Projecting the transmission dynamics of SARS-CoV-2 through the post-pandemic period

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1. Estimating seasonality of betacoronaviruses
Beta coronavirus incidence in the US
Decomposing $R_e$

$log(R_{sij}) = log(R_0S_0) + \alpha_{sj} + \lambda_s d_{sij} + \delta_s d_{rij} + \sum_{n=1}^{10} \theta_n B_n(i) + \epsilon_{sij}$
Transmission model
Model fit

% positive x % ILI

- OC43
- HKU1

Actual
Simulated

Year
2015 2016 2017 2018 2019

$R_e$
OC43
HKU1

2015 2016 2017 2018 2019

$R_e$

Seasonality of betacoronaviruses

- 21% best fit amplitude of seasonal forcing
- Rest is accounted for by depletion of susceptibles
- This would not be enough alone to control SARS-CoV-2 in summer
- Limitations: incidence proxy, national data, lack of mechanism
- For excellent work on early evidence of SARS-CoV-2 seasonality see preprints of Tamma Carleton (Chicago) and Mauricio Santillana (Harvard)
2. Projecting with and without intervention
Scenarios

Short immunity: annual outbreaks

More seasonality: more punctuated outbreaks

Cross immunity: possible resurgence

 Longer immunity: sporadic outbreaks

Permanent immunity: elimination

OC43
HKU1
SARS–CoV–2
Interventions

\[ b(t) \sum (I_*) \]

\[ \beta(t) \sum (I_*) \rightarrow E \]

\[ S \rightarrow E \]

\[ \beta(t) \sum (I_*) \rightarrow I_R \quad 95.6\% \quad p_{RV} \]

\[ 4.6 \text{ days} \]

\[ I_R \rightarrow R_R \quad \gamma \quad 5 \text{ days} \]

Minor illness/asymptomatic arm

\[ I_R \rightarrow I_H \quad 3.08\% \quad p_{HV} \]

\[ I_H \rightarrow H_H \quad \gamma \quad 5 \text{ days} \]

Hospitalization arm

\[ H_H \rightarrow R_H \quad \delta_H \quad 8 \text{ days} \]

\[ H_H \rightarrow I_C \quad 4.6 \text{ days} \]

\[ I_C \rightarrow H_C \quad \gamma \quad 5 \text{ days} \]

\[ H_C \rightarrow C_C \quad \delta_C \quad 6 \text{ days} \]

\[ C_C \rightarrow R_C \quad \xi_C \quad 10 \text{ days} \]

Critical care arm
One-time social distancing (with seasonality)
Intermittent social distancing

No seasonality:

Seasonality:
Intermittent social distancing, double ICU capacity (similar: treatment halves demand)

No seasonality:

Seasonality:
Key conclusions

• One time distancing not enough – impact not monotonic in duration or intensity
• If estimates are correct about proportion of cases mild vs severe/critical, then several years of intermittent distancing required to get to herd immunity without overwhelming ICU
• Seasonality can exacerbate or improve impact of one-time distancing, but improves outcome of multiple rounds
4. Design of seroprotection studies

Rebecca Kahn, Lee Kennedy-Shaffer, Yonatan Grad, James Robins, Marc Lipsitch.

Potential biases arising from epidemic dynamics in observational seroprotection studies

To appear MedRxiv
Does past infection protect against future infection?

Geographic structure + epidemic dynamics
Job (healthcare worker)

Prior infection → Seropositivity → Infection
Methods overview

• Simulate an SEIS’ outbreak in a network model
  • Control vs. no control

• Seroprotection
  • 0 (null)
  • 50% reduction in force of infection
  • 95% reduction in force of infection

• Communities
  • 1 vs. 10
  • Well mixed vs. clustered

• Enroll into observational study & assess serostatus
  • Random sample all on the same day
  • Random sample on different days
  • Matched enrollment (on community & day of enrollment)

• Cox proportional hazards comparing infection after enrollment in sero+ vs. sero-
Well mixed, no control, null (HR = 1)

A. Well mixed, null

1 community, same day of enrollment, no match
1 community, different day of enrollment, no match
1 community, different day of enrollment, match
10 community, same day of enrollment, no match
10 community, different day of enrollment, match

Hazard Ratio (sero+ / sero-) (Median & IQR)

Stratified by community & day of enrollment

More sero+ & more likely to get infected each day after enrollment

Fewer sero+ & less likely to get infected each day after enrollment
Well mixed, clustered, null (HR = 1)
Well mixed, control, 50% efficacy (HR = 0.5)

More sero+ & less likely to get infected each day after enrollment
5. Infomercial: simple Bayesian stats for serosurveys

https://larremorelab.github.io/covid19testgroup

Estimating SARS-CoV-2 seroprevalence and epidemiological parameters with uncertainty from serological surveys

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Extra slide
One-time social distancing (without seasonality)