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Opinions and vaccination during an epidemic ☆

Josselin Thuilliez [a], Nouhoum Touré [b,*]

[a] CNRS - Centre de Recherche en économie et Management, UMR6211 CNRS-Université de Rennes, France
[b] Université Paris 1 - Centre d'Économie de la Sorbonne, UMR8174 CNRS-UP1, France

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ABSTRACT

High levels of vaccine hesitancy remain poorly understood during an epidemic. Using high-frequency data in France at departmental level and exploiting the Covid-19 vaccination campaign calendar, we observe that vaccination among the elderly influences vaccination among young adults. We then propose a simple epidemiological economic model with two partially vaccinated demographic groups – the young and the elderly – and two opinions on vaccination - "vaxxers" and "antivaxxers". The utility to get vaccinated for the young depends on the vaccination behavior of the elderly, their opinion of the vaccine and the epidemic environment. Our results suggest that mutual interactions between individuals' vaccination opinions and infection prevalence may lead to the emergence of oscillations and disease traps. The vaccination behavior of the elderly can be harnessed to promote vaccination.

1. Introduction

The epidemiological economics literature experienced a recent revival during the coronavirus disease 2019 (COVID-19) pandemic (Boucekkine et al., 2021). However, the number of papers specifically addressing optimal age-specific vaccination strategies or vaccination behaviors remains limited (Amir and Boucekkine, 2022; d'Albis et al., 2022).[1] Mass vaccination appears to be very effective in controlling many infectious diseases, with COVID-19 being no exception (Pritchard et al., 2021; Milman et al., 2021; Chodick et al., 2021; Haas et al., 2021). Nevertheless, in countries where vaccination is not mandatory, vaccination refusal by a certain segment of the population may reduce vaccination coverage levels to below those recommended to achieve herd immunity (Gauri and Khaleghian, 2002; Chevallier et al., 2021). Vaccine refusal or hesitancy may be caused by many factors, such as the underestimation of disease risks, the overestimation of vaccine risks, and complacency due to vaccine-generated herd immunity (Shim et al., 2012; Horne et al., 2015; Betsch et al., 2015; Brewer et al., 2016; Hirani, 2021; Barber and West, 2022). In some cases, a genuine "vaccine scare" can lead to widespread vaccine refusal, such as that occurring with the whole-cell pertussis vaccine in the 1970s or, in fact, with the new COVID-19 vaccines in the first vaccination waves (Salmon et al., 2015).

Although there has been an overall increase in the acceptance of mRNA vaccines for COVID-19, a considerable percentage of the population still expresses hesitancy toward them (Wong et al., 2021; Caserotti et al., 2021; Paul and Fancourt, 2022). A large body of empirical literature—in social psychology and economics—also underscores the significant impact of individuals' opinions, beliefs or subjective expectations on their health behaviors (Dupas and Miguel, 2017; Bargain and Aminjonov, 2020). For instance, Wooten et al. (2012) find a strong connection between high vaccination rates and positive vaccine opinions or beliefs. Similarly, Saied et al. (2021) reveal that among medical students in Egypt, the most prominent barriers to COVID-19 vaccination were rooted in the students' beliefs regarding adverse vaccine effects. Furthermore, recent studies have emphasized that individuals' attitudes toward vaccination are not static but evolve over time (Piedrahita-Valdés et al., 2021; Cadeddu et al., 2021; Lieu et al., 2015; Reich, 2020) and that socialization and interactions with others seem to drive this evolution (see Yousefinaghani et al. (2021), Neumann-Böhme et al. (2020), Khan et al. (2021), Luo et al. (2021), Giulietti et al. (2023). This finding strongly suggests that we should consider individuals' opinions about vaccination as endogenous, which raises questions about the reciprocal relationship between opinions and infectious diseases. However, in the existing theoretical literature,

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* Corresponding author.
E-mail addresses: josselin.thuilliez@cnrs.fr (J. Thuilliez), Nouhoum.Toure@univ-paris1.fr (N. Touré).

[1] The empirical literature uses age-specific vaccination rules for identification purposes. See https://lem.univ-lille.fr/fileadmin/user_upload/laboratoires/lem/Doc_de_travail_2023/DT2023-02.pdf for a literature review or for instance (Ward, 2014).

