# **COVID-19 optimal vaccination policies:**

A modeling study on efficacy, natural and vaccine-induced immunity responses, June 15, 2022

CONACYT-UNISON-ITSON Mathematical biology group



To fix ideas:

$$S'(t) = -\beta IS$$

$$I'(t) = \beta IS - \gamma I$$

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$$S(0) = S_0, I(0) = I_0, R(0) = 0$$

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"Classic" Vaccination



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"Classic" Vaccination With vaccination

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Alexander, M. E., Bowman, C., Moghadas, S. M., Summers, R., Gumel, A. B., and Sahai, B. M. (2004). A vaccination model for transmission dynamics of influenza. SIAM Journal on Applied Dynamical Systems,

3(4):503-524.

Iboi, E. A., Ngonghala, C. N., and Gumel, A. B. (2020). Will an imperfect vaccine curtail the COVID-19 pandemic in the U.S.?
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Optimal Controlled:



Hethcote, H. W. and Waltman, P. (1973). Optimal vaccination schedules in a deterministic epidemic model.

Mathematical Biosciences, 18(3-4):365-381.



Wickwire, K. (1977).

Mathematical models for the control of pests and infectious diseases: A survey.

Theoretical Population Biology, 11(2):182-238.



# Hypothesis

### Cost

The **effort** expended in "**preventing-mitigating** an epidemic" by vaccination is **proportional** to the vaccination rate  $\lambda_V$ .



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$$X(t) = 1 - \exp(-\lambda_V t),$$

estimates the fraction of vaccinated individuals. Thus, for time horizon  ${\it T}$  and vaccination coverage



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If S(0)N corresponds to HMS (812229 inhabitants)  $\approx 2668 \, \mathrm{jabs/day}.$ 



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Who to vaccine first? (Allocation)

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### Cost

$$J(u) := \varphi(x(T)) + \int_0^T f(t, x(t), u(t))$$



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## Optimal Control Problem

$$\min_{\mathbf{u} \in \mathcal{U}} J(u) = \varphi(x(T)) + \int_0^T f(t, x(t), u(t))$$

$$\dot{x}(t) = b(t, u(t), x(t)), \quad \text{a.e. } t \in [0, T],$$

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- Bubar, K. M., Reinholt, K., Kissler, S. M., Lipsitch, M., Cobey, S., Grad, Y. H., and Larremore, D. B. (2021).

  Model-informed covid-19 vaccine prioritization strategies by age and serostatus.
  - Science, 371(6532):916-921.
- Buckner, J. H., Chowell, G., and Springborn, M. R. (2021).

  Dynamic prioritization of covid-19 vaccines when social distancing is limited for essential workers.
  - Proceedings of the National Academy of Sciences, 118(16).
- Matrajt, L., Eaton, J., Leung, T., and Brown, E. R. (2020). Vaccine optimization for covid-19: Who to vaccinate first? Science Advances, 7(6).



### Common Objectives

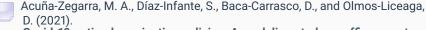
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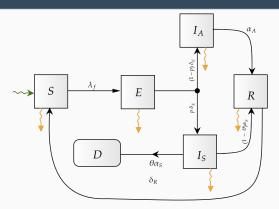
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#### Aim of this talk

To illustrate the formulation of optimal vaccination policies based in vaccination rate.



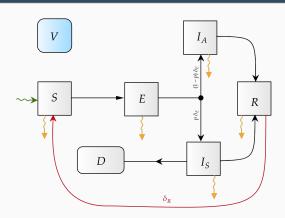


$$\lambda_f := \frac{\beta_A I_A + \beta_S I_S}{N^*}$$

$$N^* := N - D$$

$$\underset{\text{natural death}}{\longrightarrow} \text{natural death}$$

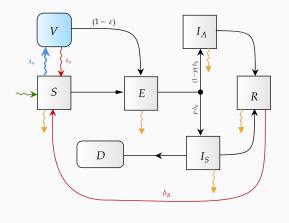




## Vaccine Hypotheses

Imperfect preventive
One dose
Symptomatic exception
Action over susceptible





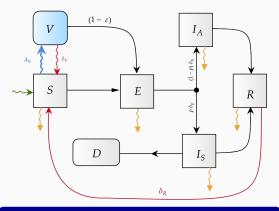


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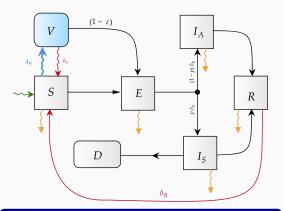
#### **Notation**

