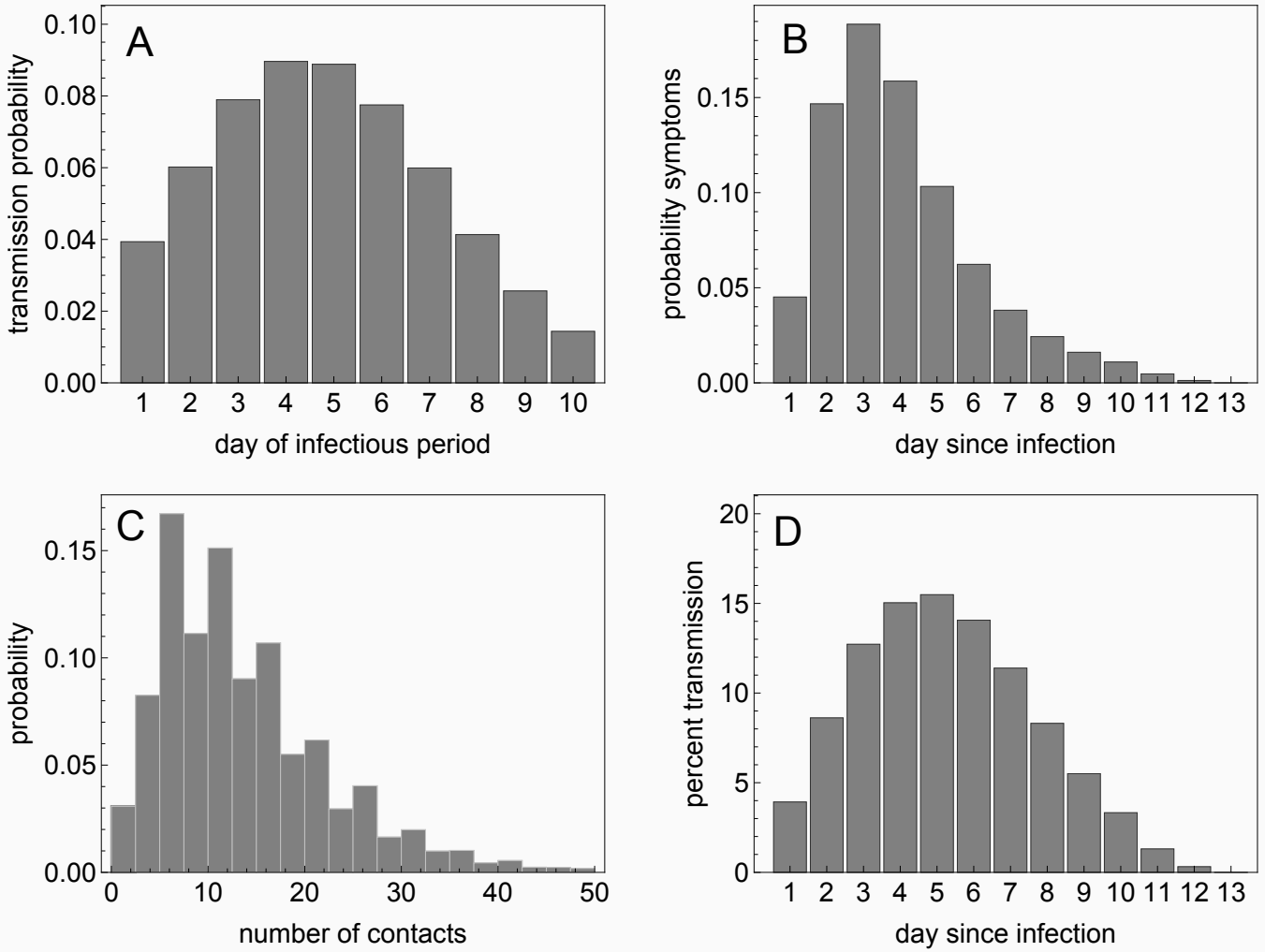
# Model description infection and transmission

- Latent period 1-3 days, infectious period 10 days
- Transmission probability proportional to infectivity, calibrated to $R_0$ value
- In casual contacts reduced by factor 0.25
- Incubation period and infectivity fitted to data (Backer et al 2020; He et al 2020; Ashcroft et al 2020)



# Model distributions




The resulting distributions used in the model are shown here.

# Diagnosis, isolation, contact tracing

Assumptions:

- Cumulative probability of developing symptoms may be <1, i.e case may remain asymptomatic
- After symptom onset, an index may be diagnosed and isolated after testing delay $D_1$
- After tracing delay $D_2$, contacts are found and and a fraction C are isolated;
- In isolation, infectivity is zero.

Main idea: For every day $\tau$ since infection, probability of diagnosis can be calculated and associated reduction in onward transmission by isolating contacts.