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vaccination choices have predominantly been treated as rational decisions solely based on the assessment of risks and benefits (Philipson, 1996; Geoffard and Philipson, 1997), while individuals' preferences and opinions have been treated as either fixed or exogenous. Hence, the interplay between individuals' opinions of vaccination and infection dynamics has not been investigated thus far. Therefore, the objective of this paper is to address this gap. To achieve this aim, we present a simplified model in which, if preferences/opinions are fixed as in the standard economic model, the dynamics of diseases can converge toward a steady state where there are no infected people at the equilibrium, leading to the elimination of the disease. Then, we demonstrate that in the context where individuals' opinions evolve with disease dynamics, the interactions between the two may lead to oscillations, that is, situations in which the economy goes through periods of high and low levels of infection. This situation leads to convergence toward the endemic equilibrium characterized by a positive level of infections at the steady state and thus to long-term disease persistence. Finally, considering the vaccination of elderly individuals as a policy choice, we discuss how increasing vaccine coverage among such individuals can serve as a lever through which to reduce long-term infection levels.

To achieve the above-mentioned objective, we consider a discrete-time dynamic model in which each period t corresponds to a season or wave. In each period, we have two demographic groups: young and old individuals. Within each demographic group, there are two types of individuals with differing opinions of the vaccine: *vaxxers* and *antivaxxers*. The latter prefers to not get vaccinated, whereas the former prefers to get vaccinated. The utility of young individuals depends on (i) the vaccination behavior of those individuals in the generation above them, (ii) their opinions of the vaccine and (iii) the epidemic environment. This enables us to link individual preferences to disease dynamics and to analyze how the vaccination behavior of elderly individuals can lead to a lower level of infections at the steady state, especially in places where vaccination hesitancy is high. Below, we elaborate on how opinions and epidemics evolve over time.

As in classical epidemiological models, at each period t, an agent randomly meets another agent. However, we assume that the distribution of opinions evolves over time via the socialization model proposed by Besley (2017): the probability of an individual adopting a specific preference is positively related to the expected utility gain associated with this trait. The economic literature offers various approaches to modeling the evolution of preferences over time (for a review, see Bisin et al.,2021). We choose (Besley, 2017) socialization because it is well framed to model the intragenerational transmission of preferences (Besley and Ghatak, 2018), unlike the strategic socialization model, where parents transmit their cultural values to their children and the first purpose of which is to model long-run cultural changes. We link this model to epidemiological dynamics by means of a simple susceptible–infectious–susceptible (SIS) model.[2] The spread of the preference trait depends on these epidemiological dynamics. If the level of infections is too high, then the probability of being infected and the cost of infection increase, resulting in the spread of vaxxer preferences throughout the economy. Therefore, the way in which opinions evolve depends on the degree of disease prevalence. However, this relationship between opinions and epidemics is, in fact, bidirectional. If antivaxxer preferences are widespread within society, then there is an increase in the likelihood of individuals becoming infected, resulting in a larger number of individuals becoming infected.

We find that the mutual interactions between the evolution of opinions and epidemic dynamics induce the emergence of endogenous cycles leading to disease persistence in the long run. To illustrate this result, let us consider an economy where infection levels are initially low. Even if an individual infects, on average, less than one person, we find that the epidemic can still persist. Indeed, a low level of infection implies a low degree of risk of infection. As a result, the relative amount of benefits from getting vaccinated remains limited, leading not only to an increase in the prevalence of antivaxxer opinions but also eventually to a resurgence of the epidemic by increasing the size of the pool of individuals susceptible to infection. This interaction between epidemic and opinion dynamics leads to an endemic equilibrium whose characteristics depend on the model's structural parameters.

Our paper is related to several strands of the literature. First, several previous articles have examined the degree to which the emergence of preventable diseases affects vaccination efforts against such diseases (Philipson, 1996; Geoffard and Philipson, 1997). This literature has been focused on price as a key determinant of whether individuals choose vaccination, and it is argued that the more the elastically infectious disease responds to prevalence—that is, the more the demand for vaccination increases with disease prevalence or incidence—the less responsive it is to price, thereby reducing the effects of subsidized vaccination programs. In more recent papers, how individual actions and decisions play a role in disease transmission has been investigated (Auld, 2003; Greenwood et al., 2019; Boucekkine et al., 2021). In particular, recent and active research has highlighted the significance of people's opinions of or beliefs about vaccines in their vaccination strategies (d'Albis et al., 2022; Benoit and Mauldin, 2021; Salali and Uysal, 2022). Our contribution to this stream of literature is that we model how individuals' opinion of the vaccine evolve and interact with disease dynamics.

