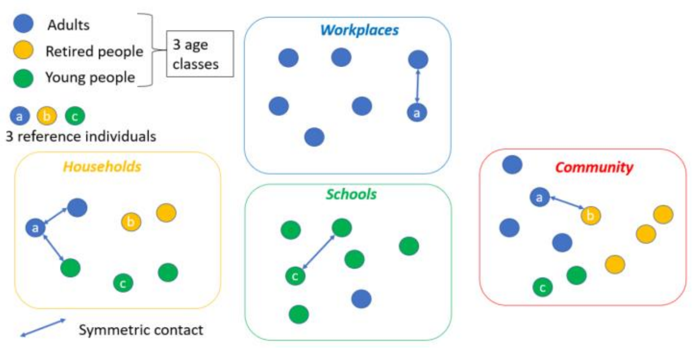
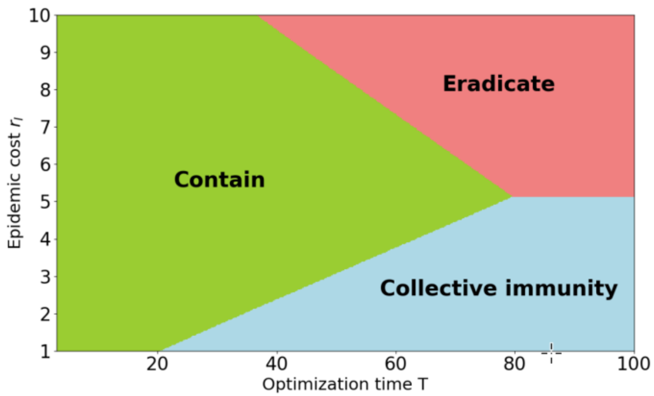
Mean Field Game Approach to Non-Pharmaceutical Interventions in a Social Structure model of Epidemics

Louis Brémaud (Université Paris-Saclay)
Olivier Giraud (CNRS, Université Paris-Saclay)
Denis Ullmo (CNRS, Université Paris-Saclay)



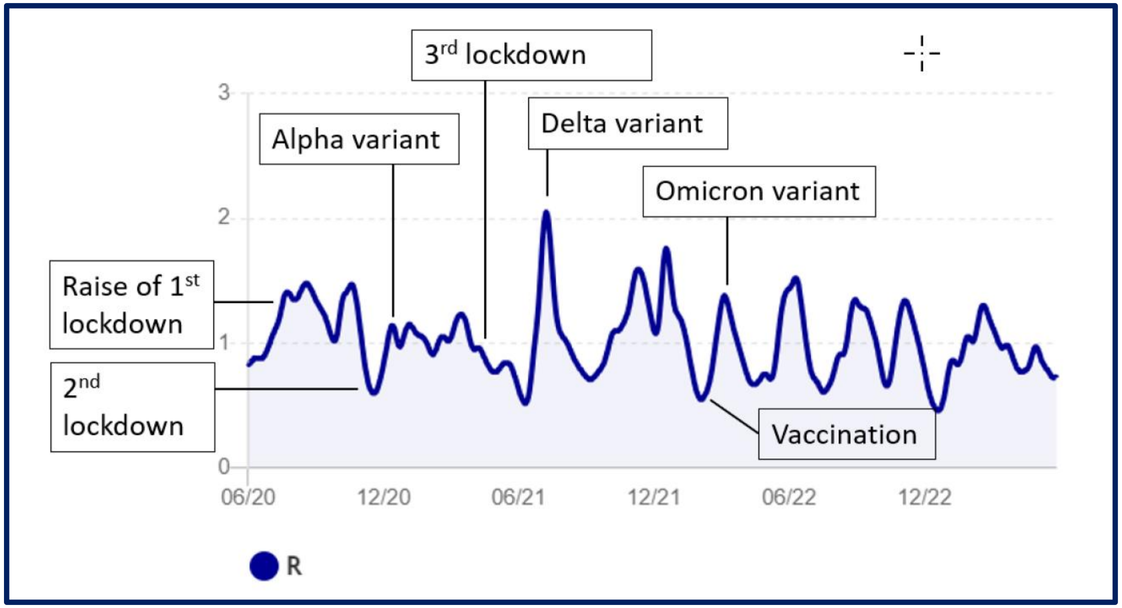


*[Phys. Rev. E **106**, L062301 (2022); arXiv:2404.08758]*

Part I : Mean Field Game & Social Structure model of Epidemics

Evolution of the "effective reproduction number" during the Covid-19 pandemic between June 2020 and June 2023

R_{eff} = average number of infected persons by a sick individual.



⇛ Significant variations

- Some with easily identified causes.
- Some of theses causes are biological in nature
- Some others are due to changes in behavior

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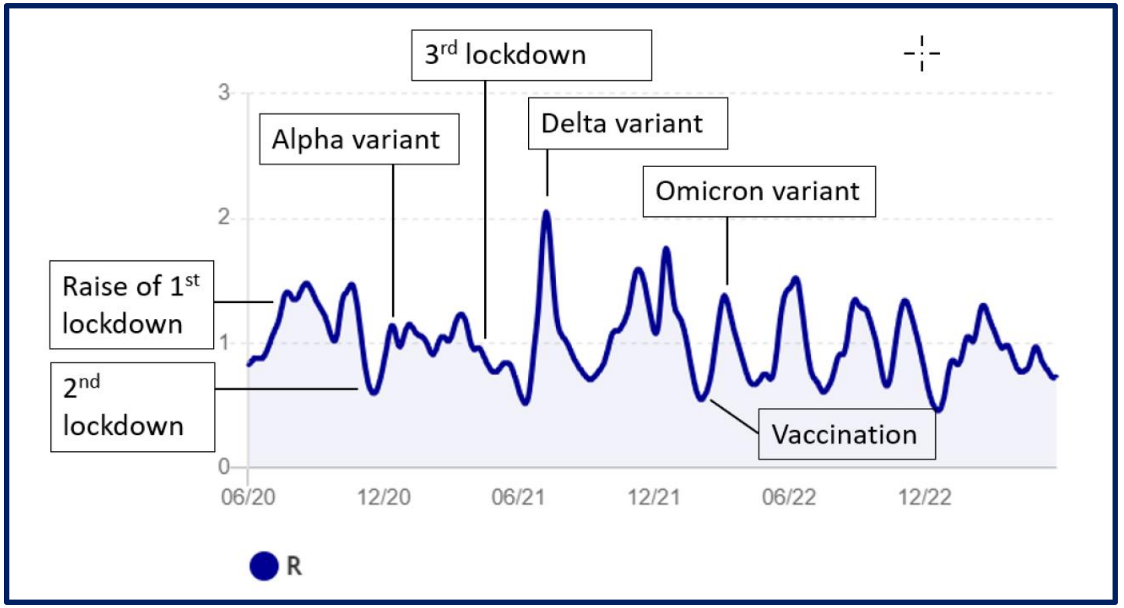

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our focus

A classical model to describe epidemics, the SIR model

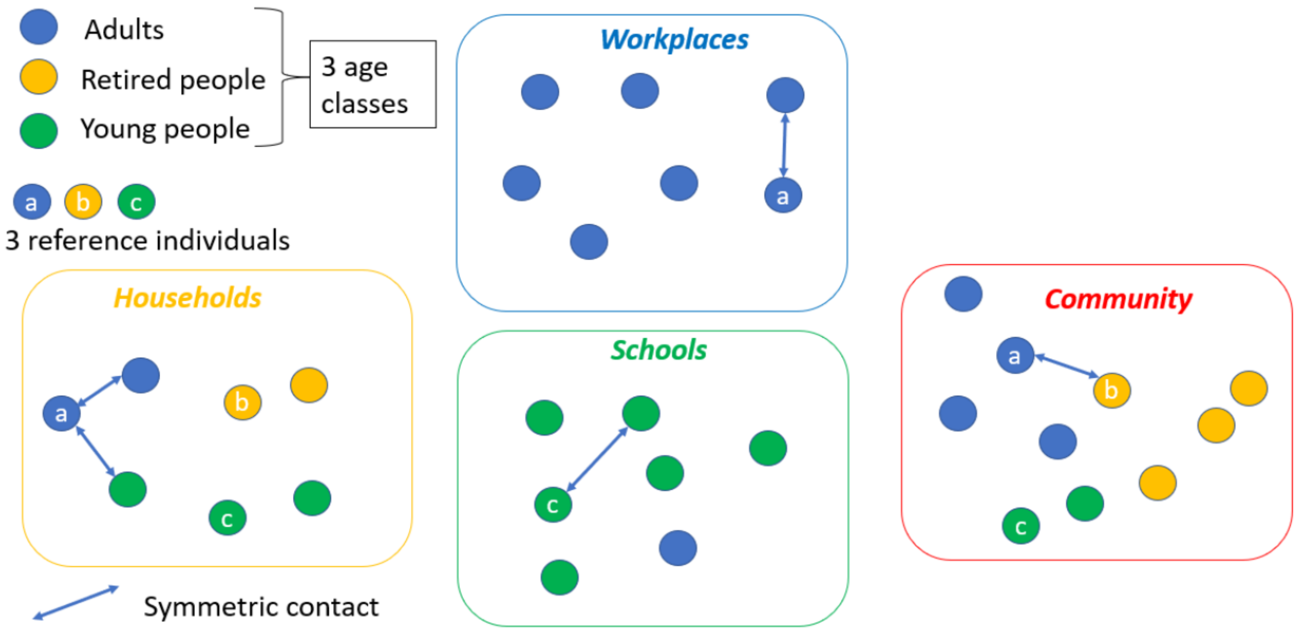
$\beta(t)$: transmission rate
γ : recovery rate