# Notation

$P_I(\tau)$ ($\tau = 1, ..., D_E$ .): probability to move from latent to infectious

$P_T(\tau)$ ($\tau = 1, ..., D_I$ .): probability of transmission upon contact

$P_S(\tau)$ ($\tau = 1, ..., D_I$ .): probability of symptom onset

$P_D(\tau)$ ($\tau = 1, ..., D_I$ .): probability of being diagnosed

$P_{ct}(\tau)$: probability for contact infected on day $\tau$ of index cases infectious period to be traced and isolated

$$P_{ct}(\tau) = \sum_{i=\tau}^{Min(D_I, \tau+w)} C\phi(i)P_D(i) \ ,$$

with $w$ window of tracing, $\phi(\tau)$ probability that index is not yet diagnosed up to day $\tau$, C tracing coverage

# Reproduction numbers and exponential growth

# Basic reproduction number $R_0$

Basic reproduction number without interventions:

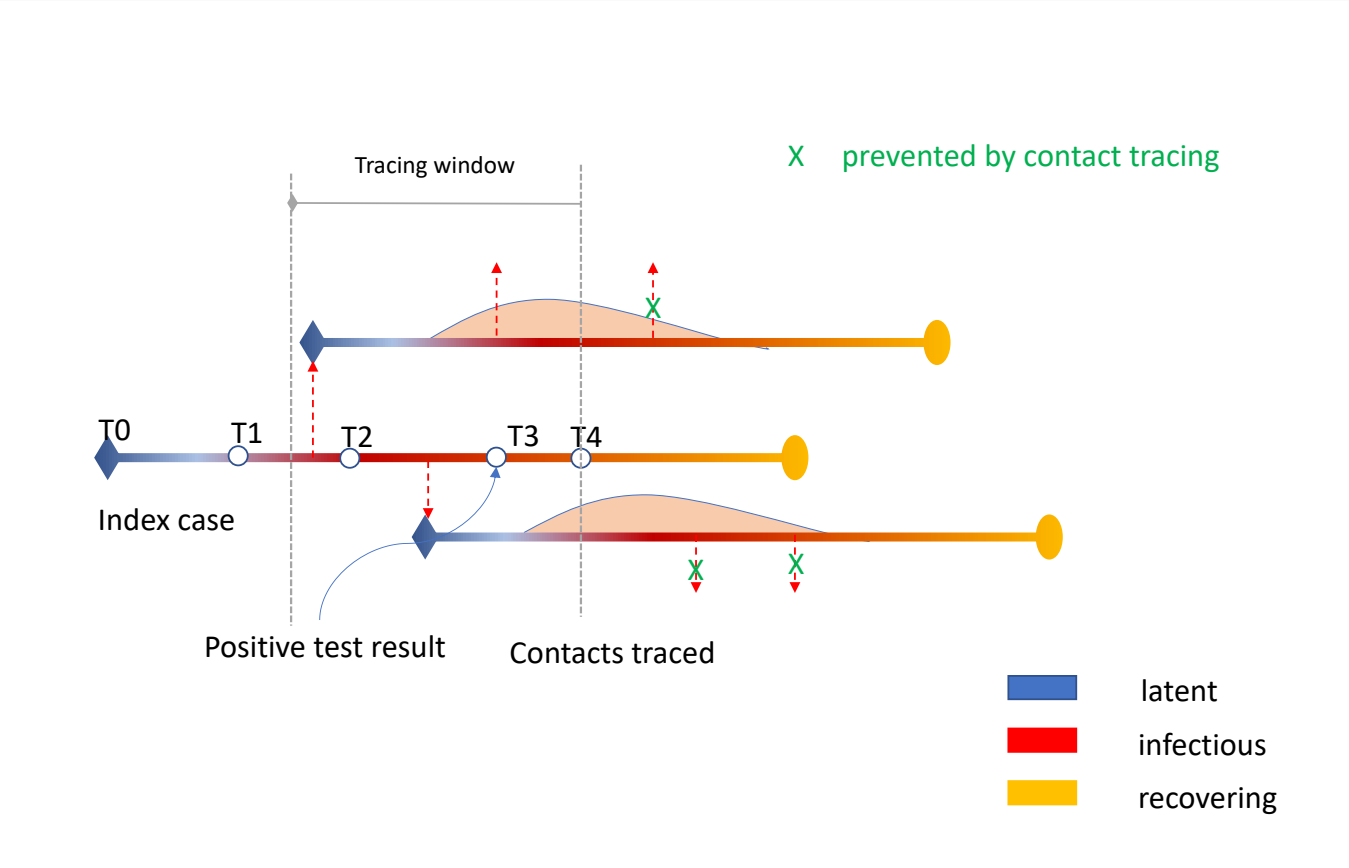
$$R_0 = \sum_{\tau=1}^{D_I} (\mu_1(\tau) P_T(\tau) + \mu_2(\tau) q P_T(\tau)) \ , \tag{1}$$

with $q$ factor by which non-household contacts are less transmissible.

