Prioritizing COVID-19 vaccination in changing social and epidemiological landscapes

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Slides and script available at
`https://git.uwaterloo.ca/pjentsch/smb_epi_talk.git`

Studying COVID-19 vaccination

- Model-based analyses are exploring which group should be the first to get the vaccine [Bubar et al., 2020, Buckner et al., 2020].
- The epidemiological landscape will change throughout the remainder of the pandemic
- Perception of risk due to the virus, and therefore perception of benefit of physical distancing, also fluctuates
- The group to vaccinate first, to most reduce mortality, is a function of this landscape

Social responses to the pandemic

- Non-pharmaceutical interventions (NPIs) can have a significant impact on SARS-CoV-2 transmission
- Pandemic waves are a creation of the population response to a pathogen
- Important to model the incentive structures informing population response

Compartmental model overview

Disease Compartments

$S(t)$: Susceptible

$S_2(t)$: Vaccinated but still susceptible

$V(t)$: Vaccinated and immune

$E(t)$: Exposed

$P(t)$: Pre-symptomatic

$I_a(T)$: Infectious and asymptomatic

$I_s(t)$: Infectious and symptomatic

$R(t)$: Recovered

Social compartments

$x(t)$: Uses NPIs

$1 - x(t)$: Does not use NPIs

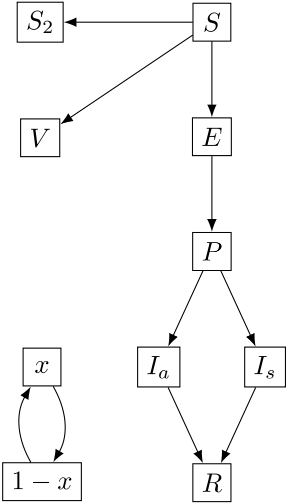


Figure: Compartments

Incorporating age-structure

- Age is an important factor in determining COVID-19 outcomes
- Different age groups exhibit different contact patterns
- Lockdowns affect age groups differently (work vs. school)
- Each disease compartment is further divided into 16 age compartments
- Interactions between age compartments defined by contact matrices

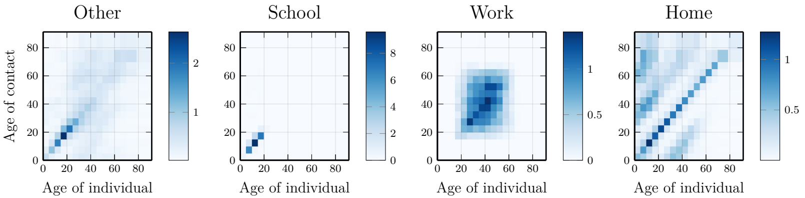


Figure: Contact matrices for Canada, mean contacts per day. Data from [Prem et al., 2017].

Game theory as a model of NPI adoption

P1 \ P2	use NPI	don't use NPI
use NPI	P2: low risk, NPIs unpleasant; P1: low risk, NPIs unpleasant	P2: med risk; P1: med risk, NPIs unpleasant
don't use NPI	P2: med risk, NPIs unpleasant; P1: med risk	P2: high risk; P1: high risk

Table: NPI adoption as a two-player game (between P1 and P2)

Replicator equation for population games

Population dynamics under a population game can be approximated by the replicator equation

$$\frac{dx}{dt} = \sigma x(1 - x)(-p(x, t)) \tag{1}$$

where

- $x(t)$ is the fraction of population using NPIs
- $p(x, t)$ is the payoff function
- σ is the rate of population response

Our model of NPI usage

The full equation for $x(t)$, in this model, is given by

$$\frac{dx}{dt} = \sigma x(1-x)\left(\frac{\sum_{i=1}^{16}\alpha_i(I_{a_i}+I_{s_i})}{\sum_{i=1}^{16}N_i} - cx\right) + p_{ul}(1-2x) \quad (2)$$

- The term $p_{ul}(1-2x)$ accounts for outside influence, where p_{ul} is small.
- α_i denotes the fraction of cases ascertained through testing.
- N_i is the population in age compartment i, $\sum_{i=1}^{16} N_i$ is the total population.
- $x(t)$ interacts with the infection dynamics by reducing the fraction of "home" and "other" contacts contributing to the infection rate