- $\beta(t)$: **extrinsic time dependent** functional parameter of the model.
- Hard to fit with experimental data (the dynamics of $\beta(t)$ is coupled to the one of the epidemic itself)

- We would like to **make this parameter intrinsic** (i.e. an output, rather than an input of the model)
  $\Rrightarrow$ **Mean Field Game** description
- We also want a **less homogenous** description of the society
  $\Rrightarrow$ **Social Structure model** of Epidemics
- Eventually, we would like to be able to use our model to discuss “**non-pharmaceutical interventions**” on the epidemics (ie, from the point of view of the health authorities, ways to control the epidemics, other than vaccine or medical treatment)

The SIR model with Social Structure

[Fumanelli et al., PLoS Computational Biology 8 (2012).]



- 3 **age classes** : Young, Adults, Retired
- 4 “**settings**” : Households, Workplaces, Schools, Community

Notations and Hypothesis

- N_α : proportion of agents in the age class α .
- $(S_\alpha , I_\alpha, R_\alpha)$: proportions of (Susceptible, Infected, Recover) in the age class α $[S_\alpha + I_\alpha + R_\alpha = 1]$
- Probability that a pair of individuals (a, b) of age class (α, β) meet in the setting γ in the time interval $[t, t + dt]$ $\rightarrow$ $W^{\gamma}_{\alpha,\beta}\, dt$
- If they meet when a is infected and b susceptible $\rightarrow$ probability q of infection.

Dynamical equation for the epidemics

$$\dot{S}_\alpha = -\lambda_\alpha(t) S_\alpha(t)$$
$$\dot{I}_\alpha = \lambda_\alpha(t) S_\alpha(t) - \xi I_\alpha(t)$$
$$\dot{R}_\alpha = \xi\ I_\alpha(t)\,.$$

$$\lambda_\alpha(t) \equiv q \sum_{\beta=1}^{n_{\rm cl}} \sum_{\gamma=1}^{n_{\rm set}} W^{\gamma}_{\alpha\beta} N_\beta I_\beta(t)$$

$\lambda_\alpha(t)$: force of infection

Mean Field Game description

*[Elie et al., Mathematical Modelling of Natural Phenomena **15** (2020)]*

Optimization for a given representative agent $\boldsymbol{a} \in \boldsymbol{\alpha}$

State variable $\quad x_a \in \{S, I, R\}$

Control variable

- $W^{\gamma}_{\alpha,\beta}\, dt$: pb that a pair of individuals meet in the time interval $[t, t+dt]$
- $W^{\gamma}_{\alpha,\beta} = w^{\gamma}_{\alpha,\beta} w^{\gamma}_{\beta,\alpha}$, with $w^{\gamma}_{\alpha,\beta}$ = "willingness of agents of class α to meet an agent of class β in setting γ" ($W_{\alpha,\beta}$ symmetric, $w_{\alpha,\beta}$ not necessarily)

hyp : $\quad w^{\gamma}_{\alpha,\beta}(\mathrm{t}) = n_\alpha(t) w^{\gamma\,(0)}_{\alpha,\beta} \quad\quad n_\alpha(t) \in [n_{\alpha,\min}, 1]$

Mean Field Game description

*[Elie et al., Mathematical Modelling of Natural Phenomena **15** (2020)]*

Optimization for a given representative agent $a \in \alpha$

<u>State variable</u> $x_a \in \{S, I, R\}$

<u>Control variable</u>

- $W^{\gamma}_{\alpha,\beta}\, dt$: pb that a pair of individuals meet in the time interval $[t, t+dt]$
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hyp : $w^{\gamma}_{\alpha,\beta}(\mathrm{t}) = n_{\alpha}(t) w^{\gamma\,(0)}_{\alpha,\beta}$ $\quad n_{\alpha}(t) \in [n_{\alpha,\min}, 1]$

Control variable

Cost function

- Cost paid by individual a susceptible at time t if infected at time τ

$$C_a\left(n_a^\gamma(\cdot),\{n_\beta^\gamma(.)\},t,\tau\right)\equiv \mathcal{I}_\alpha(I(\tau))\mathbb{1}_{\tau<T}+\int_t^{\min(\tau,T)} f_\alpha\left(n_a^\gamma(s)\right)ds$$

Strategy of agent a

Strategies of classes β

cost of infection

(social) cost of effort

- Expectation value $(P_a(\tau)=d\phi_a/d\tau \equiv$ proba to be infected at τ)

$$C_a\left(n_a^\gamma(\cdot),\{n_\beta^\gamma(.)\},t\right)\equiv\int_t^\infty d\tau\; P_a(\tau)\; C_a\left(n_a^\gamma(\cdot),\{n_\beta^\gamma(.)\},t,\tau\right)\;,$$

$$=\int_t^T\left[\lambda_a(s)\;\mathcal{I}_\alpha(I(s))+f_\alpha\left(n_a^\gamma(s)\right)\right](1-\phi_a(s))ds\,.$$

$$\phi_a(\tau)=1-\exp\left(-\int_t^\tau\lambda_a(s)ds\right)$$

$\lambda_\alpha(t)$: force of infection

Cost of infection

Saturation of sanitary system

$$\mathcal{I}_\alpha(I(s)) = \kappa_\alpha r_I \exp\left[\nu_{\text{sat}} \frac{I(t) - I_{\text{sat}}}{I_{\text{sat}}}\right]$$

$$I(\tau) \equiv \sum_\alpha N_\alpha I_\alpha(\tau)$$

age dependence

Social cost of effort (same form as Elie et al.)

Attachment to the setting

$$f_\alpha(n_a^\gamma(t)) = \sum_\gamma \left[\left(\frac{1}{n_a^\gamma(t)}\right)^{\mu_\gamma} - 1\right]$$

Bellman equation

Value function

$$U_a(t) = \begin{cases} \min\limits_{n_a^\gamma(\cdot)} C_a\left(n_a^\gamma(\cdot), t\right), & a \quad \text{susceptible at } t \\ 0 & a \quad \text{infected at } t. \end{cases}$$

Bellman

$$U_a(t) = \min_{n_a^\gamma(t)} \mathbb{E}_{x_a(t+dt)} \left[U_a(t+dt) + c_a(t)\right]$$

$$c_a(t) = \begin{cases} f_\alpha(n_a^\gamma(t))\, dt & a \text{ susceptible at } t+dt \\ \mathcal{I}_\alpha(I(t)) & a \text{ infected at } t+dt \end{cases}$$

HJB

$$-\frac{dU_a(t)}{dt} = \left[\lambda_a(t)\left(\mathcal{I}_\alpha(I(t)) - U_a(t)\right) + f_\alpha(n_a^{\gamma*}(t))\right]$$

$$n_a^{\gamma*}(t) = \underset{n_a^\gamma(t)}{\operatorname{argmin}} \left[\lambda_a(t)\left(\mathcal{I}_\alpha(I(t)) - U_a(t)\right) + f_\alpha(n_a^\gamma(t))\right]$$

