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Highlights

- We argue that behavior must be considered in evaluations of public health policies.
- We base our claim on the example of mandatory MMR vaccination.
- In this case, behavior may cause major welfare transfers between generations.
- We provide a computational tool to analyze individual behavior in epidemiology.

Cost effectiveness and policy announcement: The case of measles mandatory vaccination

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Abstract

In a vaccination game, individuals respond to an epidemic by engaging in preventive behaviors that, in turn, influence the course of the epidemic. Such feedback loops need to be considered in the cost effectiveness evaluations of public health policies. We elaborate on the example of mandatory measles vaccination and the role of its anticipation. Our framework is a SIR compartmental model with fully rational forward looking agents who can therefore anticipate on the effects of the mandatory vaccination policy. Before vaccination becomes mandatory, parents decide altruistically and freely whether to vaccinate their children. We model eager and reluctant vaccinationist parents. We provide numerical evidence suggesting that individual anticipatory behavior may lead to a transient increase in measles prevalence before steady state

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eradication. This would cause non negligible welfare transfers between generations. Ironically, in our scenario, reluctant vaccinationists are among those who benefit the most from mandatory vaccination.

Keywords: MMR, behavior, vaccination, game theory, backward induction, vaccination game, vaccination policy.

1 Introduction

In economic evaluations of disease control policies, health authorities verify whether the expected benefits of a decision outweigh its costs. Costs and benefits may be expressed as money or well-being and may be direct or indirect. In order to do that, tools were developed to reckon, measure, and add up a wide range of – sometimes subjective – aspects of a disease, from physical and psychological pain to the monetary cost of missing work (Weinstein et al., 2009; Sassi, 2006). Cost effectiveness analysis is now a routine procedure in public health (see Drummond et al. (2015) for a comprehensive textbook on the subject).

What modern economic evaluation methods have yet in common, at least in applied contexts and despite a very large academic literature on the topic, is their limited account of individual responses to the *outcomes* of a public health policy. Some studies look *retrospectively* upon individual behaviors insofar as they were directly affected by a policy (see Walker (2003); Lorenc et al. (2011) for instance). Other authors, like DePasse et al. (2017), attempt to *anticipate* the effects of individual responses to policies but individual decisions are either random or assumed *ad hoc* in their models. Besides, they only focus on responses to the *direct* effects of a policy, and not on responses to *indirect* incentive changes implied by this policy. As a rule, in applied cost effectiveness analyses, individual behavioral responses to incentive changes are overlooked *a priori*.

We see two reasons explaining why such individual behaviors are not considered by health authorities in cost effectiveness analyses before policy implementation. First, we think that they may be implicitly deemed inconsequential without further consideration. Second, considering feedback loops between individual behaviors and epidemics can be a complex task, especially when it comes to *forward looking* behaviors influencing the future spread of the disease. Let us elaborate on those two explanations.

It might first be argued that individual behavior is not always relevant to disease control. Some real life examples might even be brought up. However, this does not imply that behaviors should be disregarded in all cases. Measles is a typical example of a disease whose spread hinges essentially, at least in developed countries, on individual behaviors. This has been dramatically illustrated by the MMR vaccine controversy (McIntyre and Leask, 2008). Measles is a highly contagious[1] infectious disease with potentially severe complications (Orenstein et al., 2004; Centers for Disease Control and Prevention, 2015). An effective vaccine against measles has been available in developed countries since the 1960's and has been included in routine immunization programs since the 1980's. In some countries such as France and the United Kingdom, vaccination expenses are covered by the state or health insurances. Yet, despite the apparent incentives to vaccinate and low vaccination costs, a fraction of the population still refuses vaccination, allowing for sporadic epidemics (World Health Organization, 2017).[2] The first objective of this article is to illustrate with an internally consistent epidemiological model assuming realistic parameter values, how individual behaviors can substantially influence disease dynamics, and show that they can be relevant to economic evaluation. In order to meet this objective, we study the example of measles vaccination in France, where MMR vaccination was made mandatory for all children born after January 1st 2018. Recent studies of the possible

[1]The reproduction number ranges from 12 to 18 (see Guerra et al. (2017)), and high levels of immunization (90 to 95%, see Nokes and Anderson (1988)) are necessary to reach herd immunity.

[2]Examples of such epidemics include the 2014–2015 California outbreak (Clemmons et al., 2015; Halsey and Salmon, 2015), and the 2018 epidemics in Ireland, Italy (WHO Europe, 2018), and southwestern France (Santé Publique France, 2018).

benefits of mandatory measles vaccination (Trentini et al., 2019) overlook the effects of individual behaviors. We use numerical simulations to show that individual anticipatory behaviors may give rise to substantial generational effects. Also, we show that reluctant vaccinationists may be among those who benefit the most from mandatory vaccination.

Let us now turn to the complexity argument for overlooking individual behavior in economic evaluations, and the second objective of the present study. Arguably, individuals vaccinate if the risk of getting infected outweighs their vaccination cost. This cost encompasses vaccination expenses, but also medical visit inconvenience, religious and political motives, or the fear of side effects.[3] As for the risk of ever getting infected, it depends on the present and future number of infectious individuals, which in turn depends on how many people got vaccinated in the past, and will in the future. Analyzing the complex feedback loop between individual behaviors and disease dynamics can be technically challenging, even more so with cost effectiveness analysis in view. The second objective of this article is to show how this can be done and provide a tool to do so. The interplay between vaccination behaviors and the spread of a disease has been formalized as *vaccination games*. We refer our readers to Funk et al. (2010); Manfredi and D'Onofrio (2013); Chen and Toxvaerd (2014); Verelst et al. (2016); Wang et al. (2016) for literature reviews. As will be seen, a meaningful vaccination game analysis cannot, in many cases, rely only on steady states; we will need to compute fully time-dependent solutions. Computing such solutions is nontrivial, especially when agents are assumed to be forward-looking – that is able to anticipate. In France, mandatory vaccination was clearly announced during the 2017 French presidential campaign, that is several months before implementation, so it could be anticipated and agents could act accordingly. In order to overcome the difficulty of including this feature in the model and meet our second objective, we will use the framework proposed by Flaig et al. (2018).[4] This study was among the firsts to solve a vaccination

[3]See Kata (2010) for a review of anti-vaccination arguments.

[4]The similar work by Salvarani and Turinici (2018) applied to the case of flu is also worth mentioning.

game with fully rational intertemporal utility maximizing agents, a measles-like complex disease, simulation over a long time horizon, and vital dynamics. Most previous studies of vaccination games considered simplified epidemiological models amenable to analytic work or without vital dynamics, or focused on steady states only. Finally, we want to emphasize that solving the vaccination game is not the sole technical difficulty faced by the analyst (think of the estimation of population parameters, for instance) but these are left outside the scope of this study.

Our model is presented in Section 2. Simulation results are analyzed in Section 3. First, we show the effect of anticipatory behaviors on the dynamics of measles (Section 3.1). Then, we compare the welfare of the different generations and sub-populations (Section 3.2). Section 4 concludes.

2 Model

2.1 Epidemiological assumptions

We describe measles dynamics with a SIR compartmental model with homogeneous mixing and vaccination. Individuals are born *Susceptible*. Following infection, individuals remain *Infectious* for five days on average.[5] Then, they *Recover* and stay immunized for the rest of their lives. Birth and death rates are low and equal, which is characteristic of developed countries. We overlook passive immunity through maternal antibodies. While most infants are born immune to measles, they usually become susceptible several months before scheduled vaccination. Also, studies have found that children lose immunity earlier where measles is not endemic. For a recent review of this topic, see Guerra et al. (2018).

Real life vaccination schedules vary depending on the vaccine and from one country

[5]Infected individuals are infectious four days before rash onset (Centers for Disease Control and Prevention, 2015). Our assumption is that sick individuals are (self-)quarantined after five days of positive infectiousness.

to another (World Health Organization, 2017). We model a MMR-like vaccine, with a simplified vaccination schedule. We assume that children have access to vaccination when they are 14 months (420 days) old. Hence, two age categories are relevant for our study: younger and older than 14 months. Vaccination is only offered as part of routine vaccination schedules, and has an efficacy of 97% (Centers for Disease Control and Prevention, 2015). Figure 1 sums up the epidemiological assumptions.

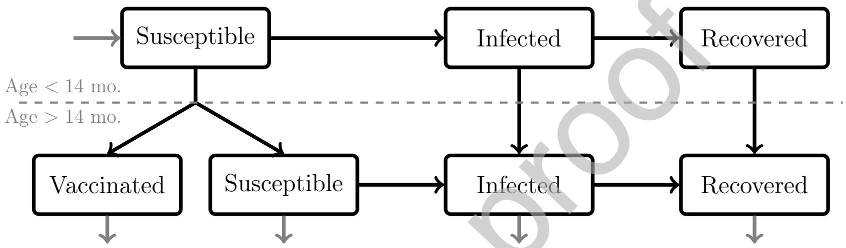


Figure 1: Compartmental model for measles with vaccination. *Gray arrows:* births and deaths. Aging is probabilistic.