Lockdown mechanics

- There have been a few government-initiated lockdowns in Ontario, affecting schools and workplaces
- Implemented in the model by reducing the contribution of the "work" and "school" contact matrices to the infection rate
- Assume the government will initiate a partial or complete shutdown of workplaces and schools when the observed cases exceed some threshold T
- We express T as a percentage of the peak active cases during the first wave of the pandemic

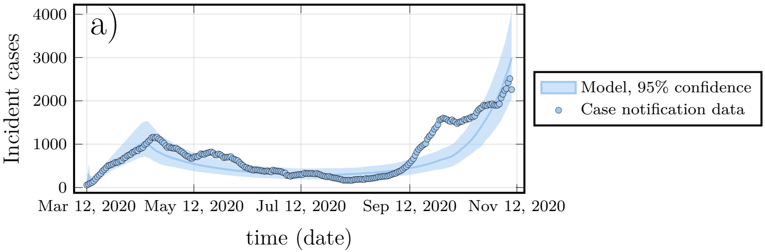
Vaccination mechanics

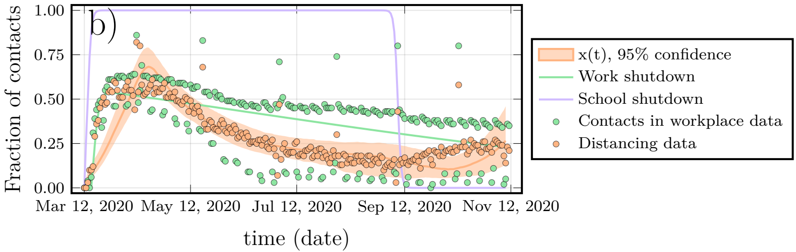
- Implemented as an impulsive process, where we have ψ vaccines available per day
- The fraction of the ψ people in age group i that are immunized against severe disease is ν_{D_i}
- The fraction immunized against disease *and* transmission is ν_{T_i}
- The allocation of vaccines to each age group i is referred to as the vaccination strategy
- Leftover vaccines are allocated uniformly to remaining non-empty compartments.
- We also assume that some vaccines are "wasted" on people who are already recovered or infected, by modifying the vaccination per compartment by $\frac{S_i(t)}{N_i - V_i}$.

Parameterization

- We used an approximate bayesian method to fit the model to case data from Ontario, Canada from March 12 to Nov 12, 2020.
- $x(t)$, proportion of people using NPIs was fit to google mobility data for Ontario
- Also fit the population seroprevalence to a point estimate from June 2020 for Ontario
- Provincial shutdowns (school and workplace) that occurred in Ontario were also implemented at their respective dates
- The efficacy of work shutdowns were fit to google mobility to account for work that could not be moved to remote
- Results were evaluated with 400 points sampled from the posterior distributions from this method

Parameterization





Results

We compare four vaccination strategies

- >60 first
- <20 first
- Uniform
- Contact-based

with respect to reduction in cumulative mortality after 5 years.

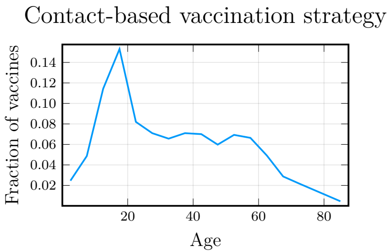


Figure: The contact-based strategy is the normalized leading eigenvector of the sum of the contact matrices