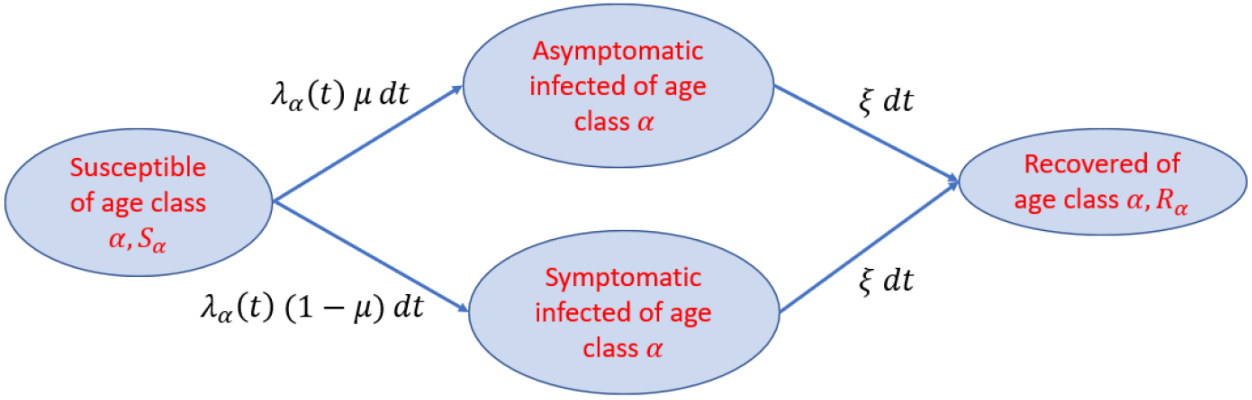
Optimization at *t* only

What about infected agent behavior ?

The force of infection $\lambda_a(t)$ depend on the strategies (i.e. the $\{n_\beta\}$) of infected agents.

Possible assumptions :

- Infected agents stay at home $\rightarrow \lambda_a(t) = 0$, no propagation
- Infected agents do not care $\rightarrow n_\beta(t) = 1$
- **Our choice** : propagation of the epidemics is due to a small number of **asymptomatic agents** (who behave as susceptible ones).



Mean Field Game equations

Dynamics ("Kolmogorov")

$$\dot{S}_\alpha = -\lambda_\alpha(t) S_\alpha(t)$$
$$\dot{I}_\alpha = \lambda_\alpha(t) S_\alpha(t) - \xi I_\alpha(t)$$
$$\dot{R}_\alpha = \xi \, I_\alpha(t) \, .$$

$$\lambda_\alpha(t) \equiv \mu q \sum_{\beta=1}^{n_{\rm cl}} \sum_{\gamma=1}^{n_{\rm set}} n_\alpha^\gamma(t) n_\beta^\gamma(t) W_{\alpha\beta}^{\gamma(0)} N_\beta I_\beta(t)$$

Optimization ("HJB")

$$-\frac{dU_a(t)}{dt} = [\lambda_a(t) \left(\mathcal{I}_\alpha(I(t)) - U_a(t)\right) + f_\alpha(n_a^{\gamma *}(t))]$$

$$n_a^{\gamma *}(t) = \underset{n_a^\gamma(t)}{\operatorname{argmin}} \left[\lambda_a(t) \left(\mathcal{I}_\alpha(I(t)) - U_a(t)\right) + f_\alpha(n_a^\gamma(t))\right]$$

$$\Rightarrow \left(\frac{\mu q}{\mu_\gamma} \left[\mathcal{I}_\alpha(I(t)) - U_a(t)\right] \sum_{\beta=1}^{n_{\rm cl}} n_\beta^\gamma(t) W_{\alpha\beta}^{\gamma(0)} N_\beta I_\beta(t) \right)^{-\frac{1}{\mu_\gamma+1}}$$

Self consistence (Nash equilibrium)

$$n_a^{\gamma *}(t) = n_\alpha^\gamma(t) \, .$$

Parameters of the model

Biology

$$(\xi = 1.2, q = 0.2, \mu = 0.1)$$

Social Structure $(M^{\gamma}_{\alpha\beta} \equiv W^{\gamma}_{\alpha\beta} N_{\beta})$

M^S	M^W	M^C	M^H	N_α
$\begin{pmatrix} 100 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 75 & 0 \\ 0 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 12.5 & 25 & 12.5 \\ 12.5 & 25 & 12.5 \\ 12.5 & 25 & 12.5 \end{pmatrix}$	$\begin{pmatrix} 15 & 25 & 10 \\ 12.5 & 32.5 & 5 \\ 10 & 10 & 30 \end{pmatrix}$	$(0.25, 0.5, 0.25)$

[Fumanelli et al.]

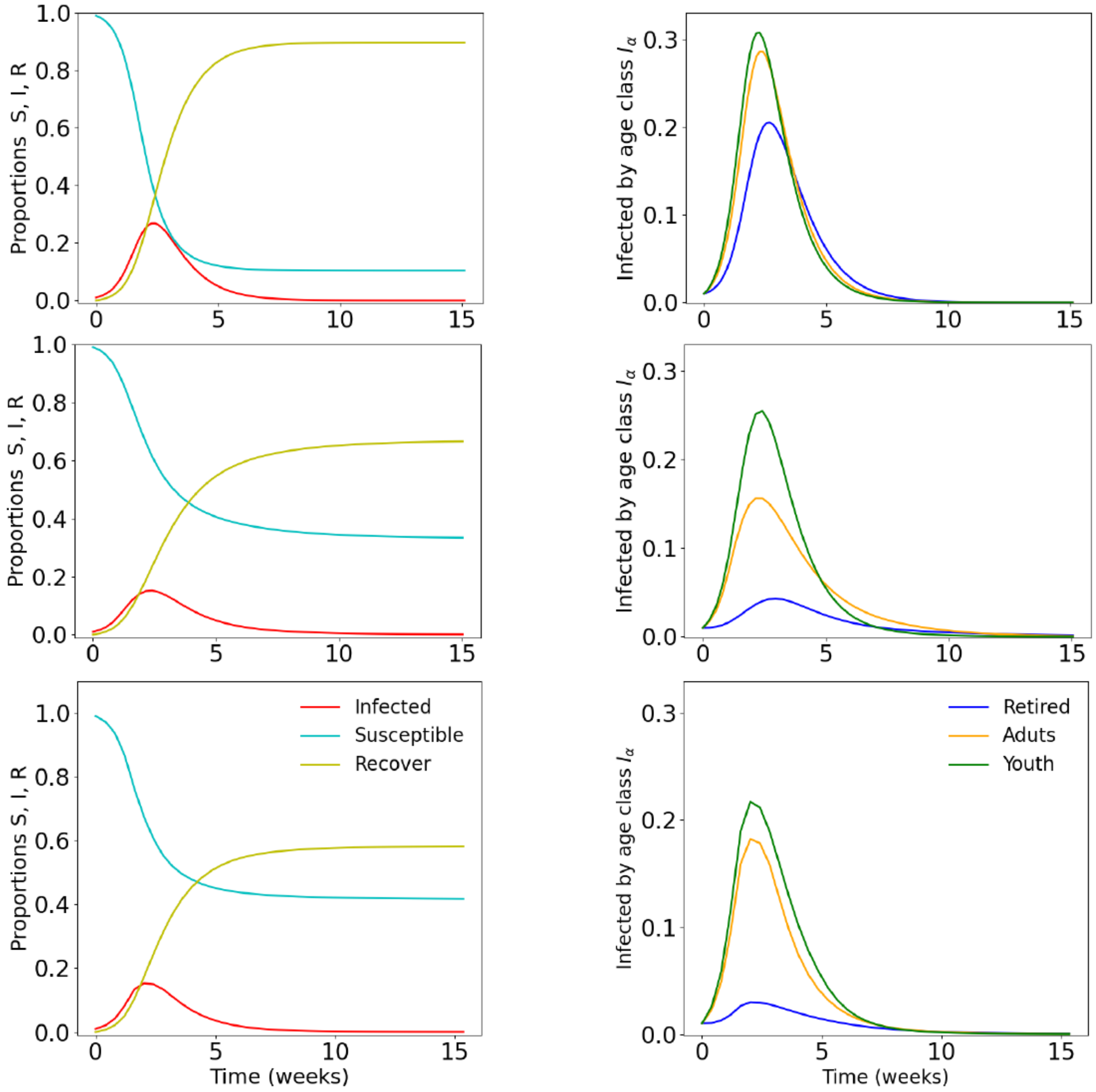
Cost of infection

r_I	κ_α	$(I_{\text{sat}}, \nu_{\text{sat}})$
1	$(1, 10, 100)$	$(0.1,0.1)$

Social cost

n^{γ}_{min}	μ_γ
$(\frac{1}{3}, \frac{1}{5}, \frac{1}{5}, \frac{1}{2})$	$(2, 2, 1, 3)$