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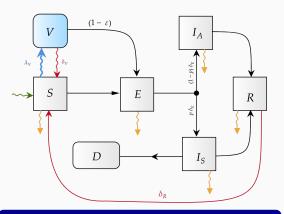
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Vaccine profile (Efficacy, immunity)

Coverage

Time Horizon





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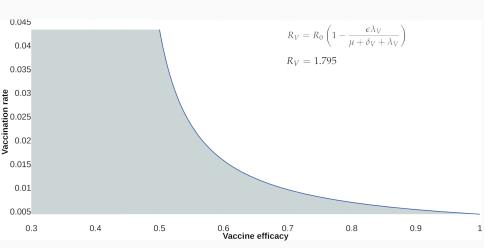
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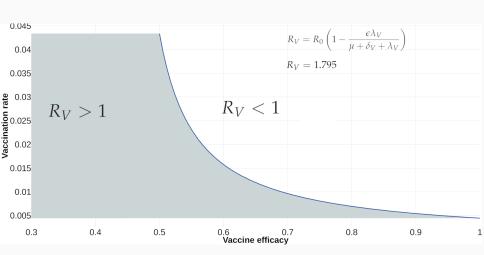
Immunity: natural (reinfection) vaccine-induced

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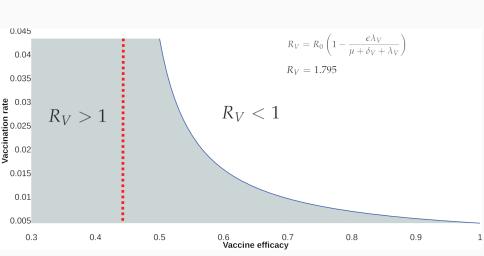




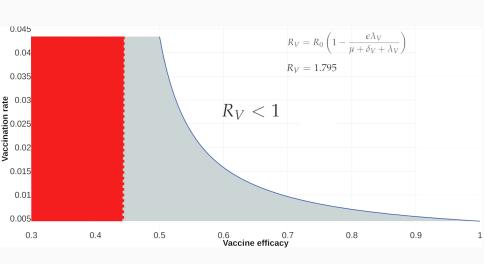






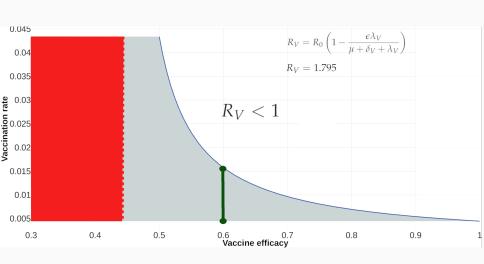






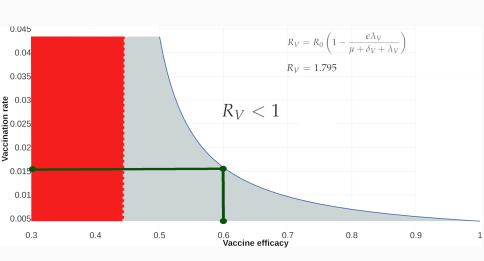
# **Reproductive number**



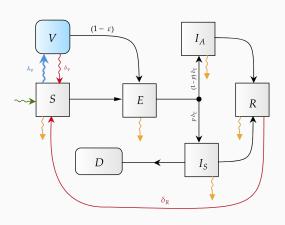


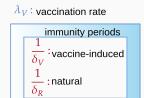
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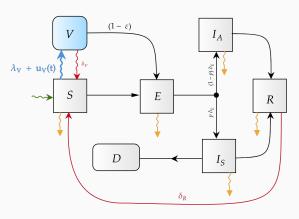