Results

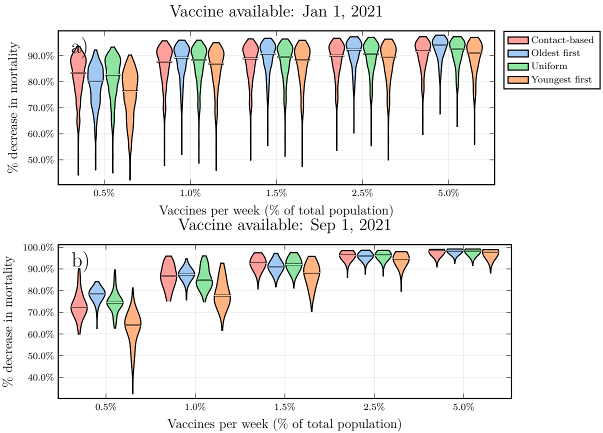
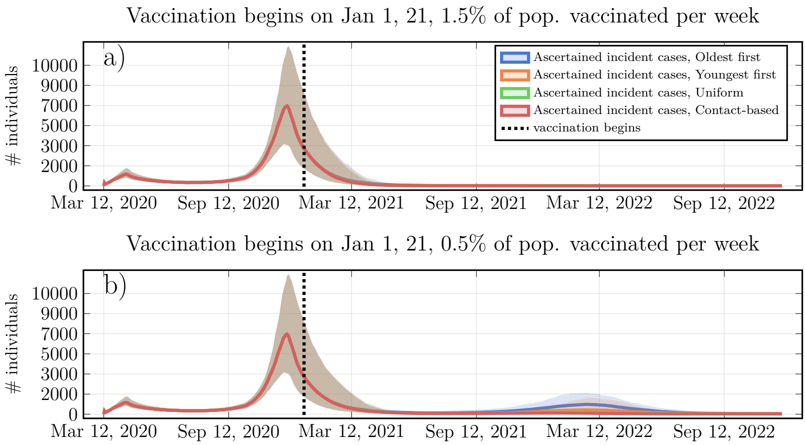
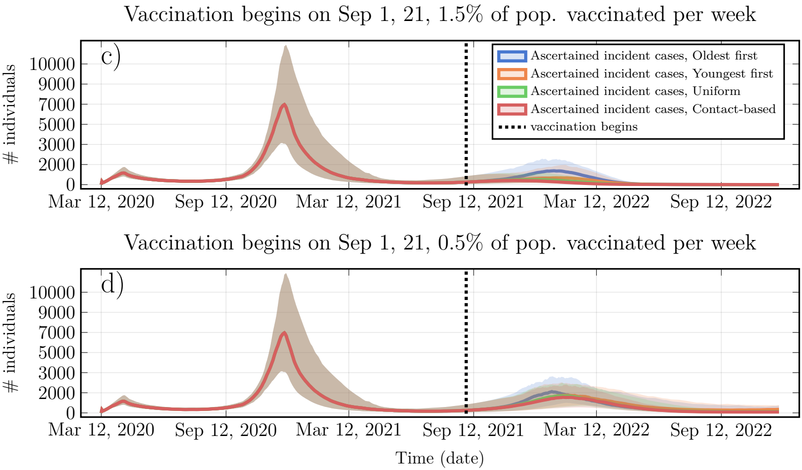


Figure: Percentage reduction in cumulative mortality due to COVID-19 after 5 years with respect to *psi*, expressed as a percentage of the total population per week. Here $v_{D_i} = v_{T_i} = 0.75$, shutdown at 200% of first wave. Percentage reductions are relative to no vaccination.



Vaccination begins on Jan 1, 21, 1.5% of pop. vaccinated per week
a)
individuals
10000
9000
7000
5000
3000
2000
0
Ascertained incident cases, Oldest first
Ascertained incident cases, Youngest first
Ascertained incident cases, Uniform
Ascertained incident cases, Contact-based
vaccination begins
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022
Vaccination begins on Jan 1, 21, 0.5% of pop. vaccinated per week
b)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022


Vaccination begins on Sep 1, 21, 1.5% of pop. vaccinated per week
c)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022
Ascertained incident cases, Oldest first
Ascertained incident cases, Youngest first
Ascertained incident cases, Uniform
Ascertained incident cases, Contact-based
vaccination begins
Vaccination begins on Sep 1, 21, 0.5% of pop. vaccinated per week
d)
individuals
10000
9000
7000
5000
3000
2000
0
Mar 12, 2020
Sep 12, 2020
Mar 12, 2021
Sep 12, 2021
Mar 12, 2022
Sep 12, 2022
Time (date)

Results

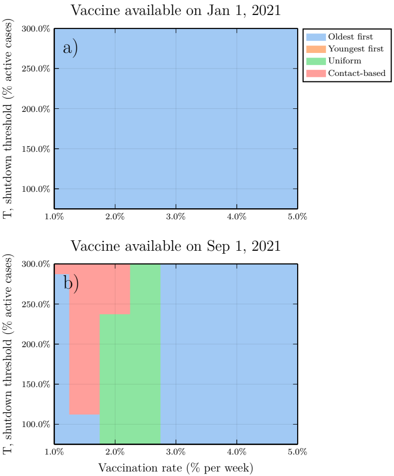


Figure: Each parameter pair is colored according to the strategy that prevents most deaths on average, over all realizations of the model.