With $R_0(\tau)$ the number of secondary cases on day $\tau$ of infectious period, the proportion of onward transmission generated up to day $\tau$ is

$$\rho(\tau) = \frac{1}{R_0} \sum_{i=1}^{\tau} R_0(i) \ . \tag{2}$$

# $R_e$ with contact tracing




Proportion of onward transmissions of contact up to day $\sigma$ since infection

$$\lambda(\sigma) = \sum_{i=1}^{D_E} \prod_{j=1}^{i-1} (1 - P_I(j)) P_I(i) \rho(\sigma - i) \ ,$$

# $R_e$ with contact tracing

Probability of onward transmission prevented by tracing and isolation:

$$\psi(\tau) = \sum_{i=\tau}^{D_I} \phi(i) P_D(i) C(1 - \lambda(\tau + i + D_2)) \ .$$

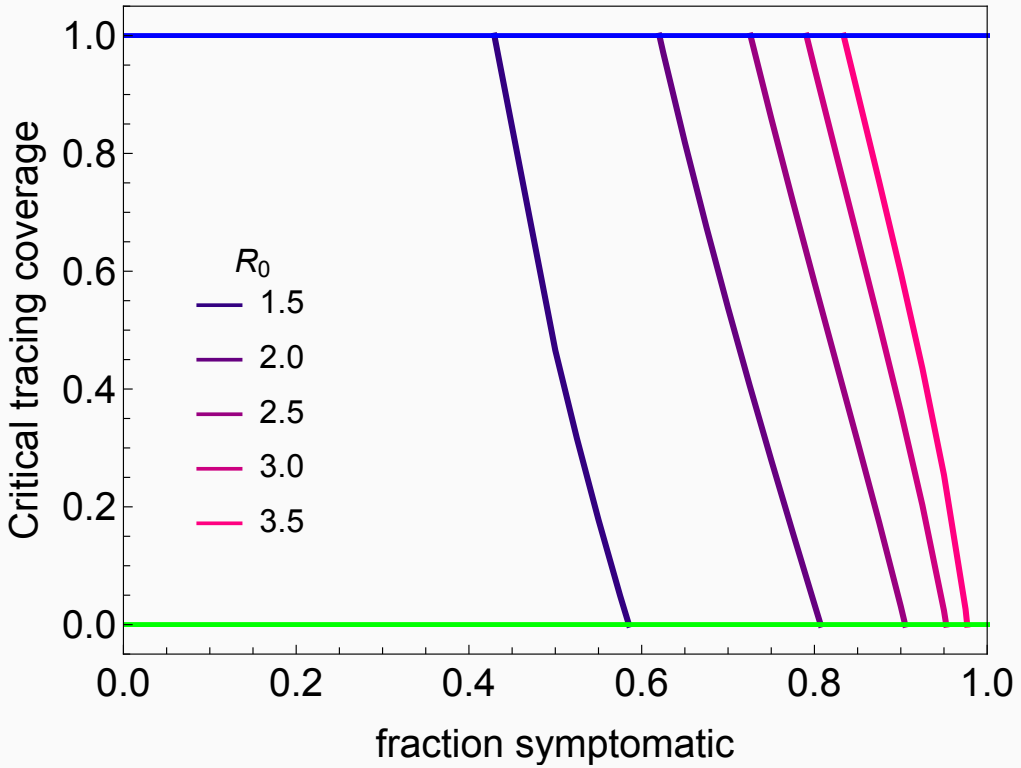
Contacts are weighted according to fraction of transmission that can be prevented.

The we get:

$$R_e = \sum_{\tau=1}^{D_I} (\mu_1(\tau) P_T(\tau)(1 - \psi_1(\tau)) + \mu_2(\tau) q P_T(\tau)(1 - \psi_2(\tau)))\phi(\tau) \ .$$

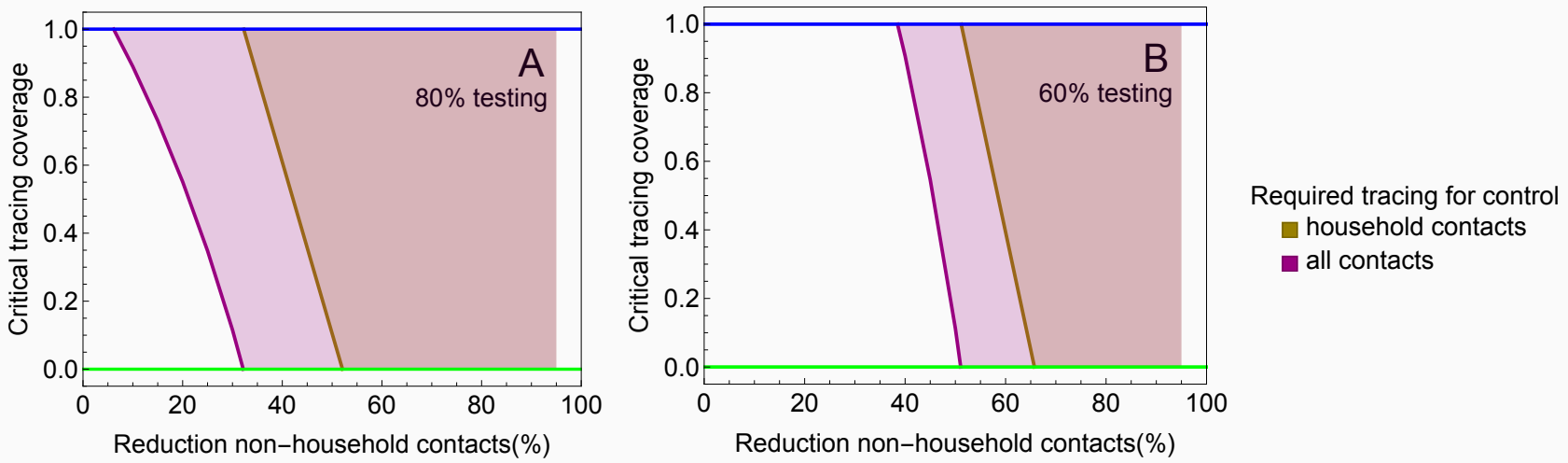
The critical tracing coverage $C_{crit}$ is obtained by computing the smallest non-negative root of the equation $R_e = 1$