Epidemic dynamics



Business as usual

$(n_\alpha^\gamma(t) \equiv 1)$

(free) Nash

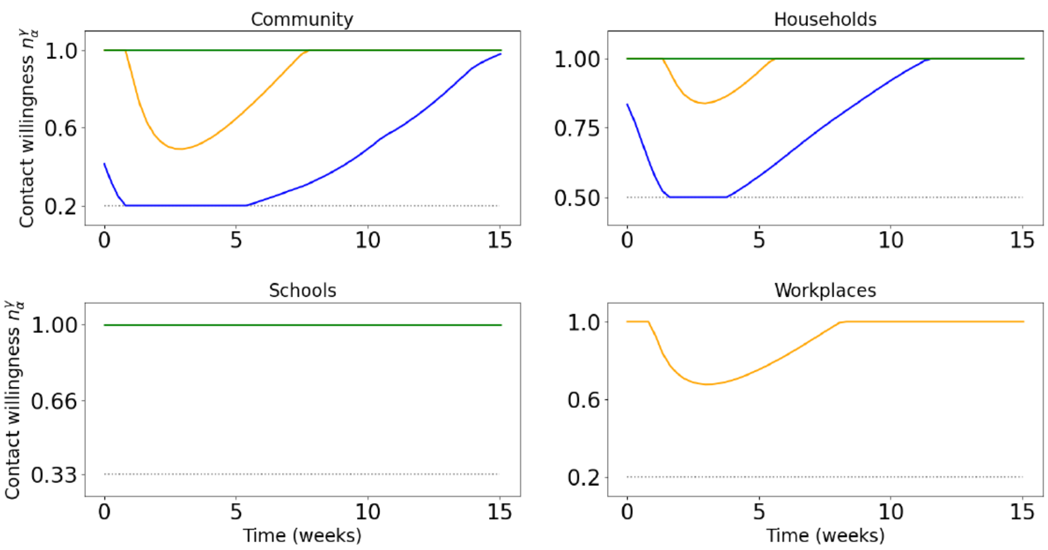
$(n_\alpha^\gamma(t)\ \leftarrow$ MFG)

Societal optimum

$n_\alpha^\gamma(t)$ obtained from the optimization of

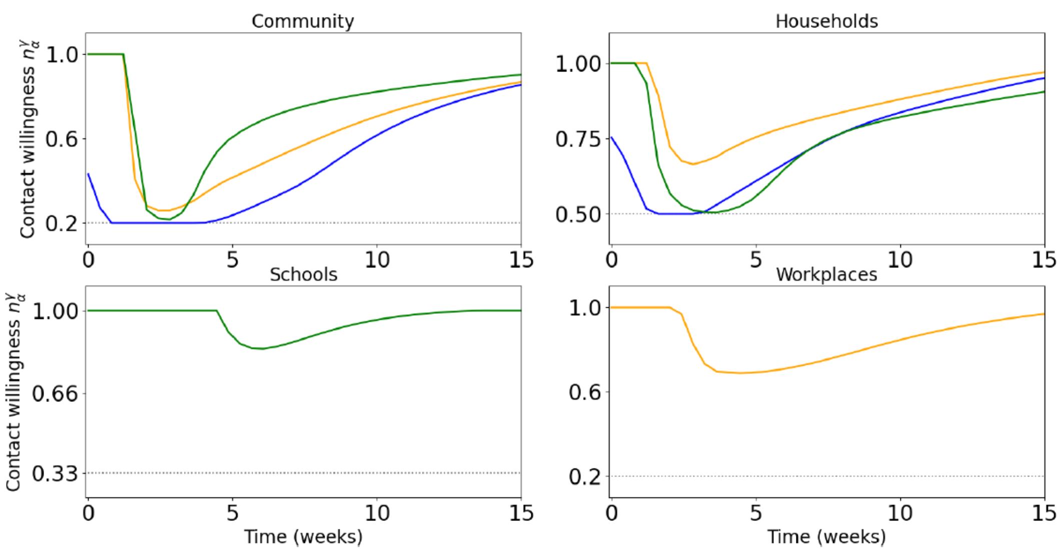
$$C_{\text{glob}}\left(\{n_\beta\}\right) \equiv \sum_\alpha N_\alpha C_\alpha\left(n_a = n_\alpha, \{n_\beta\}\right)$$

Corresponding strategies (i.e. $n_\alpha^\gamma(t)$, $\boldsymbol{\alpha}$ = (young, adults, retired), $\boldsymbol{\gamma}$ = (community, housholds, schools, workplace))



(free) Nash

($n_\alpha^\gamma(t)$ ← MFG)



Societal optimum

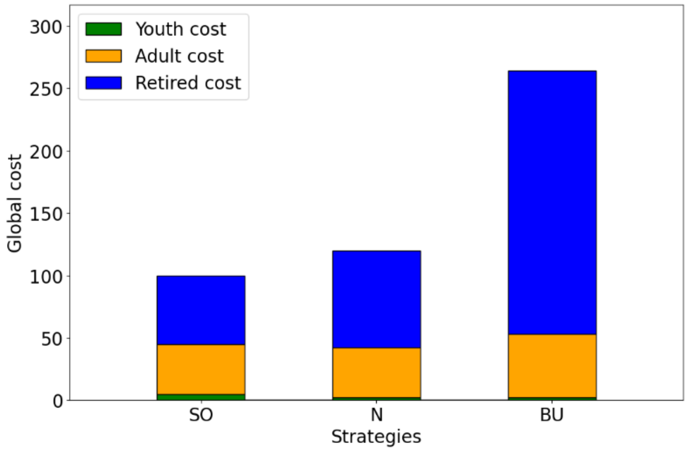
$n_\alpha^\gamma(t)$ obtained from the optimization of

$$C_{\rm glob}\left(\{n_\beta\}\right) \equiv \sum_\alpha N_\alpha C_\alpha\left(n_a = n_\alpha, \{n_\beta\}\right)$$

Constrained Nash

With our parameter choices (but this should remain true in general) :

- Nash improves very significantly over “business as usual” (especially for the older age class).
- Still the global cost is ~ 20% higher than the one of the “societal optimum”.

