Unifying epidemiological an evolutionary dynamics – June 13 2023 –

# The speed of adaptation to vaccination

Sylvain Gandon



#### SARS-CoV2 evolution



GISAID data - © W. Benhamou

#### SARS-CoV2 evolution



GISAID data - © W. Benhamou

#### Natural immunity

#### SARS-CoV2 evolution



GISAID data - © W. Benhamou

#### Natural immunity

Vaccination









How fast will the pathogen adapt to vaccination?

#### Outline

#### (1) The invasion (or not) of escape mutations

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(1) The invasion (or not) of escape mutations(2) Transient dynamics and host heterogeneity(3) Inferring variant life-history traits

#### (1) The invasion (or not) of escape mutations

with Todd L. Parsons M. Voinson A. Lambert T. Day









### A toy model



### A toy model



# $\begin{aligned} A toy model \\ \dot{S} &= \lambda (1-p) - \left(\frac{\beta_w}{N} (I_w + \hat{I}_w) + \frac{\beta_m}{N} (I_m + \hat{I}_m) + \delta\right) S - \nu S + \omega \hat{S} + \omega_R R \\ \dot{S} &= \lambda p - \left(e_w \frac{\beta_w}{N} (I_w + \hat{I}_w) + e_m \frac{\beta_m}{N} (I_m + \hat{I}_m) + \delta\right) \hat{S} + \nu S - \omega \hat{S} \\ \dot{I}_w &= \frac{\beta_w S}{N} (I_w + \hat{I}_w) - (\delta + \alpha_w + \gamma) I_w \\ \dot{I}_m &= \frac{\beta_m S}{N} (I_m + \hat{I}_m) - (\delta + \alpha_m + \gamma) I_m \end{aligned}$

$$\dot{\hat{I}}_w = e_w \frac{\beta_w S}{N} (I_w + \hat{I}_w) - (\delta + \alpha_w + \gamma) \hat{I}_w$$
$$\dot{\hat{I}}_m = e_m \frac{\beta_m \hat{S}}{N} (I_m + \hat{I}_m) - (\delta + \alpha_m + \gamma) \hat{I}_n$$
$$\dot{R} = \gamma (I_w + \hat{I}_w + I_m + \hat{I}_m) - (\delta + \omega_R) R$$

Epidemiology & evolution

#### A toy model $\lambda(1-p) - \left(\frac{\beta_w}{m}(I_w + \hat{I}_w) + \frac{\beta_m}{m}(I_m + \hat{I}_m) + \delta\right)S - \nu S + \omega \hat{S}$

$$\dot{S} = \lambda(1-p) - \left(\frac{\beta_{w}}{N}(I_{w}+\hat{I}_{w}) + \frac{\beta_{m}}{N}(I_{m}+\hat{I}_{m}) + \delta\right)S - \nu S + \omega \hat{S} + \omega_{R}R$$
  
$$\dot{S} = \lambda p - \left(e_{w}\frac{\beta_{w}}{N}(I_{w}+\hat{I}_{w}) + e_{m}\frac{\beta_{m}}{N}(I_{m}+\hat{I}_{m}) + \delta\right)\hat{S} + \nu S - \omega \hat{S}$$
  
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Epidemiology & evolution

Evolution

$$p_m = \frac{I_m + \hat{I}_m}{I_w + \hat{I}_w + I_m + \hat{I}_m}$$
$$\dot{p}_m = p_m(1 - p_m)s_m$$

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Epidemiology & evolution

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 $p_m = \frac{I_m + \hat{I}_m}{I_w + \hat{I}_w + I_m + \hat{I}_m}$  $\dot{p}_m = p_m (1 - p_m) s_m$  $\uparrow$ selection

$$s_{m} = r_{m} - r_{w}$$
$$r_{i} = \underbrace{\beta_{i}(S + e_{i}\hat{S})/N}_{birth} - \underbrace{(\mu + \alpha_{i} + \gamma)}_{death}$$

Mutation

Mutation

Flux of escape mutant:

$$\mu_m \left( I_w(t) + \theta \hat{I}_w(t) \right)$$

**Mutation** 

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 $\mu_m = 0.1, \theta = 1, \omega = 0.05, \omega_R = 0$ 

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Kendall (1948)







Mutation + Invasion






0.05  $0.05, \omega_R =$  $1, \omega =$ 11  $0.1, \theta$  $\mu_m =$ 













0.05  $0.05, \omega_R =$  $1, \omega =$ II  $0.1, \theta$  $\mu_m =$ 



0.05  $0.05, \omega_R =$  $1, \omega =$  $\|$  $0.1, \theta$  $\mu_m =$ 



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But invasion does not imply fixation

If there is invasion, what is the speed of adaptation?

# (2) Transient dynamics in heterogeneous host populations

with S. Lion

Gandon, S., & Lion, S. (2022). Targeted vaccination and the speed of SARS-CoV-2 adaptation. *PNAS*, 119(3)

The frequency of a vaccine-adapted variant changes as follows

$$\dot{p}_m = p_m (1 - p_m) s_m$$

Where:

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#### How to account for host heterogeneities in $s_m$ ?

# Host heterogeneity



# Host heterogeneity



#### Who should we vaccinate?

# Host heterogeneity



#### Who should we vaccinate?

Aim #1: reduce mortality (epidemiology) Aim #2: slow down adaptation (evolution)

Consider a mutation of small effect:  $\varepsilon = e_m - e_w$ The selection coefficient can be approximated by:

$$s_m = \varepsilon \mathbf{v} \frac{\mathrm{d} \mathbf{R}_m}{\mathrm{d} e_m} \mathbf{f}$$

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- **f** is a vector of class frequencies: host class « **quantity** » (fraction of the pathogen population in a given class)
- v is a vector of reproductive values: host class « quality » (contribution to the future of the pathogen population)

# Another toy model



Low-transmission hosts (high risk)

# Another toy model



 $\mathcal{M} > 1$ Contact rate

 $\mu^L > \mu^H \qquad \hat{\mu}^L > \hat{\mu}^H$ Mortality

$$s_{m} = \varepsilon \mathbf{v} \frac{\mathrm{d} \mathbf{R}_{m}}{\mathrm{d} e_{m}} \mathbf{f} \qquad \begin{cases} \frac{v^{H}}{v^{L}} = \mathcal{M}, & \frac{\hat{v}^{H}}{v^{L}} = \mathcal{M}\rho_{\tau} \\ \frac{f^{H}}{f^{L}} = \mathcal{M} \frac{S^{H}}{S^{L}}, & \frac{\hat{f}^{H}}{f^{L}} = \mathcal{M}\rho_{\sigma} \frac{\hat{S}^{H}}{S^{L}} \end{cases}$$

$$s_m = \beta \left( 1 - c(t) \right) \Delta E \left( \hat{S}^L + \mathcal{M}^2 \hat{S}^H \right)$$

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In addition, the evolutionary weight of hosts with more contacts is  $\mathcal{M}^2$ , so a 2-fold increase in contact number translates into a 4-fold increase in evolutionary quality (for the pathogen).

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Targeting hosts with more contacts delays the epidemic but yields higher epidemic peak

Targeting hosts with more contacts yields a higher cumulated number of death

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Numerous **extensions towards further biological realism** are possible: natural immunity, age structure, spatial structure, number of vaccine doses, multilocus dynamics...
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