2.2 Behavioral assumptions

Being healthy brings instantaneous utility (or benefit), while being sick has a relative cost. Since state changes after infection are independent of all vaccination decisions, we can assume that the intertemporal cost of being sick is paid immediately upon infection. For the sake of simplicity, we made the further assumption that this intertemporal discounted cost is equal to the total undiscounted cost of being sick. This simplifying assumption is made possible by the short duration of the symptoms, and the low discount rate value of 3% annually. Costs and utilities are in QALDs (1 QALD is 1/365 QALY). Sick individuals incur a total cost of 7 QALDs (Thorrington et al., 2014). This figure includes symptoms, time off school or work, hospitalization, and missed days of work by parents of sick children.[6] Vaccination has a cost too (monetary, logistical, ideological, etc.) that must be paid when

[6]Notice here that individuals consider their personal costs, and not a social cost of being sick.

vaccination is voluntary, but also when it is mandatory. We use this cost to model two types of individuals: *reluctant* and *eager* vaccinationists. Both types of agents make vaccination decisions based on an individual cost benefit analysis. We only assume that reluctant vaccinationists have a higher vaccination cost than eager vaccinationists. Notice that we do not specify whether vaccination costs are objective in any sense or only perceived; they can be both for both types of individuals. Also, we assume that the cost of being sick is the same for both agent types and both age classes. This is an approximation, see Thorrington et al. (2014). When vaccination is voluntary, individuals (at 14 months of age) freely choose whether they want to get vaccinated based on a personal intertemporal and far-sighted cost benefit analysis. When vaccination is mandatory, all susceptible 14 month old children get vaccinated.

Here we assume that individuals decide for themselves even though they are 14 months old. This assumption is equivalent to considering perfectly altruistic parents making the decision of having their child vaccinated considering his best interest (Ramsey, 1928). This assumption seems to be in line with observations in the case of MMR vaccination decision making (Brown et al., 2010).

We also assume that individuals either accept both vaccination and the recommended vaccination schedule, or they refuse vaccination altogether and never have the opportunity to catch up. That is, individuals do not decide *when* to vaccinate but merely *whether or not* to vaccinate. This simplifying assumption is in line with our focus on routine vaccination, however it may have to be relaxed in other applications of our approach. We refer our readers to Flaig et al. (2018) for a case where individual also decide when to vaccinate.

Timing is as follow: before time 0, individuals believe that voluntary vaccination will last forever and they behave accordingly. We start our simulations at time 0 with the epidemic steady state corresponding to this behavior. At time 0, authorities announce that vaccination will be made mandatory at time $t_{\text{mv}} > 0$. Hence, between time 0 and t_{mv}, vaccination is still voluntary but individuals can anticipate the future effects of mandatory vaccination.

2.3 Equations

Let $s_{a,j}$ (resp. $i_{a,j}$, $r_{a,j}$, $v_{a,j}$) denote the susceptible (resp. infected, recovered, vaccinated) population

- in age class $a \in \{\mathrm{y}, \mathrm{o}\}$: younger or older than 14 months,
- of type $j \in \{\mathrm{ev}, \mathrm{rv}\}$: eager or reluctant vaccinationists.

$V_{\mathrm{S}}^{\mathrm{o}}$ denotes the value of being susceptible *and* older than 14 months, and $\Lambda_j \in [0,1]$ the vaccination decision of individuals of type $j \in \{\mathrm{ev}, \mathrm{rv}\}$. A description of the input parameters with their values is given in Table 1. For all time t between 0 and final time T, the system is governed by Equations (1)–(8).

$$\frac{d}{dt} s_{\mathrm{y},j}(t) = \alpha_j \nu n_{\mathrm{o}}(t) - \left(\frac{1}{l} + \beta \frac{i(t)}{n(t)}\right) s_{\mathrm{y},j}(t) \tag{1}$$

$$\frac{d}{dt} s_{\mathrm{o},j}(t) = \frac{1}{l}\left(1 - \theta \Lambda_j(t)\right) s_{\mathrm{y},j}(t) - \left(\mu + \beta \frac{i(t)}{n(t)}\right) s_{\mathrm{o},j}(t) \tag{2}$$

$$\frac{d}{dt} i_{\mathrm{y},j}(t) = \beta \frac{i(t)}{n(t)} s_{\mathrm{y},j}(t) - \left(\frac{1}{l} + \gamma_I\right) i_{\mathrm{y},j}(t) \tag{3}$$

$$\frac{d}{dt} i_{\mathrm{o},j}(t) = \beta \frac{i(t)}{n(t)} s_{\mathrm{o},j}(t) + \frac{1}{l} i_{\mathrm{y},j}(t) - \left(\mu + \gamma_I\right) i_{\mathrm{o},j}(t) \tag{4}$$

$$\frac{d}{dt} r_{\mathrm{y},j}(t) = \gamma_I i_{\mathrm{y},j}(t) - \frac{1}{l} r_{\mathrm{y},j}(t) \tag{5}$$

$$\frac{d}{dt} r_{\mathrm{o},j}(t) = \frac{1}{l} r_{\mathrm{y},j}(t) + \gamma_I i_{\mathrm{o},j}(t) - \mu r_{\mathrm{o},j}(t) \tag{6}$$

$$\frac{d}{dt} v_{\mathrm{o},j}(t) = \frac{1}{l} \theta \Lambda_j(t) s_{\mathrm{y},j}(t) - \mu v_{\mathrm{o},j}(t) \tag{7}$$

$$-\frac{d}{dt} V_{\mathrm{S}}^{\mathrm{o}}(t) = u_{\mathrm{g}} - \left(\delta + \mu + \beta \frac{i(t)}{n(t)}\right) V_{\mathrm{S}}^{\mathrm{o}}(t) + \beta \frac{i(t)}{n(t)} \left(\bar{V}_{\mathrm{V}} - C\right) \tag{8}$$

where $i(t)$ is the total number of infected individuals,

$$i(t) = \sum_{\substack{a\in\{\text{y,o}\}\\ j\in\{\text{ev,rv}\}}} i_{a,j}(t),$$

$n_{\text{o}}(t)$ is the total population of individuals older than 14 months,

$$n_{\text{o}}(t) = \sum_{j\in\{\text{ev,rv}\}} s_{\text{o},j}(t) + i_{\text{o},j}(t) + r_{\text{o},j}(t) + v_{\text{o},j}(t),$$

and $n(t)$ is the total population at time t,

$$n(t) = \sum_{\substack{a\in\{\text{y,o}\}\\ j\in\{\text{ev,rv}\}}} s_{a,j}(t) + i_{a,j}(t) + r_{a,j}(t) + v_{a,j}(t).$$

Equations (1)–(7) govern the evolution of the population in each compartment. A proportion α_{rv} of the $\nu n_{\text{o}}(t)$ children born at time t are reluctant vaccinationists (or equivalently, have reluctant vaccinationist parents), and a proportion $\alpha_{\text{ev}} = 1 - \alpha_{\text{rv}}$ are eager vaccinationists (Equation 1). We set α_{rv} to 4%.[7] Under homogeneous mixing assumption, susceptible individuals (Equations 1 and 2) are infected with probability $\beta \times i(t)/n(t) \times dt$ at time t. Infected individuals (Equations 3 and 4) recover at rate γ_I. Aging is probabilistic in our model. At each time, individuals younger than 14 months (Equations (1), (3), and (5)) grow older than 14 months with probability $(1/l).dt$. Individuals older than 14 months (Equations (2), (4), (6), and (7)) die with probability $\mu.dt$. We assume that infected individuals do not have a higher death rate (instead, for the sake of simplicity, this probability is included in the cost of being infected).

Equation (8) is the *Bellman equation* (also known as *adjoint equation*, see Bellman

[7] Results are similar for higher values of α_{rv}. We provide results for $\alpha_{\text{rv}} = 1\%$ in Appendix C as a robustness check.

Notation	Value	Description	Source
Epidemiology			
β	2.8	Contact rate	Guerra et al. (2017)
γ_I	1/5	Rate of recovery	Wearing et al. (2005); Centers for Disease Control and Prevention (2015)
θ	97%	Vaccine efficacy	Moss and Griffin (2012); Centers for Disease Control and Prevention (2015)
Decision making			
u_{g}	1	Utility of being in good health	Normalized
C	7	Total cost of being sick	Thorrington et al. (2014)
c_{ev}	1.02×10^{-3}	Vaccination cost for eager vaccinationists	Calibrated
c_{rv}	9.41×10^{-3}	Vaccination cost for reluctant vaccinationists	Calibrated
α_{ev}	96%	Proportion of eager vaccinationists	Set
α_{rv}	4%	Proportion of reluctant vaccinationists	1-α_{ev}
δ	8.1×10^{-5}	Discount rate	Set
ϵ	10^5	Slope parameter of the sigmoid χ_ϵ	Set
Vital dynamics			
ν	3.42×10^{-5}	Birth rate	INSEE (2018)
μ	3.42×10^{-5}	Death rate	μ for stationary population
$1/l$	1/420	Aging rate	French vaccination schedule

Table 1: Input parameter values. Time unit: day. Costs and utility in QALD.

(1957)) governing the value function V_S^o. Remember that individuals are forward-looking: value functions are (future) expected utilities. Therefore, if u_g is the utility of being in good health during one day, V_S^o decreases by u_g each day spent susceptible as one day of good health is past. In other words, V_S^o decreases at rate u_g. The same reasoning goes for compartment transitions. As time passes and transitions are forgone, their net value is subtracted from the value of being susceptible. The value of being dead is normalized to 0. Then, the value of dying at time t for a susceptible old individual is $-V_S^o(t)$. Since vaccination provides lifelong immunization, V_V is equal to its steady state value $\bar{V}_V = u_g/(\delta + \mu)$. Recovered individuals also enjoy lifelong immunization so we have the net value of getting infected at time t by $\bar{V}_V - C - V_S^o(t)$, where C is the total cost of being sick. The discount rate δ stands for time preferences. See Section A in Appendix for a more formal derivation of the Bellman equation.