# Critical tracing coverage and symptomatic fraction




All household contacts are traced; critical coverage shows what percentage of non-household contacts need to be traced at least to reduced $R_e$ below 1. All symptomatic persons get tested.

# Impact of social distancing




Assumptions:

- 80% and 60% of all persons who develop symptoms get tested and diagnosed
- First close contacts (households) get traced and quarantined

# Exponential growth rate and doubling time

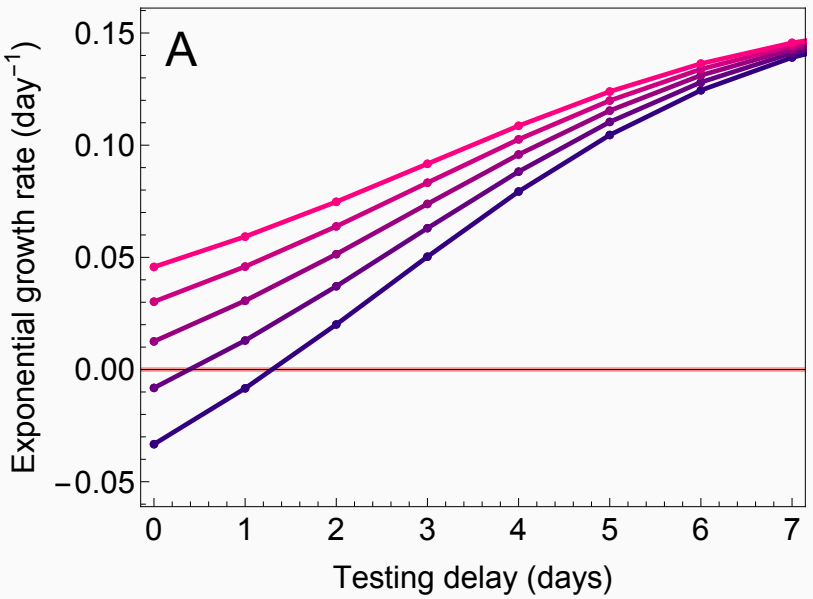
The exponential growth rate $r$ can be calculated as root of the equation

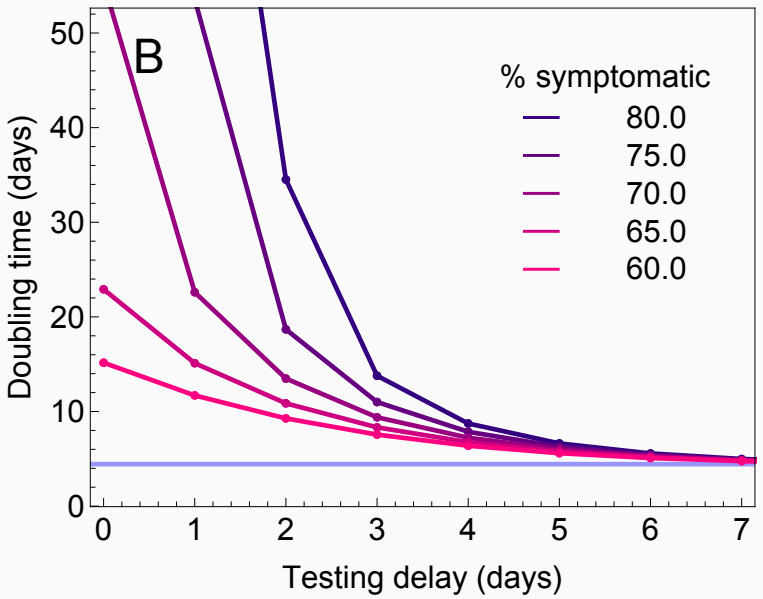
$$1 = \sum_{j=1}^{D_E} \sum_{\tau=1}^{D_I} e^{-r(j+\tau)} \epsilon(j)(\mu_1(\tau) P_T(\tau) + \mu_2(\tau) q P_T(\tau))$$