Results

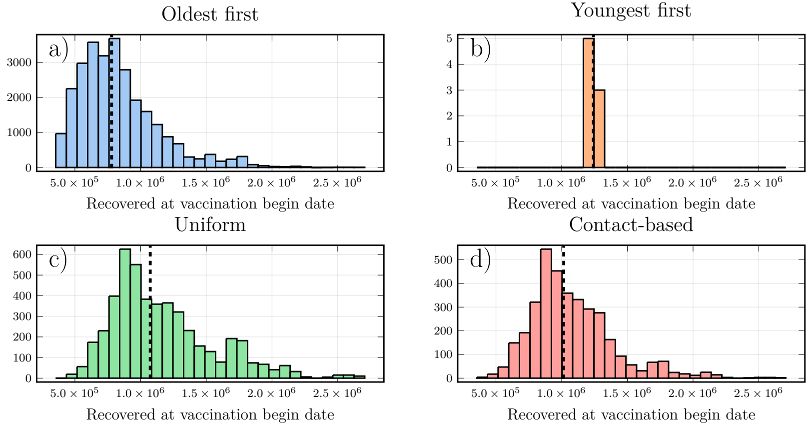


Figure: Histogram of no. recovered at vaccination begin date, according to best strategy for that realization, over all parameter values in sensitivity analysis. Vertical lines are the median.

Discussion

- We described an age structured compartmental model of Sars-CoV-2 infection and vaccination coupled to a social model
- Showed that sometimes transmission interrupting strategies can be more effective
- Depends on the pre-existing immunity in the population

Bubar, K. M., Kissler, S. M., Lipsitch, M., Cobey, S., Grad, Y., and Larremore, D. B. (2020).
Model-informed COVID-19 vaccine prioritization strategies by age and serostatus.
medRxiv.

Buckner, J. H., Chowell, G. H., and Springborn, M. R. (2020).
Optimal dynamic prioritization of scarce COVID-19 vaccines.
medRxiv.

Prem, K., Cook, A. R., and Jit, M. (2017).
Projecting social contact matrices in 152 countries using contact surveys and demographic data.
PLoS computational biology, 13(9):e1005697.

Model Equations

$$\frac{dS_i^1}{dt} = -r\rho_i s(t) S_i^1 \sum_{j=1}^{16} C_{ij}(t) \left(\frac{I_{s_j} + I_{a_j} + P_j}{N_j} \right) - \tau S_i^1 \tag{3}$$

$$\frac{dS_i^2}{dt} = -r\rho_i s(t) S_i^2 \sum_{j=1}^{16} C_{ij}(t) \left(\frac{I_{s_j} + I_{a_j} + P_j}{N_j} \right) - \tau S_i^2 \tag{4}$$

$$\frac{dE_i}{dt} = r_i s(t)(S_i^1 + S_i^2) \sum_{j=1}^{16} C_{ij}(t) \left(\frac{I_{s_j} + I_{a_j} + P_j}{N_j} \right) - \sigma_0 E_i + \tau(S_i^1 + S_i^2) \tag{5}$$

$$\frac{dP_i}{dt} = \sigma_0 E_i - \sigma_1 P_i \tag{6}$$

$$\frac{dI_{a_i}}{dt} = \eta \sigma_1 E_i - \gamma_a I_{a_i} \tag{7}$$

$$\frac{dI_{s_i}}{dt} = (1-\eta)\sigma_1 E_i - \gamma_s I_{s_i} \tag{8}$$

$$\frac{dR_i}{dt} = \gamma_a I_{a_i} + \gamma_s I_{s_i} \tag{9}$$

$$\frac{dx}{dt} = \kappa x(1-x) \left(\frac{\sum_{i=1}^{16} \alpha_i (I_{a_i} + I_{s_i})}{\sum_{i=1}^{16} N_i} - cx \right) + p_{ul}(1-2x) \tag{10}$$

$$C_{ij}(t,x) = C_{ij}^W(t) + C_{ij}^S(t) + (1 - \epsilon_P x) \left(C_{ij}^O + C_{ij}^H \right) \tag{11}$$