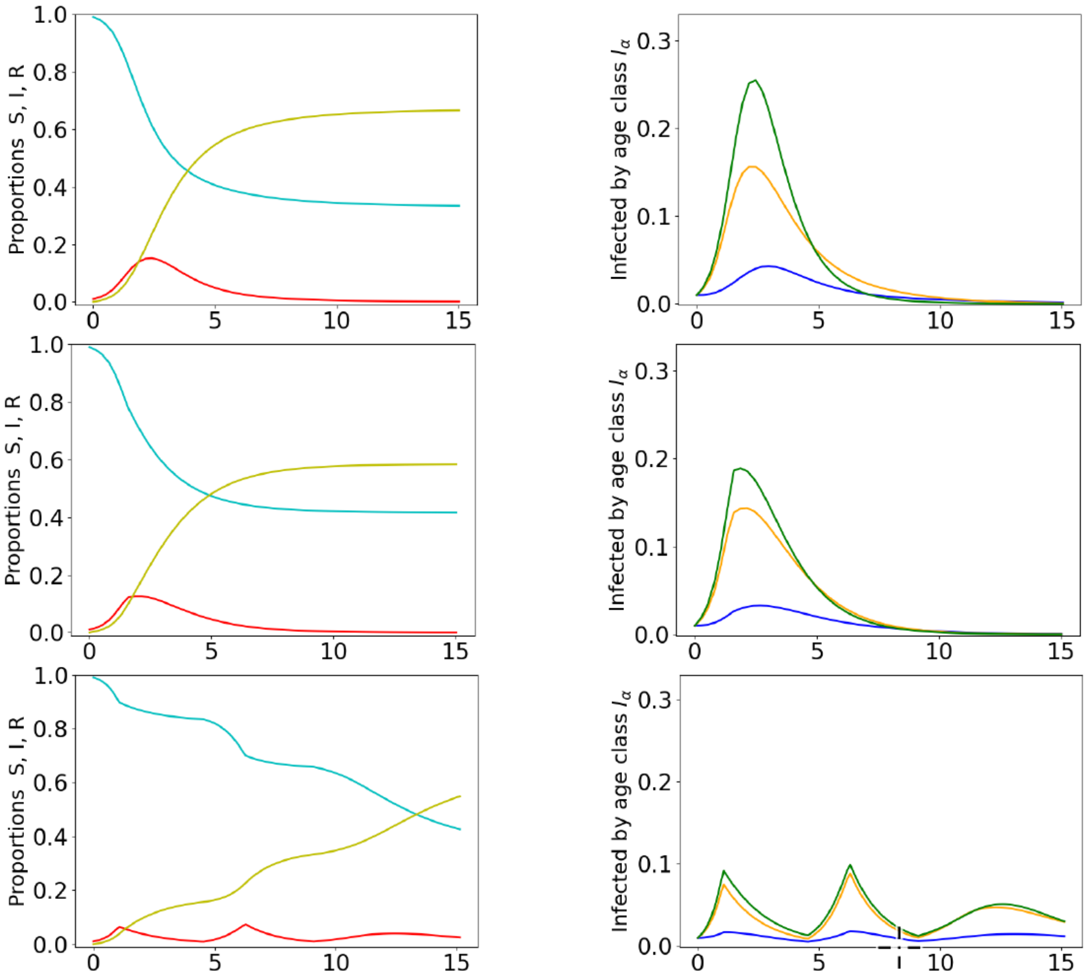


⟹ Can we bridge the gap (at least partially) by imposing **local constraints** similar to **lockdowns** ?

Constrained Nash (still a MFG)

- Two thresholds :
  - when $I(t) > I_l$: lockdown imposed
  - when $I(t) < I_d$: lockdown lifted
- Lockdown $\Longrightarrow n_\alpha^\gamma(t) \in [n_{\alpha,\min}^\gamma, n_{\alpha,l}^\gamma]$ $\qquad n_{\alpha,l}^\gamma = \sigma n_{\alpha,\min}^\gamma + (1-\sigma)$

Dynamics for constrained Nash

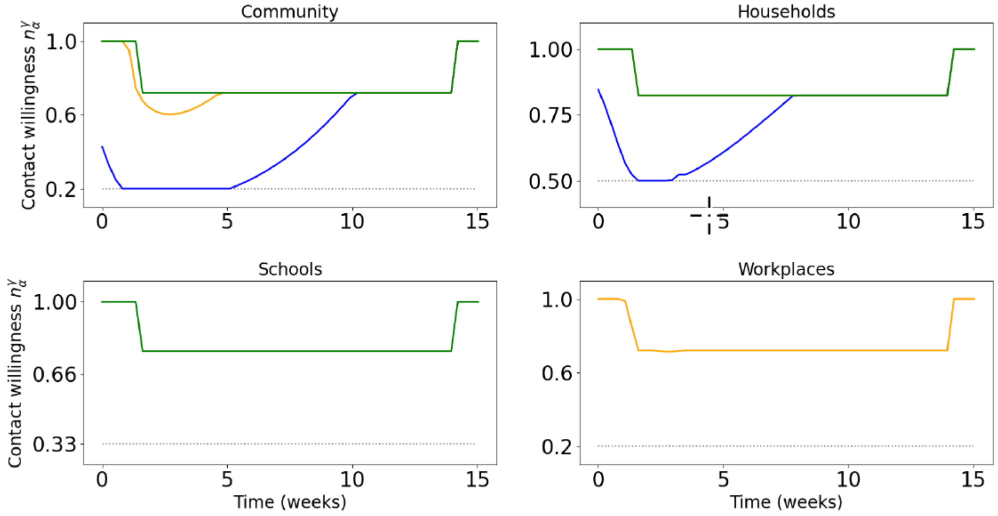


(free) Nash

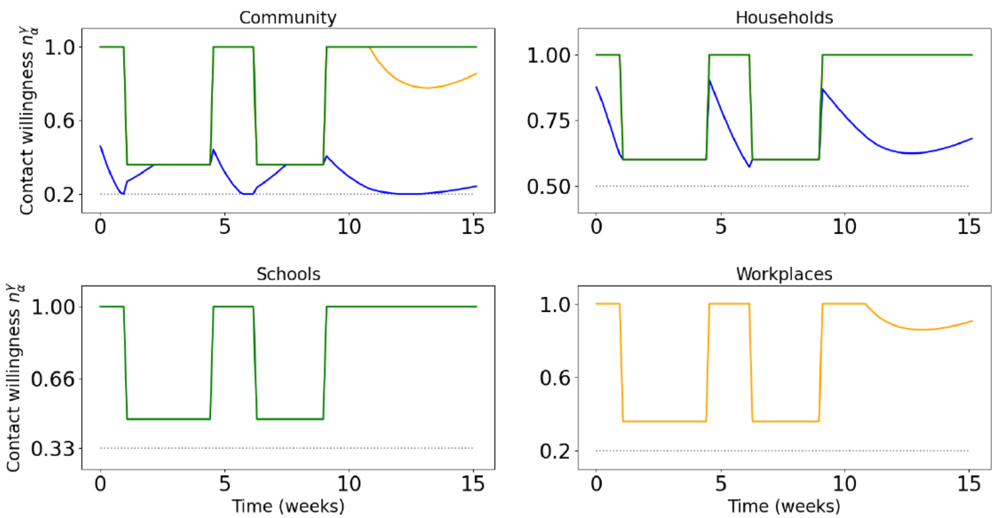
Nash with optimal constraints
$(I_l = 0.12, I_d = 4.10^{-4},$
$\sigma = 0.35\ )$

Nash with naive constraints

Strategies for constrained Nash

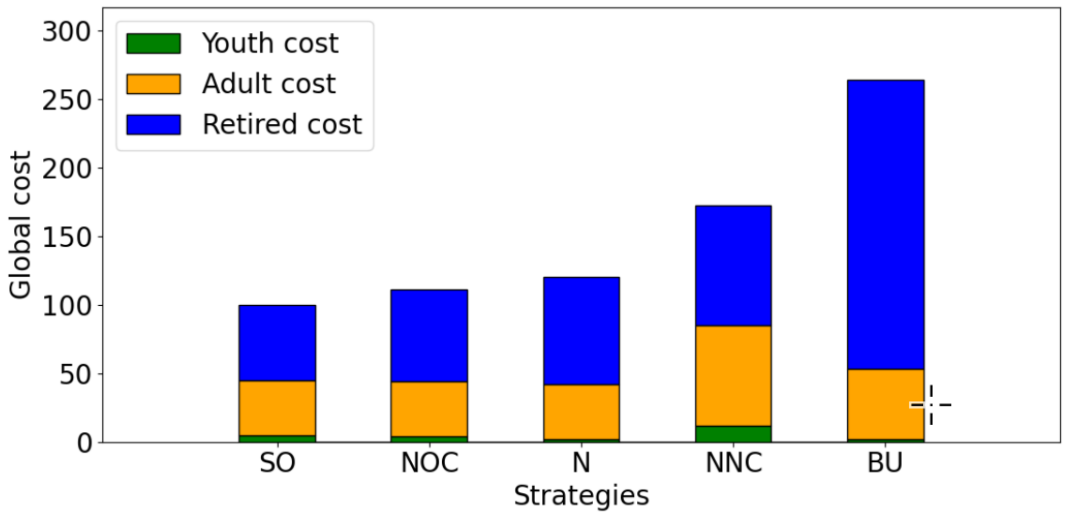


Nash with optimal constraints



Nash with naive constraints

Local conclusion



- Nash improves very significantly over "business as usual" (especially for the older age class).
- The gap between free Nash and Societal Optimum can be partially bridged by imposing well chosen constraints.
- Naïve constraints on the other hand can result in a cost significantly worse than free Nash, by degrading the situation for both adults and young without improving it for retired people.

Part II : phase transition for optimal strategies

- Until now we have assumed :
  - T (total optimization time) $\rightarrow \infty$
  - N (total number of agents) $\rightarrow \infty$

  $\Rrightarrow$ The only way out of the epidemic was **“herd immunity”.**
- However,
  - If T finite (anticipation of a vaccine, seasonality of the disease, etc.)