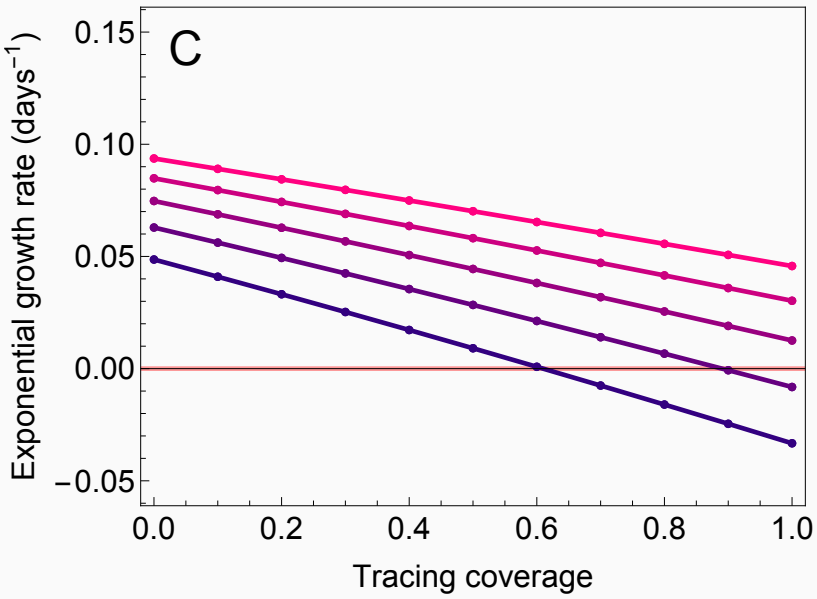
The doubling time $\delta$ is subsequently computed as