As long as vaccination is not mandatory, children decide to vaccinate by comparing the value V_S^o of being susceptible (Equation 8) with the value V_V of being vaccinated. We represent decision making by a *smoothed best response* function (Fudenberg and Levine, 1998; Xu and Cressman, 2014). We use the sigmoid $\chi_\epsilon : x \mapsto \dfrac{1}{1 + \exp\left[-\epsilon x\right]}$ as smoothed best response function. If the value difference between two alternatives, say 1 and 2, is $\Delta V = V_1 - V_2$, then alternative 1 of value V_1 is chosen with probability $\chi_\epsilon\left(\Delta V\right)$. Let $\Lambda_j(t)$ denote the proportion of children of type j who reach 14 months at time t, and who receive the vaccine. With $t_{\mathrm{mv}} \in [0, T]$ standing for the date at which mandatory vaccination comes into force, Λ_j is given by

$$\Lambda_j(t) = \begin{cases} \chi_\epsilon\left(\theta\left(\bar{V}_V - V_S^o(t)\right) - c_j\right) & \text{if } t < t_{\mathrm{mv}} \\ 1 & \text{otherwise} \end{cases}$$

where θ is the efficacy of the vaccine. In the following simulations, $\epsilon = 10^5$. For this value, *locally*, a change of $1/25,000$ QALD corresponds to a 100% change in vaccination decision.

2.4 Solution method

We solve Equations (1)–(8) numerically using a functional fixed-point iteration algorithm. Technical information about our solution procedure is provided in Section B in Appendix. For proofs of existence and uniqueness of a solution, see Flaig et al. (2018). Since birth and death rate are equal, the total population is constant. This allows us to solve with the total population older than 14 months set to its steady state value $\bar{n}_{\mathrm{o}} = 1/(1 + \nu l)$.

In order to solve, we need initial conditions for Equations (1)–(7), and a final condition for Equation (8). By final time T, vaccination is mandatory. We choose T so that solutions to Equations (1)–(7) are reasonably close to their steady state by time T under $\Lambda_{\mathrm{ev}} = \Lambda_{\mathrm{rv}} = 1$. We then set $V_{\mathrm{S}}^{\mathrm{o}}(T)$ to the steady state value of $V_{\mathrm{S}}^{\mathrm{o}}$ obtained by solving Equations (1)–(8) with the left-hand sides set to zero and $\Lambda_{\mathrm{ev}} = \Lambda_{\mathrm{rv}} = 1$.

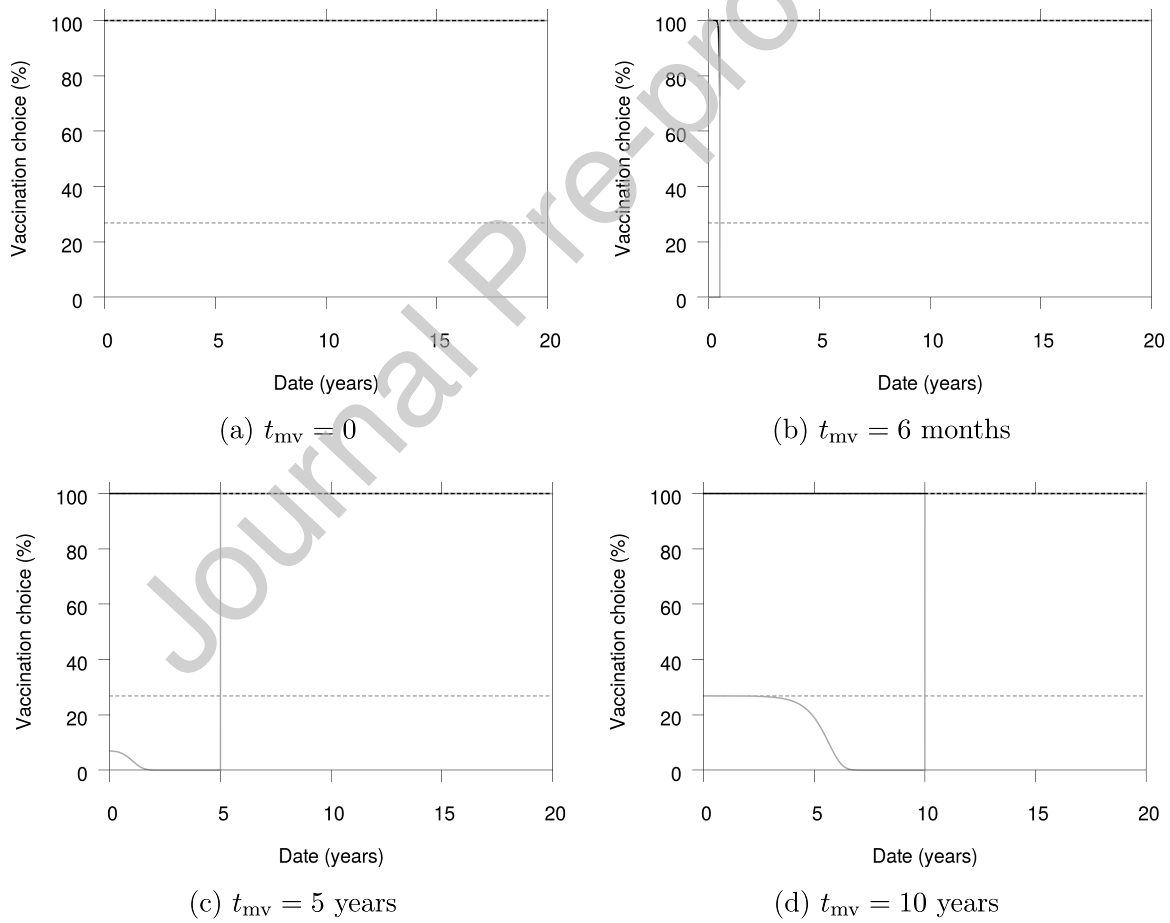
Initial conditions of Equations (1)–(7) are set to the steady state that is reached when (i) vaccination is available on a voluntary basis, and (ii) mandatory vaccination has not yet been announced. This initial state depends on the proportion α_{rv} of reluctant vaccinationists in the population, and on the respective vaccination costs c_{ev} and c_{rv} of eager and reluctant vaccinationists. After setting α_{rv}, we adjust c_{ev} and c_{rv} so as to obtain a steady state corresponding to an incidence of 250 measles cases per year in a population of 6×10^7 persons, that is the approximate population of France.[8] Measles incidence may vary greatly from one year to another. 250 cases correspond to the 2014 incidence in France. This steady state incidence level serves as benchmark in the welfare analysis.

[8]In practice, solutions are computed for a total population normalized to 1.

3 Results

3.1 Epidemiology

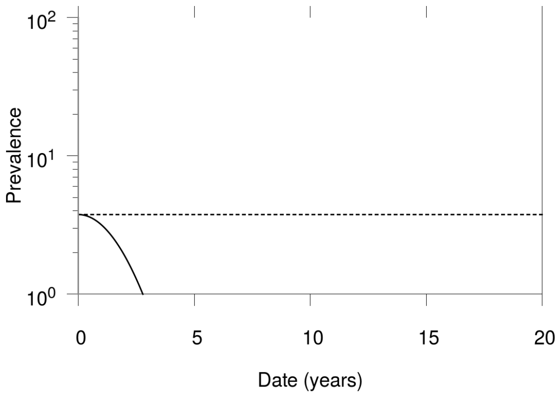
Figure 2 shows the vaccination decisions for four different values of t_{mv} under the assumption that a proportion $\alpha_{\text{rv}} = 4\%$ of the population is reluctant to vaccination. In the initial steady state, before mandatory vaccination is announced, 100% of the eager vaccinationists (dashed black lines) and 25% of the reluctant vaccinationists (dashed gray lines) vaccinate. The corresponding instantaneous prevalence is shown in Figure 3.



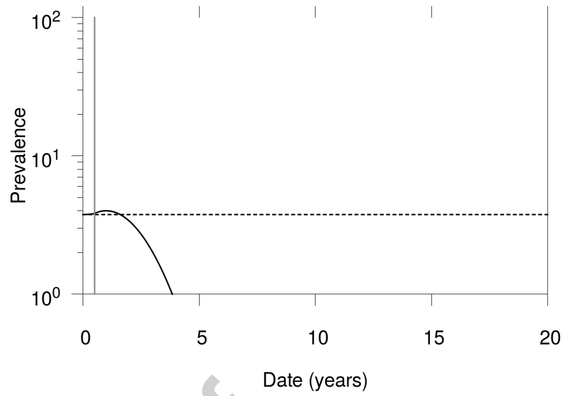
(a) $t_{\text{mv}} = 0$ (b) $t_{\text{mv}} = 6$ months

(c) $t_{\text{mv}} = 5$ years (d) $t_{\text{mv}} = 10$ years

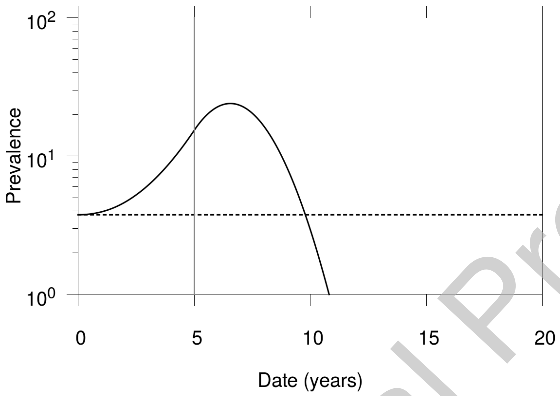
Figure 2: Vaccination decisions. *Black:* vaccination decision by eager vaccinationists. *Gray:* vaccination decision by reluctant vaccinationists. *Dashed:* initial steady state.



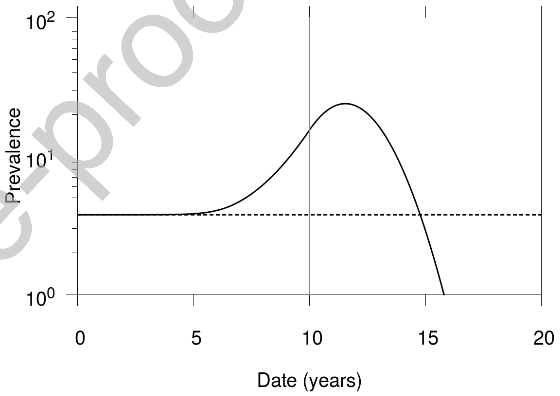
(a) $t_{\mathrm{mv}} = 0$



(b) $t_{\mathrm{mv}} = 6$ months



(c) $t_{\mathrm{mv}} = 5$ years



(d) $t_{\mathrm{mv}} = 10$ years

Figure 3: Instantaneous prevalence per 6×10^7 persons. *Gray vertical line:* t_{mv}. *Dashed:* initial steady state.