    $\Rrightarrow$ one may try to “contain” the epidemic.
  - If N finite (Island, small country with tight borders)

    $\Rrightarrow$ one may even try to “eradicate” the epidemic.

⇒ What kind of change would this imply ?

Herd immunity

Herd immunity for the basic SIR

$$\dot{S} = -q\chi S(t)I(t)$$
$$\dot{I} = q\chi S(t)I(t) - \xi I(t)$$
$$\dot{R} = \xi I(t)$$

$$\Longrightarrow \quad R = \frac{q\,\chi\,S(t)}{\xi} < 1 \;\Rightarrow\; \dot{S}(t') < 0 \,, \forall\, t' > t$$

In our case

We say we have herd immunity at t, if, without effort $\dot{S}(t') < 0 \,, \forall\, t' > t$

Reproduction number of age class α : $R_\alpha(t) = \frac{\mu q}{\xi} \sum_{\beta,\gamma} n_\alpha^\gamma(t) n_\beta^\gamma(t) W_{\alpha\beta}^\gamma N_\beta S_\beta(t)$

$$\dot{I} = \xi \sum_\alpha N_\alpha I_\alpha (R_\alpha - 1) \quad \Longrightarrow \quad \text{“Sufficient” criterion : } R_\alpha < 1,\ \forall \alpha$$

Effective criterion : $R^{(0)} \equiv \sum_\alpha N_\alpha R_\alpha^{(0)} < 1$

Herd immunity

Herd immunity for the basic SIR

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Rate of infection

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$$\dot{R} = \xi I(t)$$

$$\Rightarrow \quad R = \frac{q\,\chi\,S(t)}{\xi} < 1 \quad \Rightarrow \quad \dot{S}(t') < 0\,, \forall\, t' > t$$

(duration of infection)$^{-1}$

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Effective criterion : $$R^{(0)} \equiv \sum_\alpha N_\alpha R_\alpha^{(0)} < 1$$

Scenario classification

- Herd immunity : $R^{(0)}(T) \equiv N_\alpha R_\alpha^{(0)} < 1$
- Eradication : $I(t < T) = I_{\text{thr}} = O(\frac{1}{N})$
- Containment : $R^{(0)}(T) > 1$ && $I(T) > I_{\text{thr}}$

Can we do better ?

For each scenario : **template** = approximation for the **optimal strategies** $\boldsymbol{n}(.) \equiv \{n_\alpha^\gamma(.)\}$

- Template for herd immunity :

$$\mathbf{n}_{\text{im}}(.) = \underset{n_\beta^\gamma(.)}{\text{argmin}} \left[C_{\text{glob}} \left(\{n_\beta^\gamma(.)\}, T \longrightarrow \infty \right) \right]$$

- Template for containment

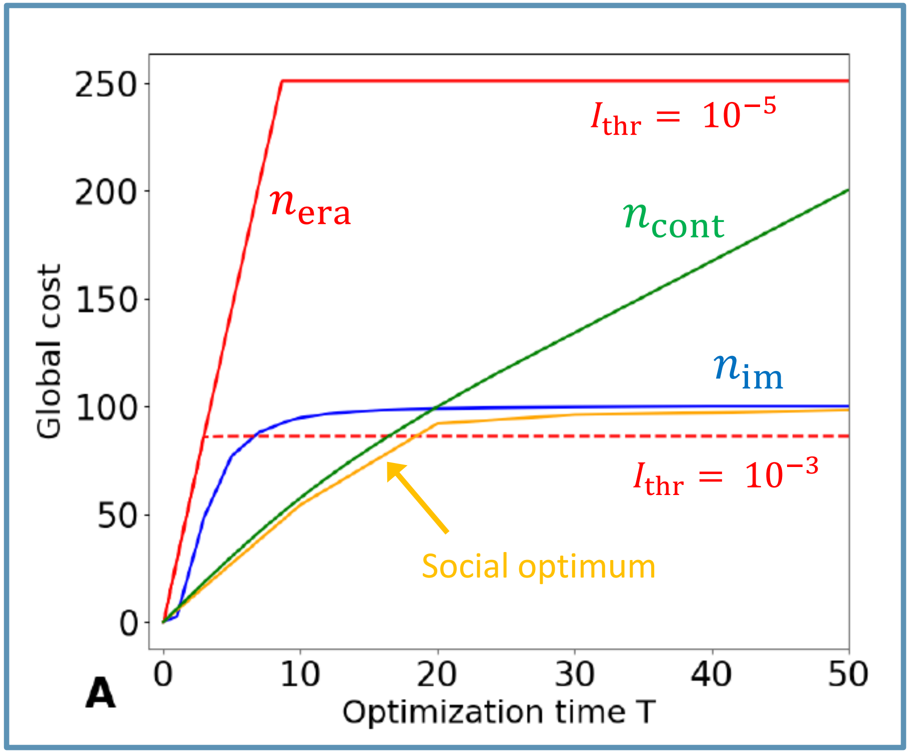
$$\mathbf{n}_{\text{cont}}(\not{t}) = \underset{\{n_\beta^\gamma\}}{\text{argmin}} \left[\sum_\alpha f_\alpha(n_\alpha^\gamma) \quad / \quad R(\{n_\beta^\gamma\}, \{S_\beta = 1\}) = 1 \right]$$

- Template for eradication

$$\mathbf{n}_{\text{era}}(\not{t}) = \{n_{\beta,\text{min}}^\gamma\} \qquad \text{(max constraints)}$$

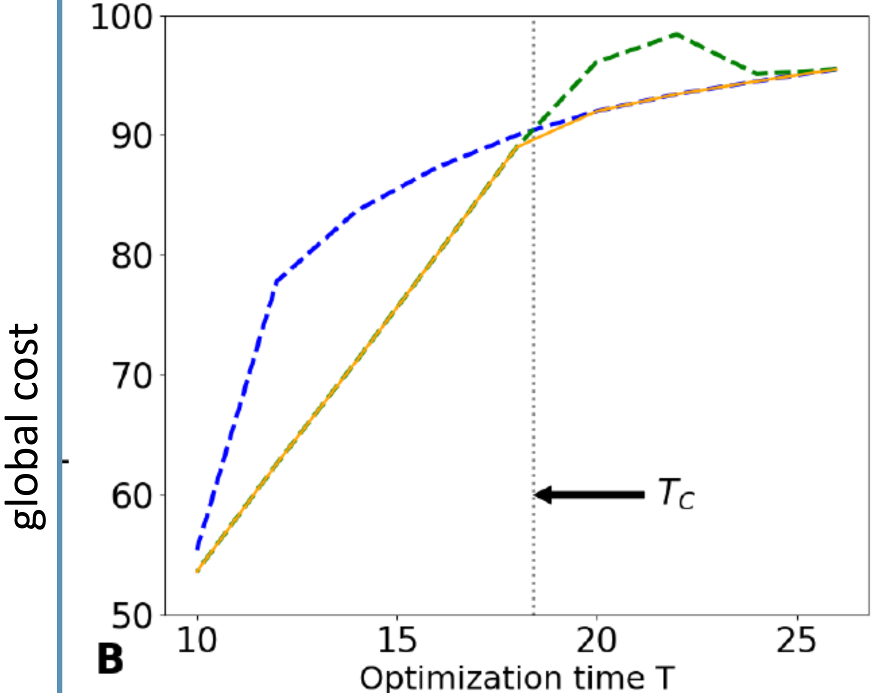
Comparison between template and social optimum strategies

Resulting global cost



Template strategies appear as good proxies for the optimal one

Phase transition between “herd immunity” and “containment



Dashed curves : local minima of global cost obtained, moving T by small step δT (green → $\delta T > 0$, blue → $\delta T < 0$) by a gradient descent initiated at the previous minima.