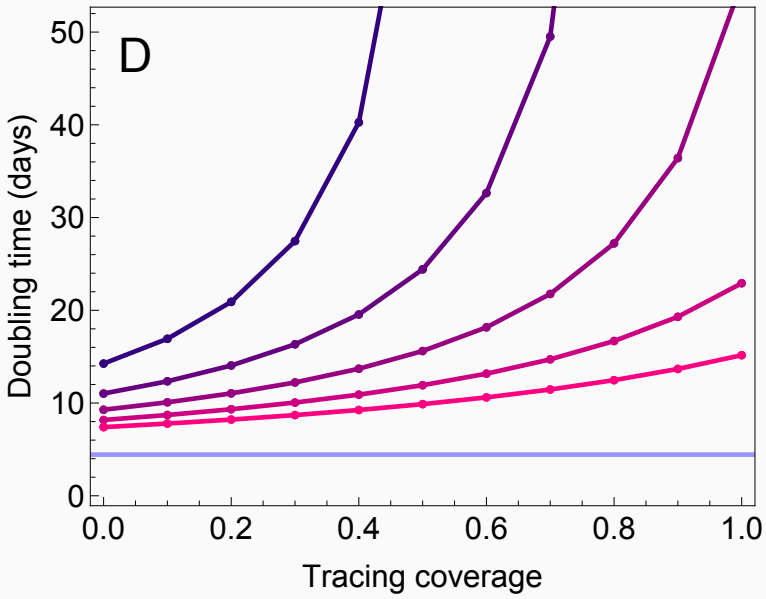
$$\delta = \frac{ln(2)}{r}$$

# Exponential growth rates and doubling times

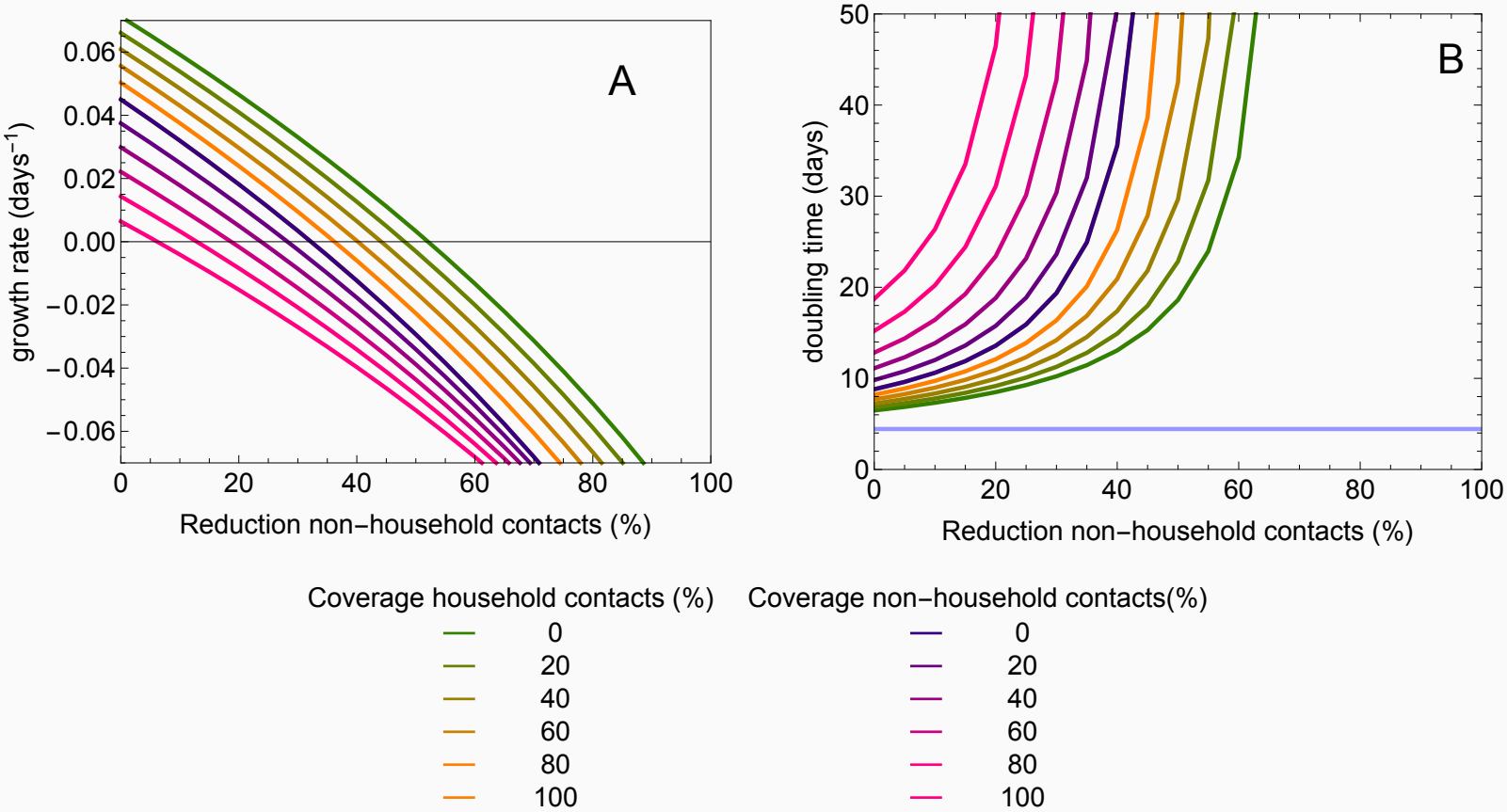


# Exponential growth rates and doubling times



# Comparison of contact tracing strategies

# Manual versus digital contact tracing

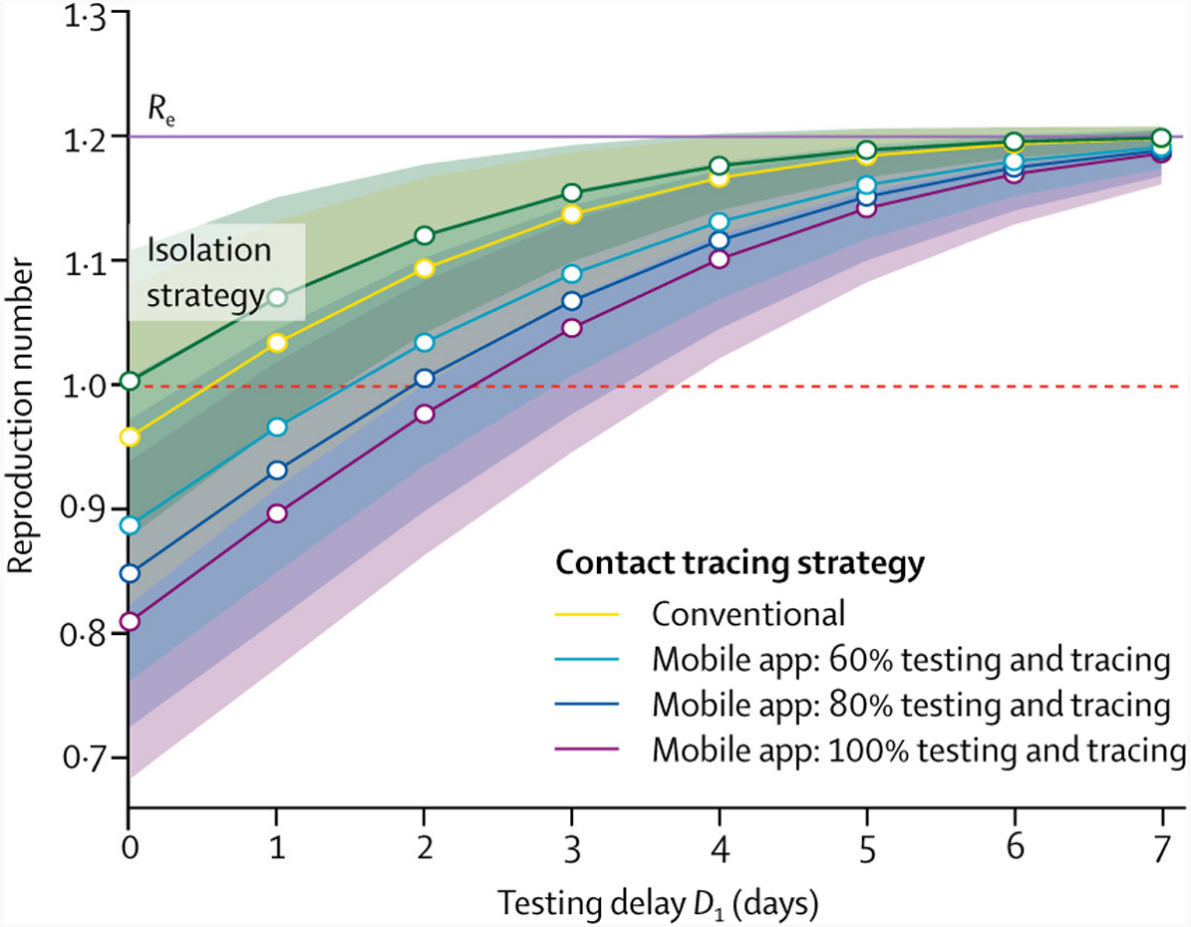
| | Isolation | Conventional contact tracing | Mobile app contact tracing |
|---|---|---|---|
| Testing coverage | 80% | 80% | 20%, 40%, 60%, 80%, 100% |
| Testing delay ($D_1$), assuming immediate isolation when testing positive | 4 days | 4 days | 0 days |
| Time to trace close contacts ($D_2$) | .. | 3 days | 0 days |
| Time to trace other contacts, assuming testing and isolation of those who test positive | .. | 3 days | 0 days |
| Tracing coverage of close contacts | .. | 80% | 20%, 40%, 60%, 80%, 100% |
| Tracing coverage of casual contacts | .. | 50% | 20%, 40%, 60%, 80%, 100% |
| Time traced back | .. | 7 days | 7 days |