In Figures 2a and 3a, mandatory vaccination immediately comes into force upon announcement at time 0 – the solid black and gray lines showing vaccination decisions in Figure 2a are overlapping at 100% from time 0 onwards. All children reaching 14 months are vaccinated against measles, and the prevalence drops to eradication levels, as shown by the solid black line in Figure 3a.

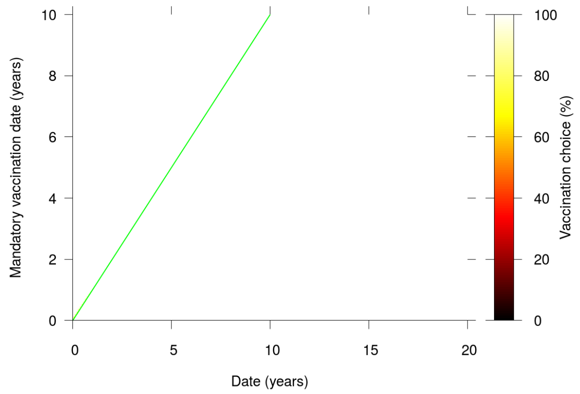
Things turn out differently when mandatory vaccination is announced before coming into force. In Figures 2b and 3b, mandatory vaccination is announced 6 months in advance. Before mandatory vaccination comes into force, reluctant vaccinationists anticipate that measles will ultimately be eradicated thanks to mandatory vaccination. This means that they will enjoy eradication for most of their life, whether vaccinated or not. Consequently, they engage in *free riding* and do not vaccinate. Between time 0 and t_{mv}, 0% of reluctant vaccinationists receive the vaccine. They do not pay the vaccination cost, yet they will benefit from the constrained effort of those who will vaccinate under mandatory vaccination. To some extent, eager vaccinationists free ride too but only right before t_{mv}. The drop in vaccination between time 0 and t_{mv} leads to a slight increase in prevalence.

This increase in prevalence amplifies as mandatory vaccination is announced earlier (Figures 3c and 3d). Indeed, the longer the interval between time 0 and t_{mv}, the longer the drop in vaccination can last. At some point, the increase in prevalence makes free riding suboptimal for eager vaccinationists. Besides, as mandatory vaccination is put off to a later time after announcement, eradication is also delayed and it becomes optimal for some reluctant vaccinationists to vaccinate their children after policy announcement.

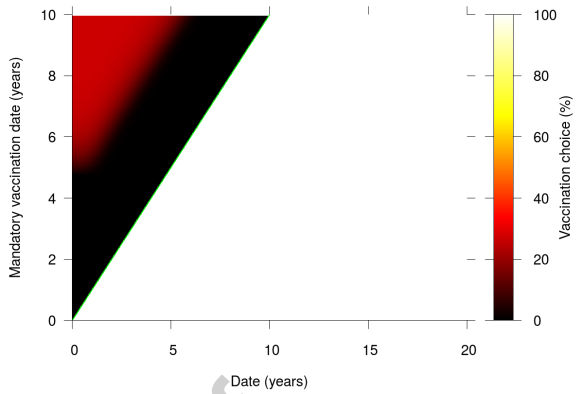
Figure 4 displays the same results as Figures 2 and 3 for all values of the implementation date t_{mv} ranging from 0 to 10 years (y-axes). The green lines show when mandatory vaccination is implemented (t_{mv}). The figure shows how a spike in measles cases (Figure 4c) develops as mandatory vaccination is announced earlier before implementation, due to the decrease of vaccination coverage among reluctant vaccinationists (Figure 4b). All eager vaccinationists vaccinate for all values of t_{mv}. The spike in prevalence and the eventual eradication of the disease imply that individuals will fare very differently depending on their birthdate and their vaccination status at a given date. Hence we must look into intertemporal effects by undertaking a full welfare evaluation.

3.2 Welfare

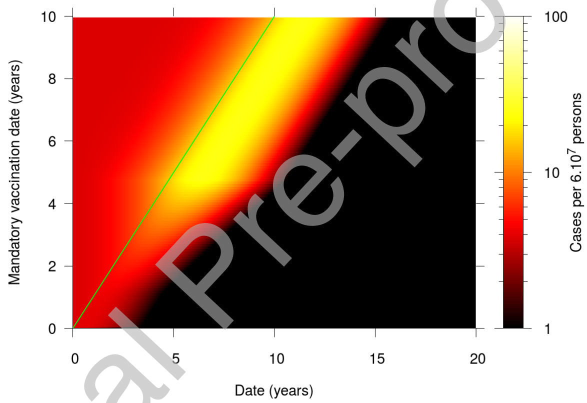
Let us turn to welfare analysis. In order to be comprehensive, we need to consider the welfare of (i) individuals who are born after the announcement of mandatory vaccination (at



(a) Vaccination decision by eager vaccinationists



(b) Vaccination decision by reluctant vaccinationists



(c) Instantaneous prevalence

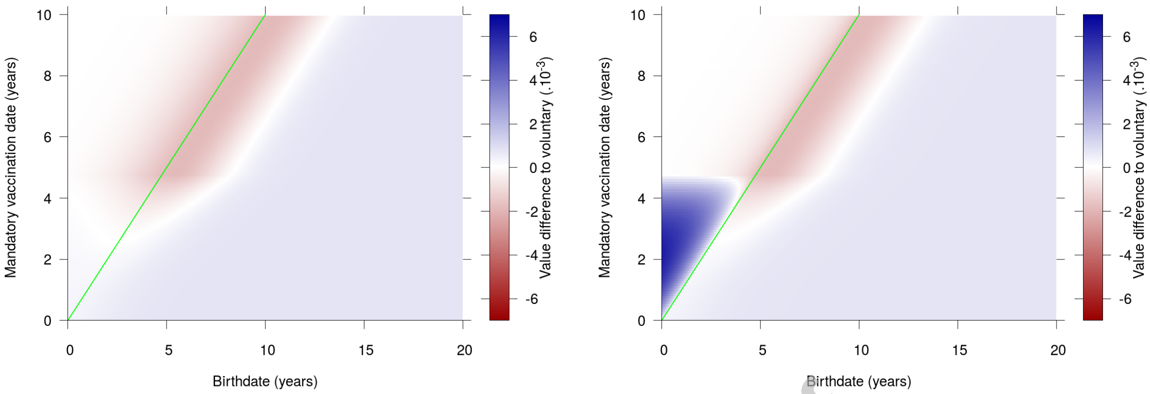
Figure 4: Vaccination decisions and prevalence for a mandatory vaccination date (t_{mv}) between 0 and 10 years. *Green:* current date $t = t_{\mathrm{mv}}$.

time 0), and (ii) individuals that were born before that time. For each of these categories, we compare

1. the value of being susceptible[9] at each time between 0 and T when vaccination becomes mandatory at time t_{mv}, with

2. the value of being susceptible under a benchmark scenario where vaccination is voluntary, that is under our initial epidemic steady state conditions.

[9]Since we consider lifelong immunity after successful vaccination or recovery, only susceptible individuals have their welfare depending on health policies. See Section A in Appendix.



(a) Eager vaccinationists (b) Reluctant vaccinationists

Figure 5: Value difference between mandatory vaccination scenario and benchmark scenario for children born after time 0 as a function of the birthdate and the mandatory vaccination implementation date t_{mv}. *Green:* birthdate $t = t_{\mathrm{mv}}$.

We denote by $V_{\mathrm{S}}^{\mathrm{y},j}(t)$, $j \in \{\mathrm{ev}, \mathrm{rv}\}$, the value of being susceptible, younger than 14 months, and of type j at time t. $\bar{V}_{\mathrm{S}}^{\mathrm{y},j}$ is the steady state of the same value function *before* policy announcement. We show how to compute $V_{\mathrm{S}}^{\mathrm{y},j}(t)$ in Section A in Appendix. Figure 5 displays the welfare gains $V_{\mathrm{S}}^{\mathrm{y},j}(t) - \bar{V}_{\mathrm{S}}^{\mathrm{y},j}$ associated with mandatory vaccination for children depending on their birthdate t, their stance toward vaccination, and policy implementation date t_{mv}. The green lines show when mandatory vaccination is implemented.

All individuals born after measles eradication benefit from mandatory vaccination (light blue area on the right of each graph). This illustrates an instance where state intervention solves the vaccination public good problem. This scenario and the corresponding welfare gain are well-known (Bauch et al., 2003). Usually, cost effectiveness analyses provide precisely this welfare gain as only measure of the impact of mandatory vaccination.

However, individuals who are born when prevalence is peaking – when mandatory vaccination is announced long enough before implementation – are worse-off (Figure 5). Indeed, newborns spend 14 months without having access to vaccination, which makes them especially vulnerable to infection. During this period, only herd immunity is protecting them.

The individuals benefiting the most from mandatory vaccination are those who will not be obliged to vaccinate and who still see many others undergo this obligation. The first of those two effects will be stronger for reluctant vaccinationists because they have a higher cost to vaccinate. The second effect will be stronger if mandatory vaccination is implemented quickly after its announcement so that there is not enough time for free riding to translate into a spike in measles cases. In this case, reluctant vaccinationists who are able to free ride are among those who benefit the most from mandatory vaccination (Figure 5b). Namely, reluctant vaccinationists in this situation benefit *around six times more* from mandatory vaccination than eager vaccinationists born *after eradication*. Obviously, the specific magnitude of this transfer of welfare between sub-populations and generations depends on many parameters. Yet, we argue that it cannot be overlooked *a priori* in a cost effectiveness analysis.