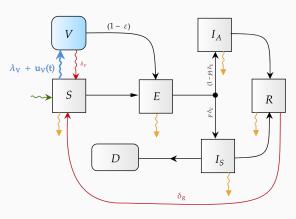




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$$\begin{aligned} \min_{\{u_v \in \mathcal{U}\}} J(u_V) &= \varphi(x(T)) \\ &+ \int_0^T f(t, x(t), u_V(t)) \\ s. \, t. \\ &\dot{x}(t) = b(t, u(t), x(t)) \\ &x(0) = x_0 \end{aligned}$$

## The disability-adjusted life year (DALY)



$$DALY(c, s, a, t) = YLL(c, s, a, t) + YLD(c, s, a, t)$$

For given cause c, age a, sex s and year t

YLL: Years of life lost due to premature death.

$$YLL(c, s, a, t) = N(c, s, a, t) \times L(s, a)$$

N(c, s, a, t): is the number of deaths due to the cause c L(s, a): is a standard loss function specifying years of life lost

YLD: Years of life list due to disability

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(years)

$$\min_{u_V \in \mathcal{U}[0,T]} J(u_V) := \underbrace{a_D(D(T) - D(0))}_{:=YLL} + \underbrace{a_S(Y_{I_S}(T) - Y_{I_S}(0))}_{:=YLD}$$



$$\begin{split} & \underset{u_V \in \mathscr{U}[0,T]}{\min} J(u_V) := \underbrace{a_D(D(T) - D(0))}_{:=YLL} + \underbrace{a_S(Y_{l_S}(T) - Y_{l_S}(0))}_{:=YLD} \\ & u_V(\cdot) \in [u_{\min}, u^{\max}], \\ & \kappa I_S(t) \leq B, \quad \forall t \in [0,T], \end{split}$$



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s.t. 
$$f_{\lambda} := \frac{\beta_{S}I_{S} + \beta_{A}I_{A}}{\bar{N}}$$

$$S'(t) = \mu \bar{N} + \delta_{V}V + \delta_{R}R$$

$$-(f_{\lambda} + \mu + \lambda_{V} + u_{V}(t))S$$

$$E'(t) = f_{\lambda}(S + (1 - \varepsilon)V) - (\mu + \delta_{E})E$$

$$I'_{S}(t) = p\delta_{E}E - (\mu + \alpha_{S})I_{S}$$

$$I'_{A}(t) = (1 - p)\delta_{E}E - (\mu + \alpha_{A})I_{A}$$

$$R'(t) = (1 - \theta)\alpha_{S}I_{S} + \alpha_{A}I_{A} - (\mu + \delta_{R})R$$

$$D'(t) = \theta\alpha_{S}I_{S}$$

$$V'(t) = (\lambda_{V} + u_{V}(t))S - ((1 - \varepsilon)f_{\lambda}V + \mu + \delta_{V})V$$