For isolation-only and conventional contact tracing strategies, we assumed a baseline testing coverage of 80% (see appendix pp 11–12 for sensitivity analyses). For mobile app contact tracing strategies, we varied the testing coverage between 20% and 100%, and assumed 80% as a best-case scenario. For conventional contact tracing, delays and coverages were chosen to reflect current practice, whereas for mobile app contact tracing, we varied coverages to reflect different levels of app use.

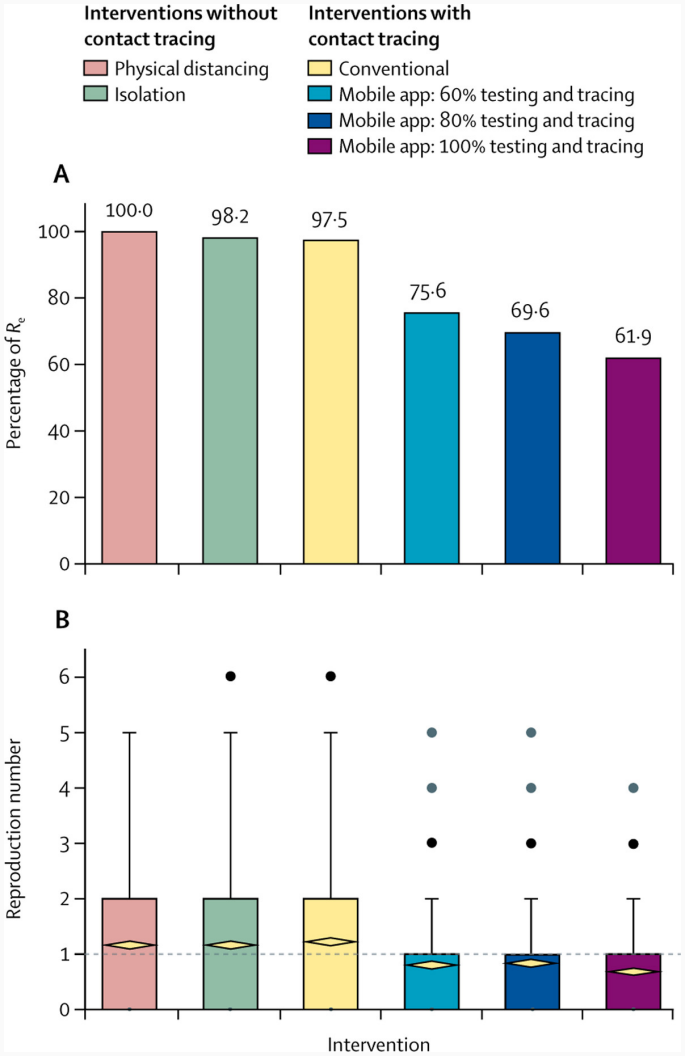
***Table 1:*** **Comparison of isolation, conventional contact tracing, and mobile app contact tracing strategies**

Assumption: there is social distancing in place such that $R_e = 1.2$.