To be exhaustive in our evaluation, we also need to take into account the population that was born *before* time 0. Figure 6 shows the difference between the value of being susceptible at time 0 and the value of being susceptible in our benchmark steady state voluntary vaccination scenario. $\bar{V}_S^o$ denotes the steady state of V_S^o before policy announcement; other notations are the same as above.

At time 0, individuals are indifferent to mandatory vaccination when it comes late after the announcement (in our instance, more than about 5 years after announcement). This is due to time discounting, and to the fact that a larger increase in prevalence offsets the benefits of subsequent eradication.

Susceptible individuals who are older than 14 months at time 0 (blue curve in Figure 6) are either those who refused vaccination, or those whose immune system did not respond to vaccination. From their point of view, the sooner mandatory vaccination is implemented the better. the less significant the spike in prevalence following the announcement and the

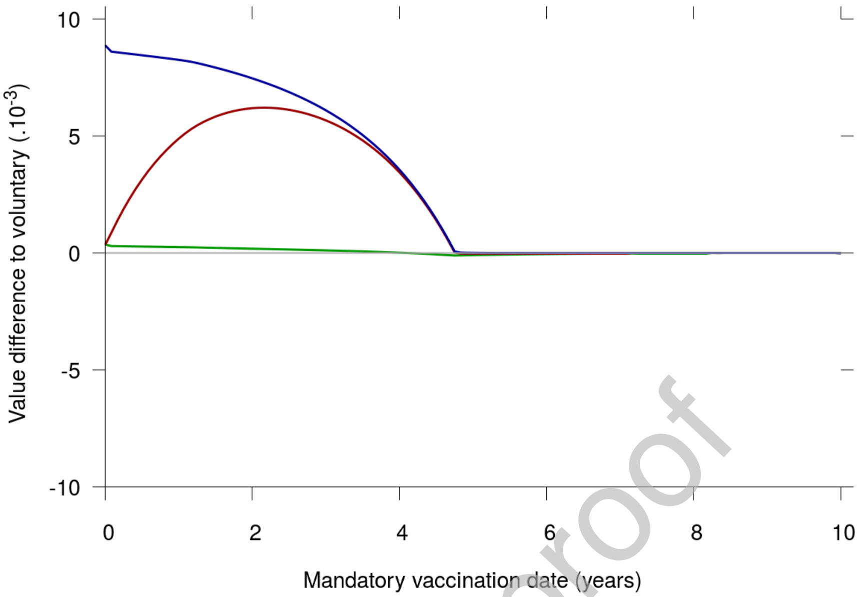


Figure 6: Value difference at time 0 for susceptible children born before time 0. *Blue:* individuals older than 14 months ($V_S^o(0) - \bar{V}_S^o$). *Green:* eager vaccinationists younger than 14 months ($V_S^{y,ev}(0) - \bar{V}_S^{y,ev}$). *Red:* reluctant vaccinationists younger than 14 months ($V_S^{y,rv}(0) - \bar{V}_S^{y,rv}$).

sooner the eradication – hence the lower the infection probability.

Since we model aging as a Poisson process, it is equivalent for a child to be younger than 14 months at time 0, or to be born exactly at time 0. Then, the green and red curves in Figure 6 corresponding to children younger than 14 months at time 0 can be read directly on Figure 5 with 0 x-axis value. Interpretation is the same as above.

4 Conclusion

We draw on the example of mandatory measles vaccination to support our claim that disregarding individual behaviors in cost effectiveness evaluations is *a priori* problematic. Our study is based on numerical simulations, and on the restricting (yet relevant) assumption that individuals are rational and far-sighted. We show that when mandatory vaccination is announced in advance, while measles is eradicated in the long run after policy implementation, individual anticipatory behaviors may cause major transition effects. As some individuals anticipate eradication, they do no vaccinate their children before mandatory vaccination comes into force. This leads to a transient increase in prevalence and, consequently, to generational welfare differences. Reluctant vaccinationists are among the ones benefiting the most from mandatory vaccination in this scenario. The transient increase in prevalence can be avoided by implementing mandatory vaccination quickly after it has been announced. Investigating transient effects due to policy announcement as well as possible ways to mitigate them requires not only to take individual behaviors into account *endogenously*, but also to compute fully time-dependent scenarios. This is not done in most current cost effectiveness analyses. We believe that our simulations allow to highlight effects whose magnitude calls for empirical investigations and possibly reconsideration of some public health policy recommendations. As of today, data is still largely missing to investigate the full extent of these phenomena associated with "rational" behavior and their welfare implications in the real world.

While this study focuses on measles vaccination decision, we use a framework that is relevant for all types of infectious diseases and anticipatory behaviors involving strategic interactions. Also, the effects we bring out are not conditional on considering a subpopulation of reluctant vaccinationists – free riding can also occur in an homogeneous population. Therefore, our approach is ultimately intended as a tool for public health professionals to be used in many different settings.

However, we want to highlight a limitation of our study and of the computational methods used here in general. The model developed in this article is deterministic. This implies that we cannot convincingly and precisely study disease eradication in our setting (Houy (2015)). When vaccination is voluntary, the incentive to vaccinate decreases with decreasing prevalence and eradication is not achievable. Therefore in this case, deterministic simulations can be deemed reasonable. However, when vaccination is mandatory, we expect to witness eradication. Eradication is relevant to our discussion if it implies changes in long-term control policy that could modify the cost effectiveness analysis. For instance, at the extreme, vaccination against a disease could be safely removed from the vaccination schedule as soon as the disease is confirmed eradicated. In a deterministic model, this policy would imply a recurrence of the epidemic that would not occur in a stochastic model. Hence, investigating eradication properly would require to implement our model in a stochastic setting. But then, agents' anticipations would be over probability distributions and it would then be necessary to work with approximate heuristics in order to deal with the dimensionality of this problem.

Potential conflict of interest

Authors declare no conflict of interest.

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A Welfare computation

A.1 Value of being a susceptible and more than 14 months old

The probability tree in Figure A.1 displays the possible transitions for a susceptible individual older than 14 months.

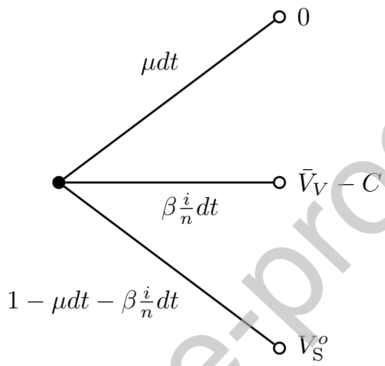


Figure A.1: Probability tree for individuals older than 14 months and susceptible.

From the probability tree in Figure A.1, we derive Equation 9.

$$V_{\mathrm{S}}^{o}(t) = u_{\mathrm{g}} dt + (1 - \delta dt) \left[\beta \frac{i(t)}{n(t)} \left(\bar{V}_{\mathrm{V}} - C \right) dt + \left(1 - \beta \frac{i(t)}{n(t)} dt - \mu dt \right) V_{\mathrm{S}}^{o}(t + dt) \right]. \quad (9)$$

A.2 Value of being a susceptible and less than 14 months old

Under the mandatory vaccination scenario, the value of being susceptible and older than 14 months is given by V_{S}^{o}, the solution of Equation (8). We compute the value of being susceptible, younger than 14 month, and of type $j \in \{\mathrm{ev}, \mathrm{rv}\}$ at time $t \in [0, T]$ as

$$V_{\mathrm{S}}^{\mathrm{y},j}(t) = u_{\mathrm{g}}dt + (1-\delta dt)\left[\beta\frac{i(t)}{n(t)}\left(\frac{u_g+\bar{V}_{\mathrm{V}}/l}{\delta+1/l} - C\right)dt + \frac{1}{l}\Lambda_j(t)\theta\left(\bar{V}_V - c_j\right)dt + \frac{1}{l}\Lambda_j(t)\left(1-\theta\right)\left(V_{\mathrm{S}}^{\mathrm{o}}(t+dt) - c_j\right)dt + \frac{1}{l}\left(1-\Lambda_j(t)\right)V_{\mathrm{S}}^{\mathrm{o}}(t+dt)dt + \left(1-\beta\frac{i(t)}{n(t)}dt - \frac{1}{l}dt\right)V_{\mathrm{S}}^{\mathrm{y},j}(t+dt)\right]. \quad (10)$$

The probability tree in Figure A.2 may clarify Equation (10).

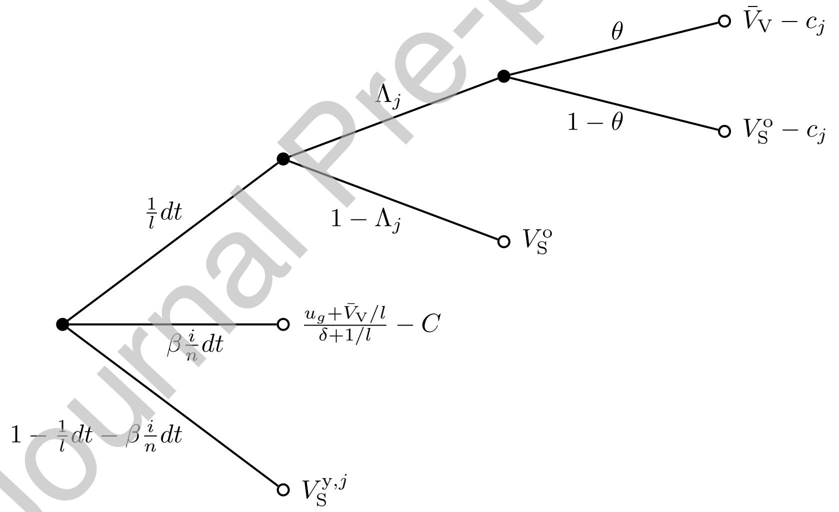


Figure A.2: Probability tree for individuals younger than 14 months old, susceptible and of type j.