Second, by considering the proportion of elderly individuals who are vaccinated as a policy tool with which to improve the level of immunity attained by younger generations, we also add to the literature on immunity and age-specific control policies (Gollier, 2020b,a; Acemoglu et al., 2021; Brotherhood et al., 2021). Indeed, we show that an increase in the proportion of older people getting vaccinated can have a significant impact on the vaccination coverage of the remaining population due to intergenerational peer effects, as well as a reduction in the number of susceptible individuals. This effect is particularly important for countries or regions where immunization rates are low and may help relax the focus on age-specific containment for older people, thus increasing their level of protection through the positive effects of the actions of younger people .

Third, our paper is also related to the research on the formation and evolution of cultural preferences. In this stream of literature, cultural changes are modeled as an intergenerational process (Bisin and Verdier, 2001, 2011).[3] They distinguish between two different levels of preference transmission: vertical transmission (from parents to children) and oblique transmission (from members of the parent generation to children). These models are designed to analyze preference traits that evolve slowly over a long period. Conversely, we adopt an intragenerational framework to model the dynamics of preferences, which allows us to link epidemic and opinion dynamics.

Lastly, our result may be related to a set of studies that explain the persistence of an epidemic (Gersovitz and Hammer, 2004). Indeed, empirical evidence shows that people tend to change not only their behaviors but also their opinions or beliefs during an epidemic (Adhvaryu, 2014; Wooten et al., 2012; Peretti-Watel et al., 2013; Raude et al., 2020; Attema et al., 2021). Such changes in beliefs may have perceptible effects on epidemic dynamics (Tyson et al., 2020; Du et al., 2021). Other socially determined processes, such as self-esteem, stigma,

[2] Susceptible individuals can become infected when they come into contact with other individuals who already carry the disease. Once infected, these individuals can contribute to the spread of the disease when they come into contact with other people. Over a certain period, these infected people can become susceptible again.

[3] Recently, cultural transmission models have been applied to various topics, such as marriage (Hiller et al., 2022), the industrialization process (Touré, 2021), and religious legitimacy (Bisin et al., 2021). See Verdier and Bisin (2023) for a recent advance in that field.