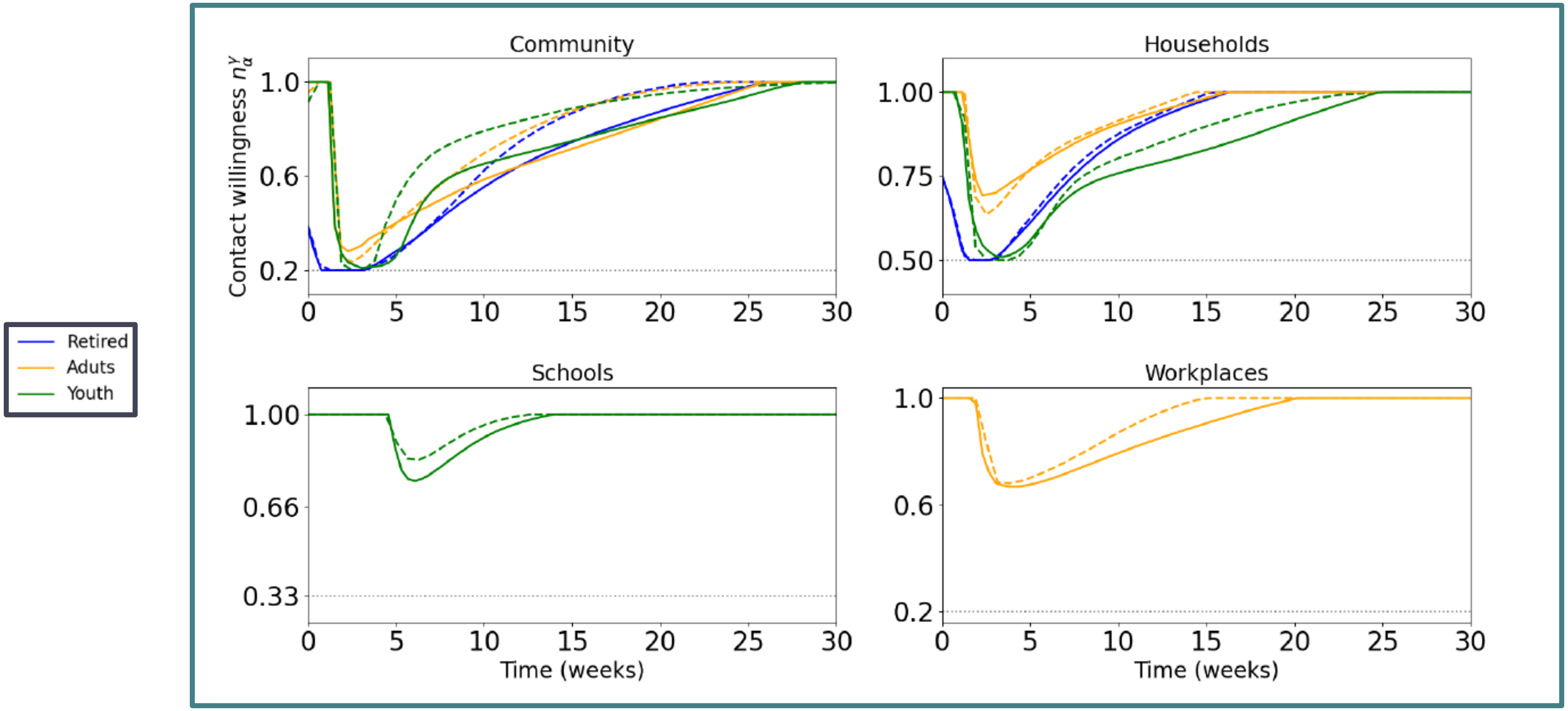
- Existence of local minima of the global cost in a relatively large region around T_C.
- Local minima ~ template strategies ⇒ we expect discontinuous change of the optimal strategy at T_C.
- Also discontinuous derivative of C_{glob} at T_C.

⇒ What we have here is a first order phase transition

Comparison between template strategies (dash) and true optimal ones (solid)

Herd immunity regime

$(T = 30, I_{\text{thr}} = 0)$

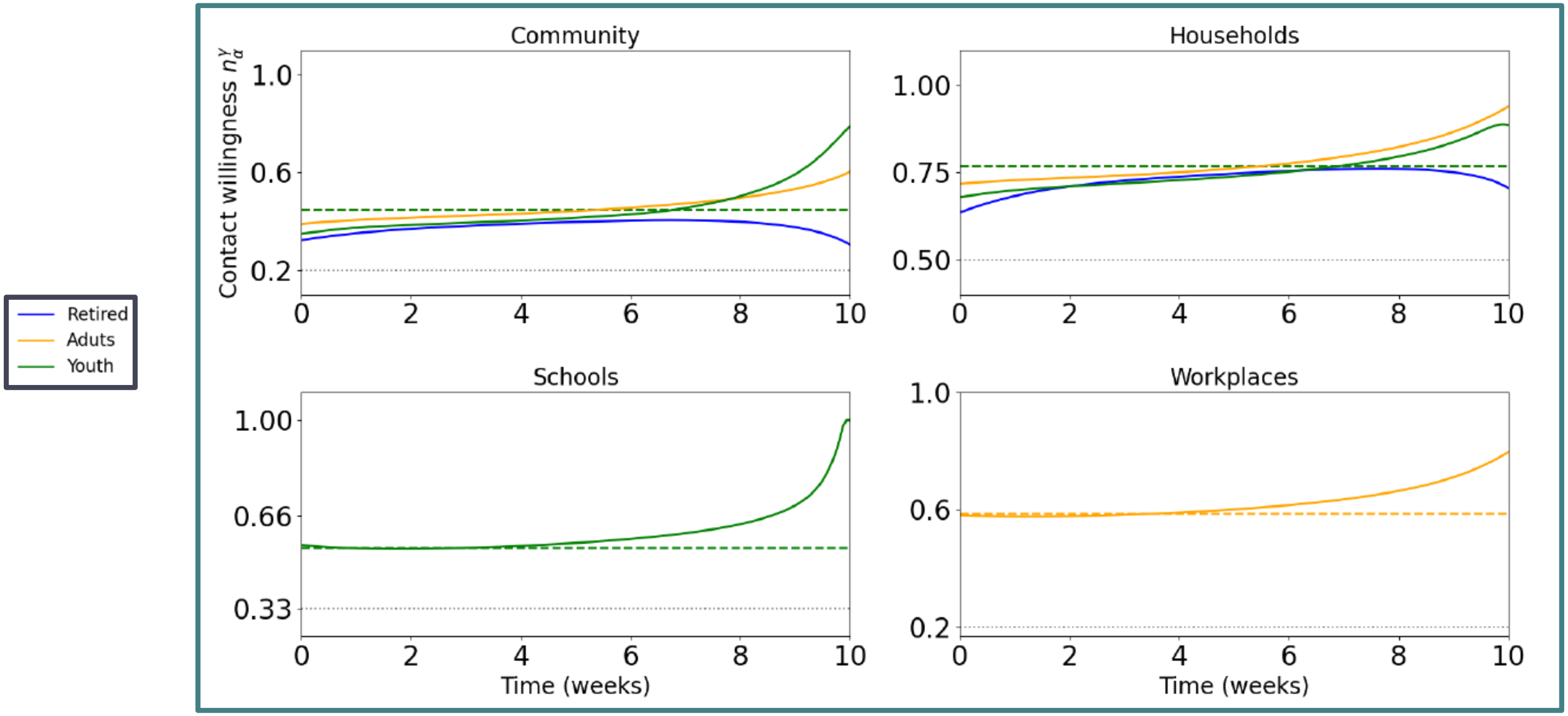


Extra effort, especially from the youth, appears beneficial to limit the number of infected.

Comparison between template strategies (dash) and true optimal ones (solid)