B Technical appendix

In order to find a solution to Equations (1)–(8), we first notice that the system (1)–(8) could be rewritten in a system (11)–(12) coupled via a couple of functions (Λ_0, Λ_1) : the forward equation

$$\frac{d}{dt}\begin{pmatrix} s_{\mathrm{y},0} \\ s_{\mathrm{y},1} \\ s_{\mathrm{o},0} \\ s_{\mathrm{o},1} \\ \vdots \\ \vdots \\ \vdots \\ v_{\mathrm{o},0} \\ v_{\mathrm{o},1} \end{pmatrix}(t) = F \begin{pmatrix} s_{\mathrm{y},0} \\ s_{\mathrm{y},1} \\ s_{\mathrm{o},0} \\ s_{\mathrm{o},1} \\ \vdots \\ \vdots \\ \vdots \\ v_{\mathrm{o},0} \\ v_{\mathrm{o},1} \end{pmatrix}(t) + \begin{pmatrix} 0 \\ 0 \\ -\frac{1}{l}\theta\Lambda_0(t)s_{\mathrm{y},0}(t) \\ -\frac{1}{l}\theta\Lambda_1(t)s_{\mathrm{y},1}(t) \\ 0 \\ \vdots \\ 0 \\ \frac{1}{l}\theta\Lambda_0(t)s_{\mathrm{y},0}(t) \\ \frac{1}{l}\theta\Lambda_1(t)s_{\mathrm{y},1}(t) \end{pmatrix} \tag{11}$$

and the backward equation

$$\begin{cases} -\frac{d}{dt}V_{\mathrm{S}}^{\mathrm{o}}(t) = u_{\mathrm{g}} - \left(\delta + \mu + \beta\frac{i(t)}{n(t)}\right)V_{\mathrm{S}}^{\mathrm{o}}(t) + \beta\frac{i(t)}{n(t)}\left(u_{\mathrm{g}}/(\delta+\mu) - C\right) \\ \Lambda_j(t) = \begin{cases} \chi_\epsilon\left(\theta\left(u_{\mathrm{g}}/(\delta+\mu) - V_{\mathrm{S}}^{\mathrm{o}}(t)\right) - c_j\right) & \text{if } t < t_{\mathrm{mv}} \\ 1 & \text{otherwise} \end{cases} \end{cases} \tag{12}$$

Therefore, we have to find a fixed point to the following operator

$$\Gamma : (\Lambda_0, \Lambda_1) \in C([0,T],[0,1]) \mapsto \begin{pmatrix} s_{\mathrm{y},0} \\ \vdots \\ v_{\mathrm{o},1} \end{pmatrix} \text{ solution to (11)} \mapsto V_{\mathrm{S}}^{\mathrm{o}} \text{ solution to (12)}$$

$$\mapsto (\tilde{\Lambda}_0, \tilde{\Lambda}_1) = (G_0(V_{\mathrm{S}}^{\mathrm{o}}(t)), G_1(V_{\mathrm{S}}^{\mathrm{o}}(t))) \in C([0,T],[0,1]), \tag{13}$$

where

$$\Lambda_j(t) = G_j(V_{\mathrm{S}}^{\mathrm{o}}(t)) := \begin{cases} \chi_\epsilon\left(\theta\left(u_{\mathrm{g}}/(\delta+\mu) - V_{\mathrm{S}}^{\mathrm{o}}(t)\right) - c_j\right) & \text{if } t < t_{\mathrm{mv}} \\ 1 & \text{otherwise} \end{cases}$$

The operator Γ is compact on $C([0,T],[0,1])$ and, using the Schauder theorem, we have the existence of a solution. Since Γ is not a contraction operator, a direct application of the Banach-Picard theorem/algorithm is not possible. Nevertheless, we notice that by construction Γ is decreasing (antitone, see Sommariva and Vianello (2000))

$$\Lambda_0^0 \leq \Lambda_0^1\ ,\ \Lambda_1^0 \leq \Lambda_1^1 \Rightarrow \Gamma(\Lambda_0^0, \Lambda_1^0) \geq \Gamma(\Lambda_0^1, \Lambda_1^1),$$

and it is natural to use a relaxed algorithm, i.e., search a fixed point to the following operator $\Gamma_\epsilon(\Lambda_0, \Lambda_1) = (1-\epsilon)(\Lambda_0, \Lambda_1) + \epsilon\Gamma(\Lambda_0, \Lambda_1)$. The numerical algorithms is the application of this principle to the discrete operator

$$\begin{aligned}
\Gamma^N : (\Lambda_0^N, \Lambda_1^N) \in \mathbb{R}^{TailleVecteur} \times \mathbb{R}^{TailleVecteur} &\mapsto \begin{pmatrix} s_{\mathrm{y},0}^N \\ s_{\mathrm{y},1}^N \\ s_{\mathrm{o},0}^N \\ s_{\mathrm{o},1}^N \\ i^N \\ i_1^N \\ v_{\mathrm{o},0}^N \\ s_{\mathrm{o},1}^N \end{pmatrix} \text{ numerical solution to (11)} \\
&\mapsto V_{\mathrm{N,S}}^{\mathrm{o}} \text{ numerical solution to (12)} \\
&\mapsto (\tilde{\Lambda}_0, \tilde{\Lambda}_1) = (G_0(V_{\mathrm{N,S}}^{\mathrm{o}}), G_1(V_{\mathrm{N,S}}^{\mathrm{o}})) \in \mathbb{R}^{TailleVecteur} \times \mathbb{R}^{TailleVecteur} \qquad (14)
\end{aligned}$$

where

- Numerical solutions to (11) are obtained by semi-implicit Euler method (with time step equal to .5, time forward)

```
for (int i=0;i<TailleVecteur-1;i++)
{
```

```
S_{y,0}[i+1]=(S_{y,0}[i]+dt*(1-alpha)*nu/(1+l*mu))/(1+dt*(1/l+lambda*(I[i])));
S_{y,1}[i+1]=(S_{y,1}[i]+dt*alpha*nu/(1+l*mu))/(1+dt*(1/l+lambda*(I[i])));
S_{o,0}[i+1]=(S_{o,0}[i]+dt*S_{y,0}[i]*(1-Theta*Soft_max_v[i])/l)/(1+dt*(mu+lambda*(I[i])));
S_{o,1}[i+1]=(S_{o,1}[i]+dt*S_{y,1}[i]*(1-Theta*Soft_max_nv[i])/l)/(1+dt*(mu+lambda*(I[i])));
I[i+1]=(I[i]-dt*(mu*I1[i]))/(1+dt*(gamma_I-lambda*
 (S_{o,0}[i+1]+S_{o,1}[i+1]+S_{y,0}[i+1]+S_{y,1}[i+1])));
I1[i+1]=(I1[i]+dt*((lambda*(S_{o,0}[i]+S_{o,1}[i])+1/l)*I[i]) )/(1+dt*(mu+gamma_I+1/l));
}
```

- Numerical solutions to (12) are obtained by semi-implicit Euler method (with time step equal to .5, time backward)

```
for (int i=TailleVecteur-1;i>=1;i--)
  {
     W[i-1]=(W[i] +dt*(I[i]*(C_calcul*lambda)))/(1.+dt*(delta+mu+lambda*I[i-1]));
  }
```

  where $W[i] = u_{\mathrm{g}}/(\delta+\mu) - V^{\mathrm{o}}_{\mathrm{S,N}}[i]$.

The algorithm is then :

```
Let epsilon (here=1e-2 (in the function $\chi_\epsilon$))
Let relaxation (here=1e-3)
Let errMax (here errMax=1e-5)

 while (error>errMax)
       {
       (Soft_max_v1,Soft_max_nv1)=Gamma^N(Soft_max_v,Soft_max_nv);
       error=norm((Soft_max_v1,Soft_max_nv1)-(Soft_max_v,Soft_max_nv));
       (Soft_max_v,Soft_max_nv)=relaxation*(Soft_max_v1,Soft_max_nv1)+(1-relaxation)*(Soft_max_v,Soft_max_nv);
       }
```

As we see in Figure B.3, we have (as expected for a Banach Picard algorithm) a linear convergence, i.e. $log(error) \sim p_1 Iter + p_0$ with p_1 depending of the relaxation parameter. Moreover, we expect that the speed rate parameter $p(1) \sim log(1 - relaxation) \sim -relaxation$ which is the case for both cases given in Figure B.3. This is not a very fast method (about 5 minutes on a 3,4 GHz Intel Core i5 processor, using C++ language, for a 10^{-5} precision, $TailleVecteur = 120000$ and an $\epsilon = 10^2$). Nevertheless, the lack of contraction (mostly due to the fact that $\max |\frac{d}{dx}\chi_\epsilon(x)| = 1/(4\epsilon) >> 1$) implies that a Newton method is no more effective. A shooting method (trying to find $V_S^o(0)$ such that $V_S^o(T)$ is equal to some *ad hoc* value by changing time evolution from backward to forward in the equation (12)) is theoretically possible, but changing time evolution makes this equation "unstable" and so application of a shooting method needs to have a precision on $V_S^o(0)$ smaller than the machine epsilon.

C Results for $\alpha_{\mathbf{rv}} = 1\%$

In this section, we provide results for $\alpha_{\rm rv} = 1\%$ as a robustness check. We also performed simulations for $\alpha_{\rm rv}$ as high as 12% but there was little qualitative difference with the case $\alpha_{\rm rv} = 4\%$ presented in the main text.