# Impact on $R_e$

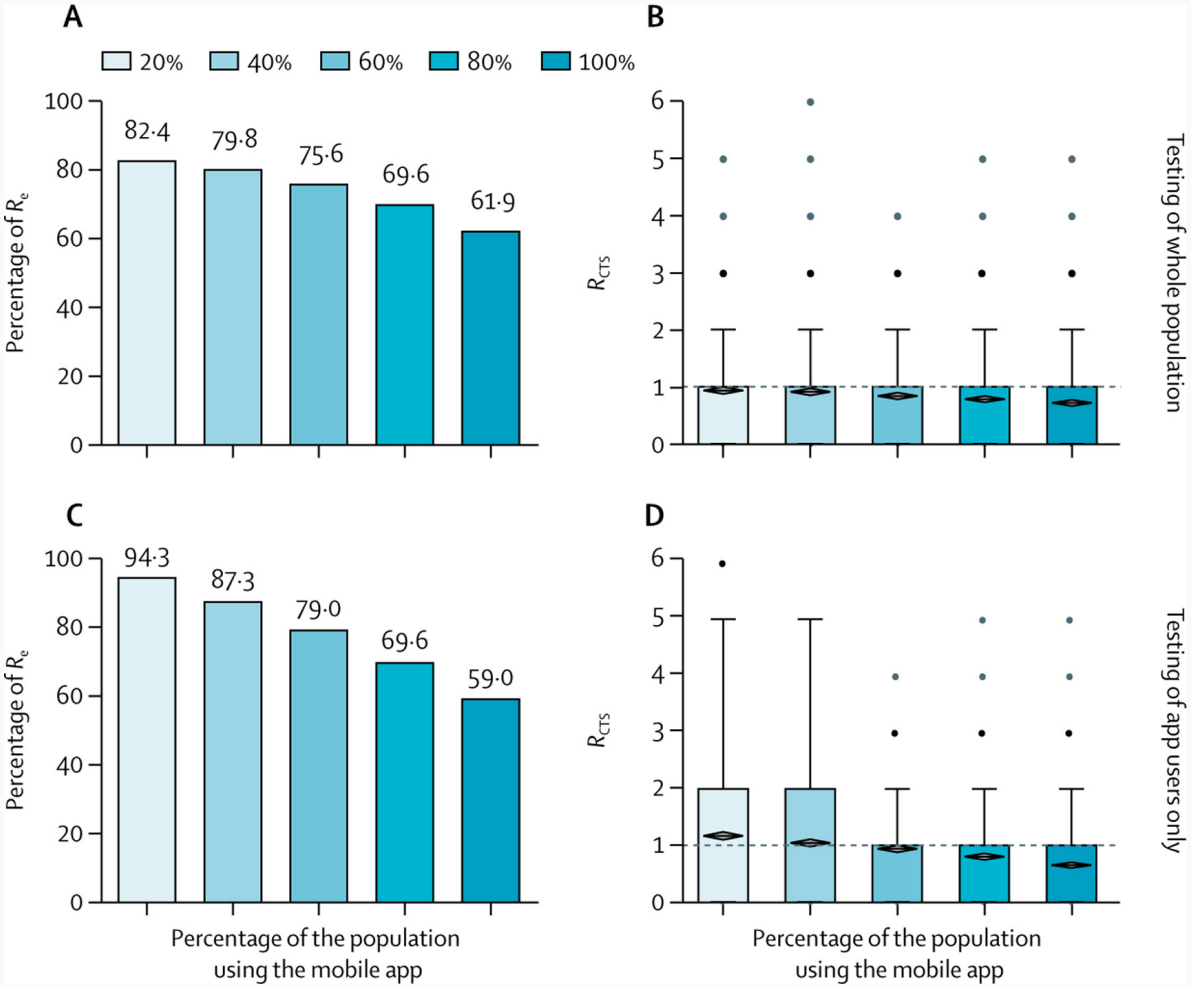

1·3
1·2
1·1
1·0
0·9
0·8
0·7
$R_e$
Isolation strategy
Reproduction number
Contact tracing strategy
Conventional
Mobile app: 60% testing and tracing
Mobile app: 80% testing and tracing
Mobile app: 100% testing and tracing
0
1
2
3
4
5
6
7
Testing delay $D_1$ (days)

# Percent reduction of $R_e$




Individual reproduction numbers are calculated by drawing from all probability distributions defining $R_e$.

# Coverage of App use




A and B: 80% of all symptomatic persons are tested.

C and D: only symptomatic app users are tested.

# Onward infections prevented

| | Isolation only | Isolation plus contact tracing | | | |
|---|---|---|---|---|---|
| | | $D_2$=3 | $D_2$=2 | $D_2$=1 | $D_2$=0 |
| $D_1$=0 | 50·4% | 62·4% | 67·8% | 73·9% | 79·9% |
| $D_1$=1 | 35·7% | 47·3% | 53·4% | 60·7% | 68·5% |
| $D_1$=2 | 23·4% | 33·0% | 38·9% | 46·5% | 55·4% |
| $D_1$=3 | 14·2% | 21·0% | 26·0% | 32·9% | 41·8% |
| $D_1$=4 | 7·8% | 11·9% | 15·7% | 21·4% | 29·1% |
| $D_1$=5 | 3·8% | 5·9% | 8·4% | 12·5% | 18·4% |
| $D_1$=6 | 1·6% | 2·4% | 3·8% | 6·4% | 10·4% |
| $D_1$=7 | 0·5% | 0·7% | 1·3% | 2·8% | 4·9% |

Interventions explored are isolation of only the index case or isolation of the index case with tracing and isolation of 80% of infected contacts, according to tracing delay $D_2$, ranging from 0 to 3 days. All interventions are varied by testing delay $D_1$, ranging from 0 to 7 days.

*Table 2:* **Percentage of onward transmissions prevented per diagnosed index case for various interventions**

# Conclusions

- In a population with social distancing, CT can keep $R_e$ below 1
- Reducing the testing delay (time between onset of symptoms and a positive test result) is the most important factor for CT effectiveness
- Reducing the tracing delay (time to trace contacts) might further enhance CT effectiveness
- Fast CT can prevent large fraction of onward transmissions
- Effectiveness of digital CT declines with lower app use coverage, but remains potentially more effective than conventional CT due to its inherent speed

# Thank you!