$$X'(t) = (\lambda_{V} + u_{V}(t))(S + E + I_{A} + R)$$

$$S(0) = S_{0}, E(0) = E_{0}, I_{S}(0) = I_{S_{0}},$$

$$I_{A}(0) = I_{A_{0}}, R(0) = R_{0}, D(0) = D_{0},$$

$$V(0) = 0, X(0) = 0, X(T) = x_{coverage},$$

$$V(t) = [u_{min}, u^{max}],$$

$$KI_{S}(t) \leq B, \quad \forall t \in [0, T],$$

$$\bar{N}(t) = S + E + I_{S} + I_{A} + R + V.$$

### Vaccine efficacy



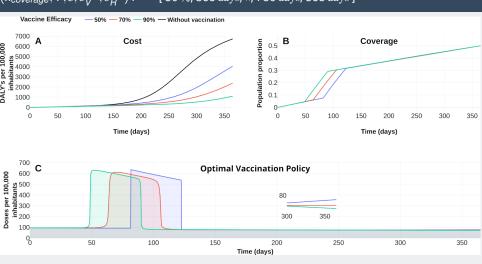
Developer	Vaccine Name	Efficacy %, (95% CI)	Reference
Pfizer-BioNTech Gamaleya Institute Oxford University-	BNT162b2 Sputnik V AZD1222	95 (90.3–97.6) 91.6 (85.6–95.2) 74.6 (41.6-88.9)	[1] [4] [2]
AztraZeneca Johnson & Johnson* Sinovac Biotech*	Ad26.COV2.S CoronaVac	57 %, 66 % or 72 % 50.4 %	[3] [5]

Table: Vaccine efficacy of some of the approved developments for emergency use. (\*) No available information about the confidence intervals.

# The response of COVID-19 burden due to vaccine efficacy



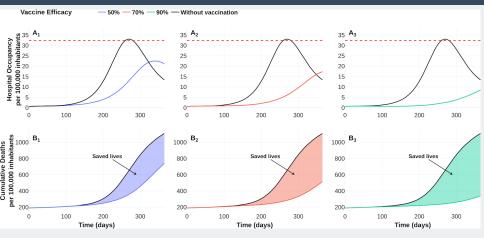




# The response of COVID-19 burden due to vaccine efficacy

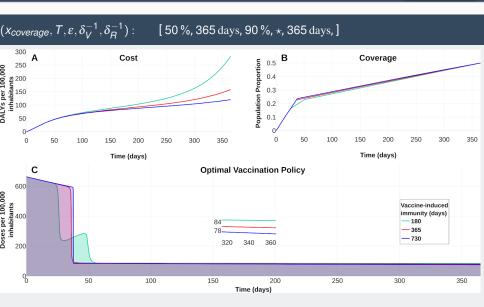






# The response of COVID-19 burden due to vaccine-immunity

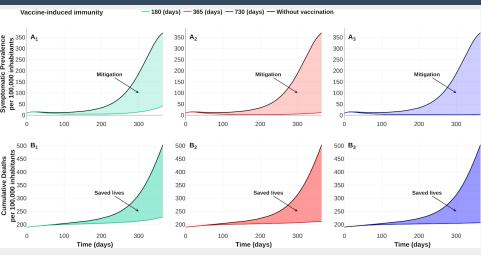




# The response of COVID-19 burden due to vaccine-immunity

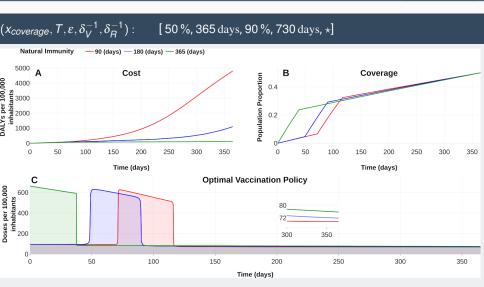






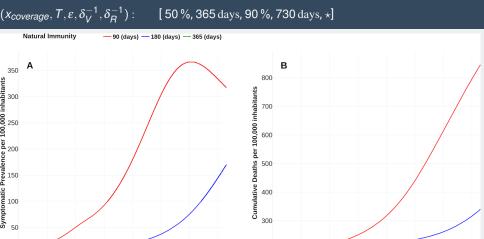
# The response of COVID-19 burden due to natural-immunity





# The response of COVID-19 burden due to natural-immunity





Time (days)

Time (days)

#### Important questions



- (\*) Optimal vaccination strategies in terms of target groups and under different possible supply scenarios
  - Two or more vaccine platforms
  - Multi-doses
- Potential reduction in infectiousness of breakthrough infections among vaccinated individuals
- (\*) Potential differences in vaccine efficacy against mild or severe/fatal COVID-19 disease

#### Important questions



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# Thanks a lot

GitHub



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