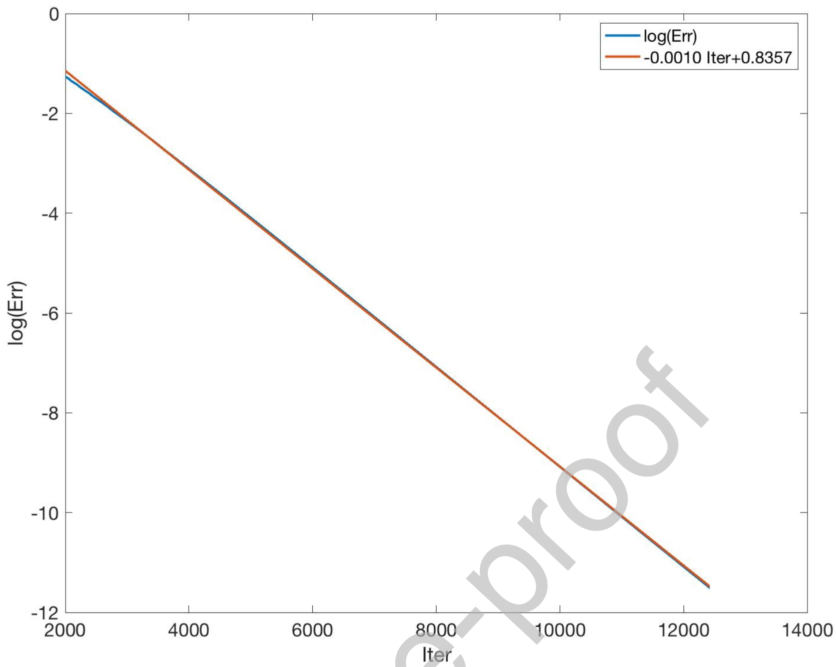
For $\alpha_{\rm rv} = 1\%$, calibration to a 250 cases per year per 6×10^7 individuals yields $c_{\rm ev} = 8.08 \times 10^{-3}$ and $c_{\rm rv} = 1.14 \times 10^{-2}$. Vaccination costs are higher than for $\alpha_{\rm rv} = 4\%$ (Table 1).

Due to higher vaccination costs, less than 100% of the eager vaccinationists and 0% of the reluctant vaccinationists vaccinate initially (Figure C.4). For the same reason, vaccination by eager vaccinationists drops significantly before mandatory vaccination date $t_{\rm mv}$. As a consequence, prevalence increases faster and is significant for a wider range of $t_{\rm mv}$ values (Figures C.5 and C.6c).

When vaccination is mandatory, both sub-populations have to pay a substantially higher cost than for $\alpha_{\rm rv} = 4\%$, which reduces their welfare (Figure C.7). In the case of reluctant vaccinationists (Figure C.7b), the herd immunity externality does not compensate for this higher vaccination cost.

In Figure C.8, the value of being susceptible at time 0, when mandatory vaccination is announced, only increases as mandatory vaccination date t_{mv} gets very close from 0. This is because prevalence increases significantly even for relatively small values of t_{mv}. The spike in prevalence offsets the benefits of eradication if mandatory vaccination comes into force more than a few months after announcement.

The value of being susceptible and less than 14 months (green and red curves on Figure C.8) is low or negative as children have a high probability of turning 14 months after t_{mv}. If they do, they have to pay their high vaccination cost. Their value increases as the probability of turning 14 months after t_{mv} decreases.



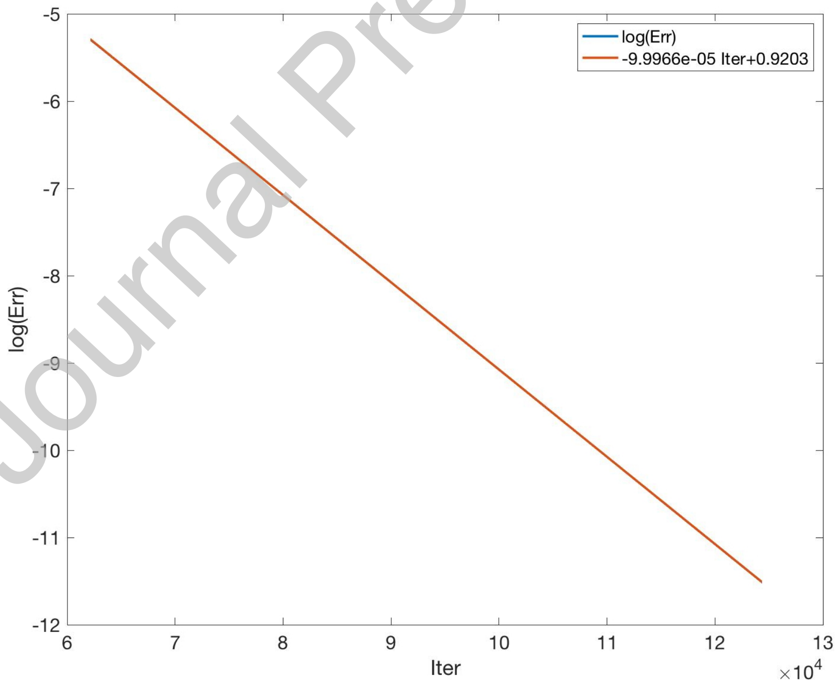
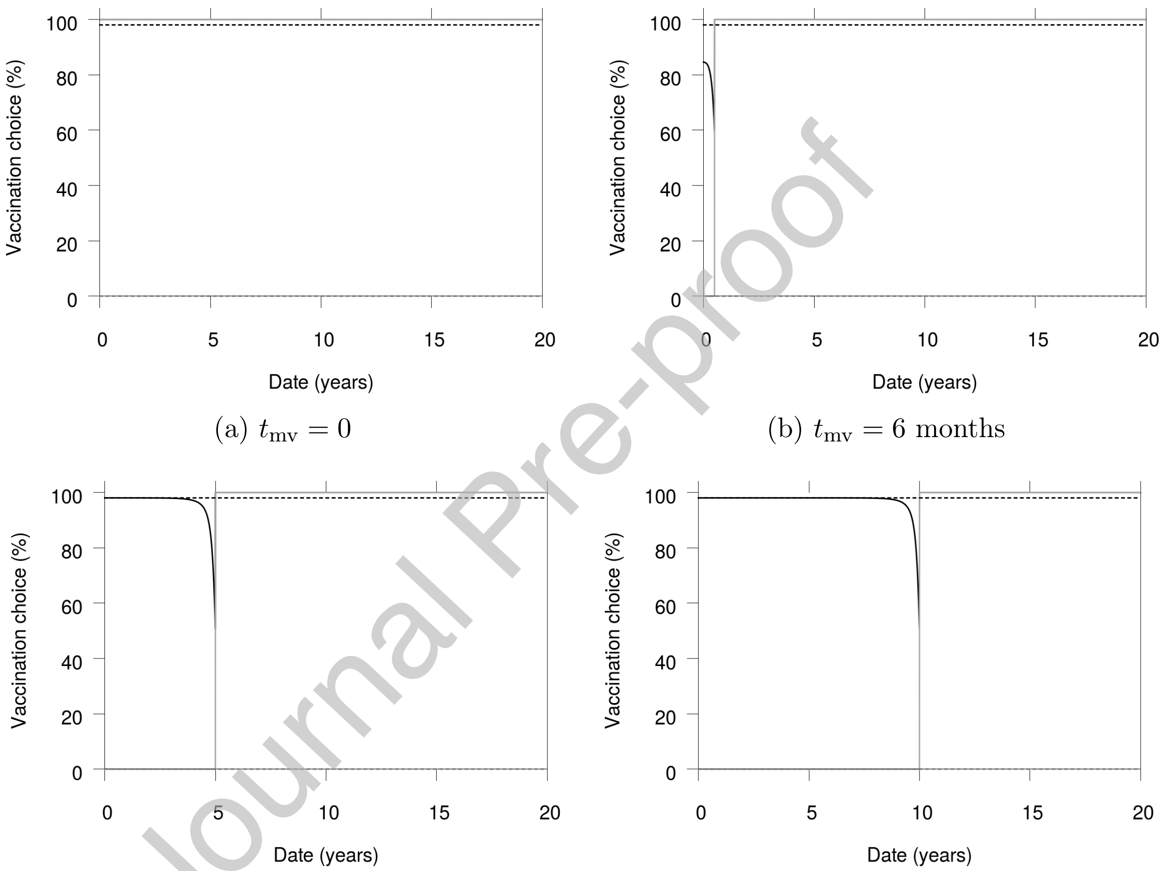


Figure B.3: Speed of convergence. We plot the logarithm of the error with respect to the number of iteration of the relaxed Banach-Picard algorithm. The up figure for the relaxation parameter equal to 10^{-3} and the down figure for the relaxation parameter equal to 10^{-2}.