Containment regime

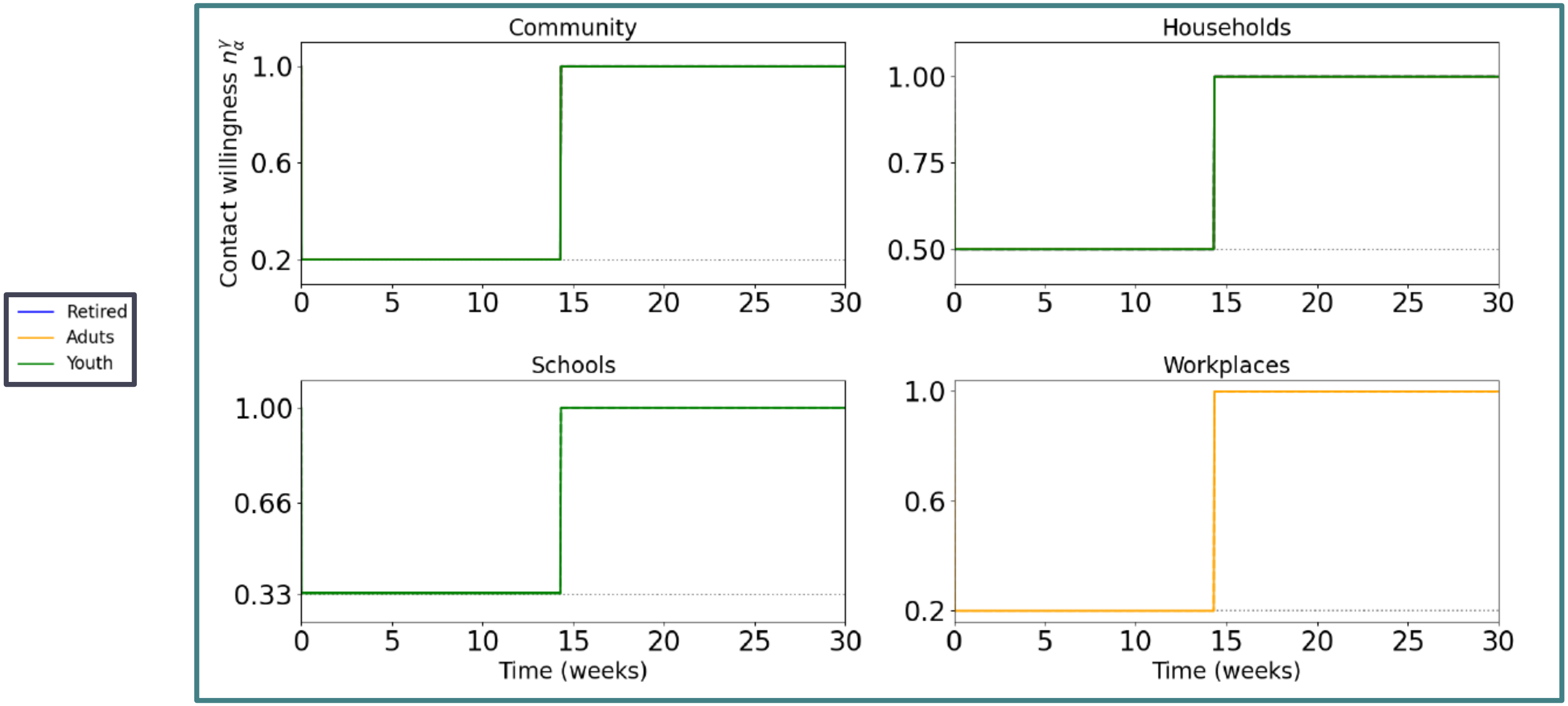
$(T = 10, I_{\text{thr}} = 0)$



Slightly more effort at the beginning, and quite a bit less in near the end (except for the retired who have to compensate for it), appears beneficial.

Comparison between template strategies (dash) and true optimal ones (solid)

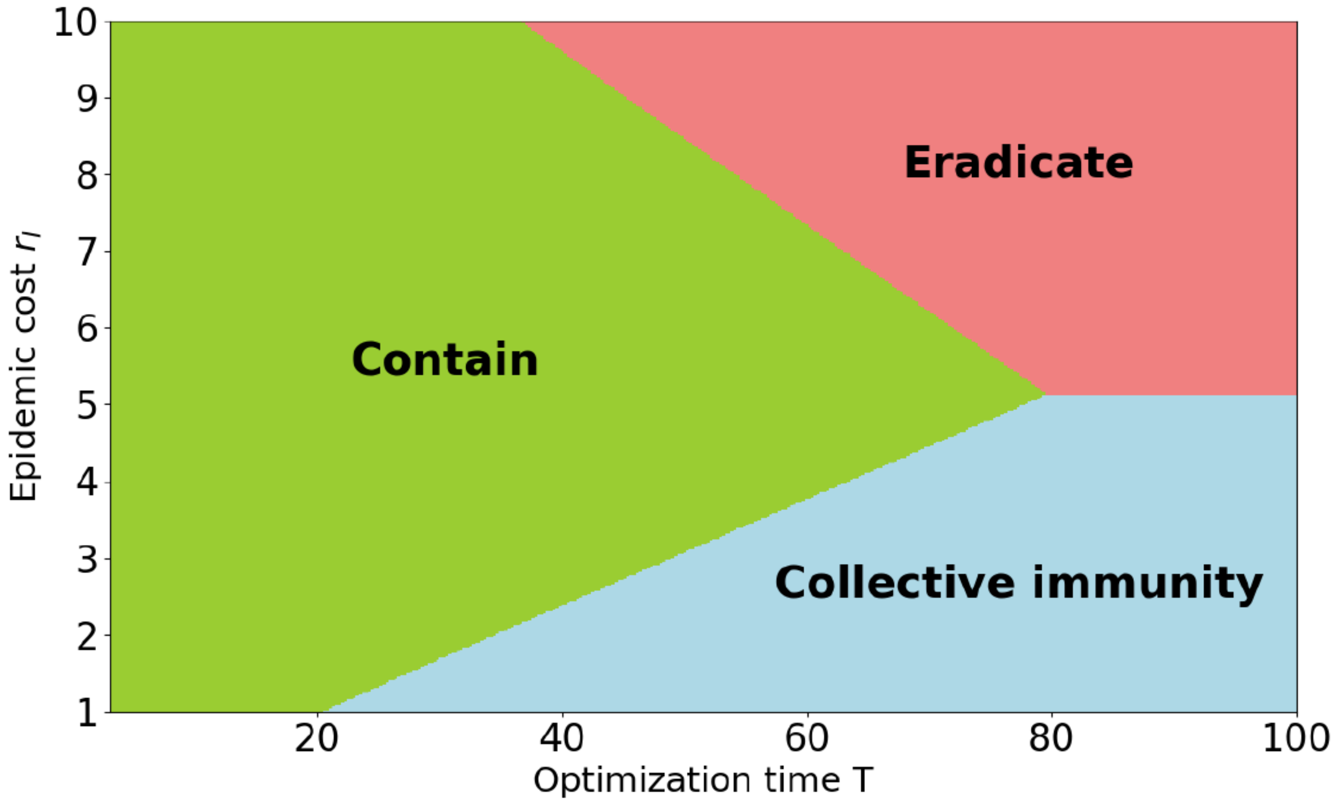
Eradication regime
$(T = 30, I_{\text{thr}} = 10^{-5})$



Here the template is the optimal strategy

Phase diagram (T, r_I)

$$\mathcal{I}_\alpha(I(s)) = \kappa_\alpha r_I \exp\left[\nu_{\text{sat}} \frac{I(t) - I_{\text{sat}}}{I_{\text{sat}}}\right]$$



Phase diagram derived from template strategies

Previous phase diagram obtained from (the proxies of) optimal strategies : what about Nash / MFG ?

- **Herd immunity** : **Nash**, or even better, the **optimized constrained Nash**, provides a good approximation of the societal optimal.
- However the **Containment** and **Eradication** strategies are characterized by very low I_α (thus small force of infection λ_α)

  ⇒ for an individual a optimizing for himself, the best strategy is always to do no effort at all ($n_a^\gamma \equiv 1$).

  ⇒ for these two strategies, the societal optimum cannot be approached by a Nash / MFG approach.

⇒ In the MFG context, phase diagram becomes trivial (only one phase = "collective-immunity-like"). The green and red regions of the previous figure now correspond to parameter values for which the "cost of anarchy" is large.

Conclusion

- We have a “tractable” model, which is detailed enough that we can recover many qualitative aspects that we know to exist about epidemics (difference of behavior between retired people and young, rebound of epidemics when lockdown are not well designed, etc..).

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- It provides a conceptual framework in which “non-pharmaceutical interventions” (ie ways to deal with an epidemics beyond trying to find a vaccines or cure) can be discussed in a relatively objective way.

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- It provides a conceptual framework in which “non-pharmaceutical interventions” (ie ways to deal with an epidemics beyond trying to find a vaccines or cure) can be discussed in a relatively objective way.

- Could this be of interest for “real” epidemiologist ?

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- We have a “tractable” model, which is detailed enough that we can recover many qualitative aspects that we know to exist about epidemics (difference of behavior between retired people and young, rebound of epidemics when lockdown are not well designed, etc..).

- It provides a conceptual framework in which “non-pharmaceutical interventions” (ie ways to deal with an epidemics beyond trying to find a vaccines or cure) can be discussed in a relatively objective way.

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  ⇒ but one may argue that a rough approximation can be better than just guesswork as a negotiation basis.

- In particular, even at a qualitative level, the role of Nash equilibrium is presumably not well thought.