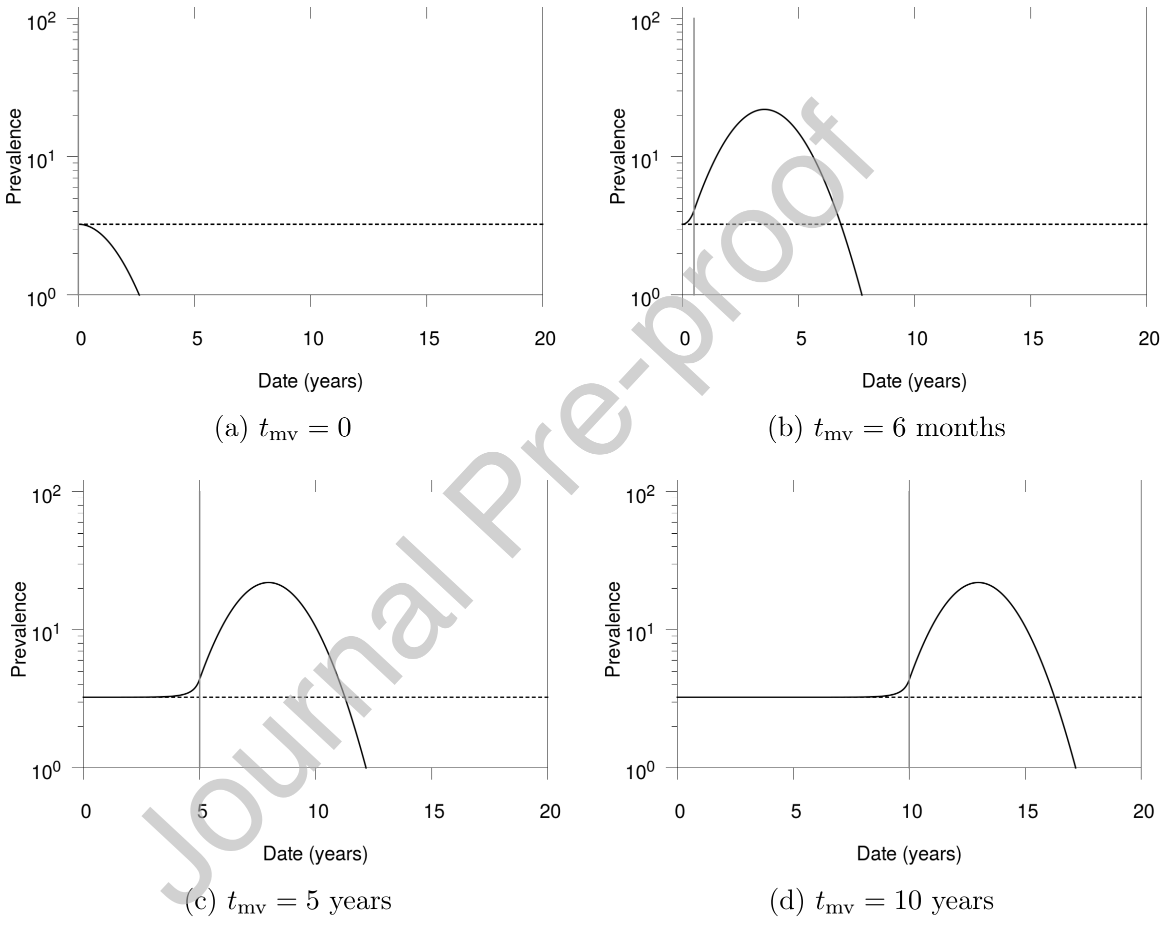
(a) $t_{\mathrm{mv}} = 0$

(b) $t_{\mathrm{mv}} = 6$ months

(c) $t_{\mathrm{mv}} = 5$ years

(d) $t_{\mathrm{mv}} = 10$ years

Figure C.4: Vaccination decisions for $\alpha_{\mathrm{rv}} = 1\%$. *Black:* vaccination decision by eager vaccinationists. *Gray:* vaccination decision by reluctant vaccinationists. *Dashed:* initial state.



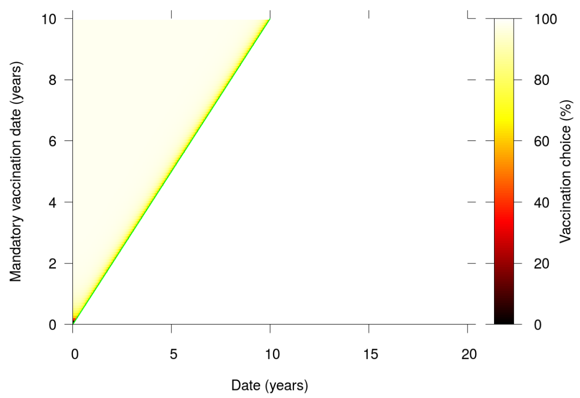
(a) $t_{\mathrm{mv}} = 0$

(b) $t_{\mathrm{mv}} = 6$ months

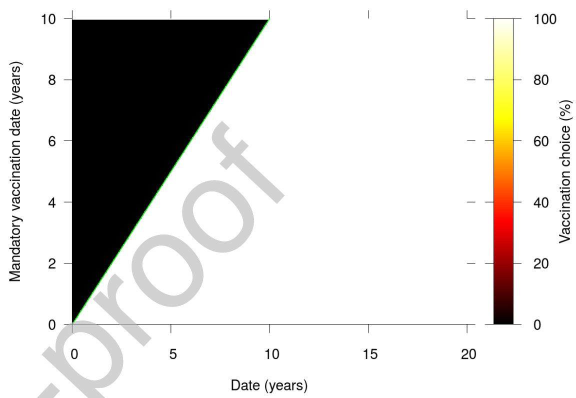
(c) $t_{\mathrm{mv}} = 5$ years

(d) $t_{\mathrm{mv}} = 10$ years

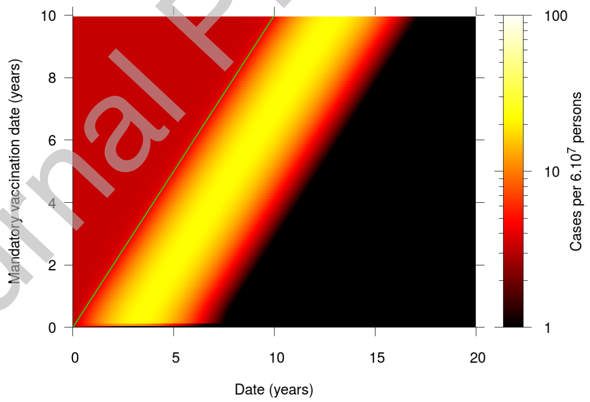
Figure C.5: Instantaneous prevalence per 6×10^7 persons for $\alpha_{\mathrm{rv}} = 1\%$. *Gray vertical line:* t_{mv}. *Dashed:* initial state.



(a) Vaccination decision by eager vaccinationists

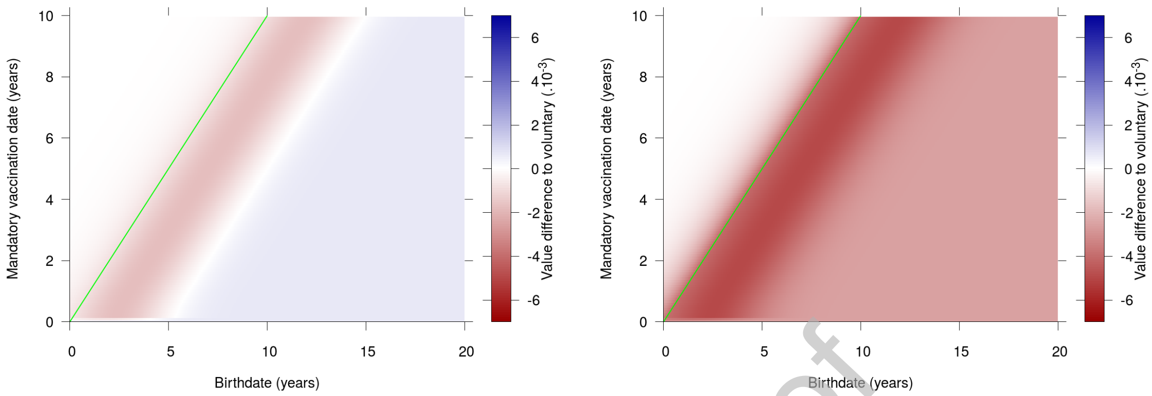


(b) Vaccination decision by reluctant vaccinationists



(c) Instantaneous prevalence

Figure C.6: Vaccination decisions and prevalence for a mandatory vaccination date (t_{mv}) between 0 and 10 years for $\alpha_{\mathrm{rv}} = 1\%$. *Green:* date $t = t_{\mathrm{mv}}$.



(a) Eager vaccinationists

(b) Reluctant vaccinationists

Figure C.7: Value difference between mandatory vaccination scenario and benchmark scenario for children born after time 0 for $\alpha_{\text{rv}} = 1\%$. *Green:* birthdate $t = t_{\text{mv}}$.

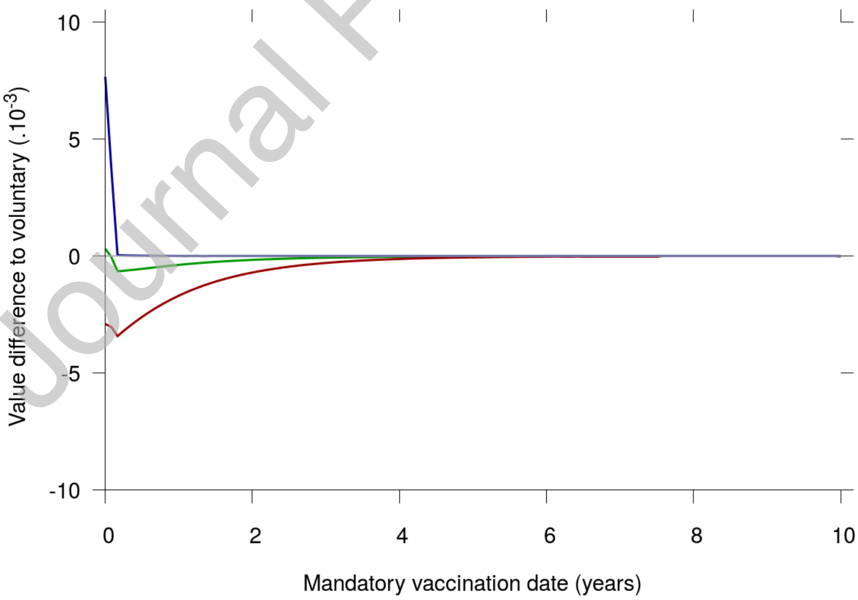


Figure C.8: Value difference at time 0 for susceptible children born before time 0 for $\alpha_{\text{rv}} = 1\%$. *Blue:* individuals older than 14 months. *Green:* eager vaccinationists younger than 14 months. *Red:* reluctant vaccinationists younger than 14 months.