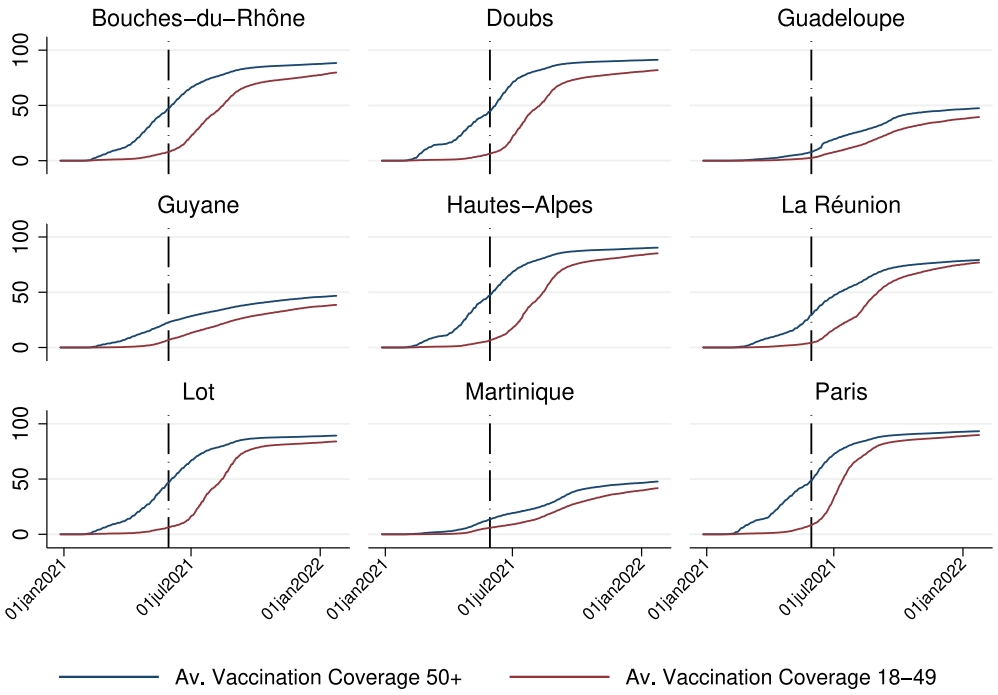


Fig. 1. Average vaccination coverage rate over time in selected French departments among two age groups in France (18–49 and 50+ years). The vertical dashed line shows the date when vaccination was first available to young adults.

and socially determined preferences, may also affect the spread of the epidemic (Alfano and Guarino, 2023). Thus, we propose a new mechanism that highlights how an epidemic can persist, even long after its first appearance, based on the dynamic interplay between beliefs about vaccines and the degree of disease prevalence.

The remainder of the paper proceeds as follows. Section 2 provides stylized facts and an empirical test based on a quasi-experiment across age groups and French departments to illustrate our main assumption that vaccination preferences among young and old individuals are linked. In Section 3, we present the general model setup. In Section 4, we explore the dynamic properties of the model and present comparative static results. Section 5 concludes the paper. All proofs are relegated to the Appendix.

2. Stylized empirical evidence

We propose a stylized empirical framework. We consider French departments with different vaccination coverage rates for those individuals above age 50 years before vaccination was officially opened up to the 18-to-50 year age group on May 30, 2021. Before this date, only individuals aged above 50 years were eligible for vaccination. Although the introduction of vaccination was gradual among this older age group, we adopt this threshold for the sake of simplicity. We discuss potential endogeneity issues—particularly the determinants of vaccination coverage among old and young individuals who may be driven by unobserved factors—in Section 2.3.

2.1. Vaccination campaign in France

The vaccination strategy initially defined by the French High Authority for Health was to vaccinate the most vulnerable elderly individuals and those medical staff who were in contact with them. The French government had planned a slow, gradual start to vaccination to avoid any inherent risks. Importantly, the government decided that (i) vaccination was not mandatory (at least for the majority of people); (ii) vaccination was free of charge; (iii) vaccination was subject to high safety standards according to the principle of test, alert, and protect; and (iv) screening site locations were available on a public website, with a filter on reverse transcription-polymerase chain reaction (RT-PCR) or antigen tests, department by department. The campaign started on December 27, 2020, when retirement home residents received the first doses, followed by health professionals and other very exposed people. After a slow start, due to a lack of available doses, the campaign was opened up gradually according to age and comorbidity (those individuals over 75 years, followed by those over 65 years, those over 50 years, etc.) but also according to the marketing authorizations for the various products. Until the end of May 2021, people aged above 50 years were able to enter this scheme gradually. On May 30, 2021, vaccination was opened up to all adults over 18 years of age. We exclude children under 18 years of age from our analysis since vaccination choices for minors may be strongly influenced by their parents.

As shown in Fig. 1, the timing and evolution of vaccination coverage by age group may, however, vary across departments. The average vaccination coverage rate on May 30, 2021, in the 50+ years age group—including all departments—was 43.89%. Overseas departments such as Martinique, Guyane, Guadeloupe and even La Réunion show a singular pattern characterized by lower and slower vaccination coverage rates,[4] which is also true of other hexagonal departments such as Corsica, Gard, or Haute-Vienne (not shown here). We note that in principle, the vaccination campaign followed the same timetable in all departments.

Our empirical strategy is based on the fact that vaccination introduction by age group was difficult for the French population to anticipate. Indeed, no ex ante timetable was published at the start of December 2020. Vaccination introduction on a precise date by age group also enables us to define a precise before–after framework. Moreover, those departments with low (high) vaccination rates for individuals above 50 years old just *before* the extension to younger age groups may serve as a good counterfactual that is not affected by future

[4] The average vaccination coverage rate on May 30, 2021, in the 50+ years age group was 20.26% in overseas departments.

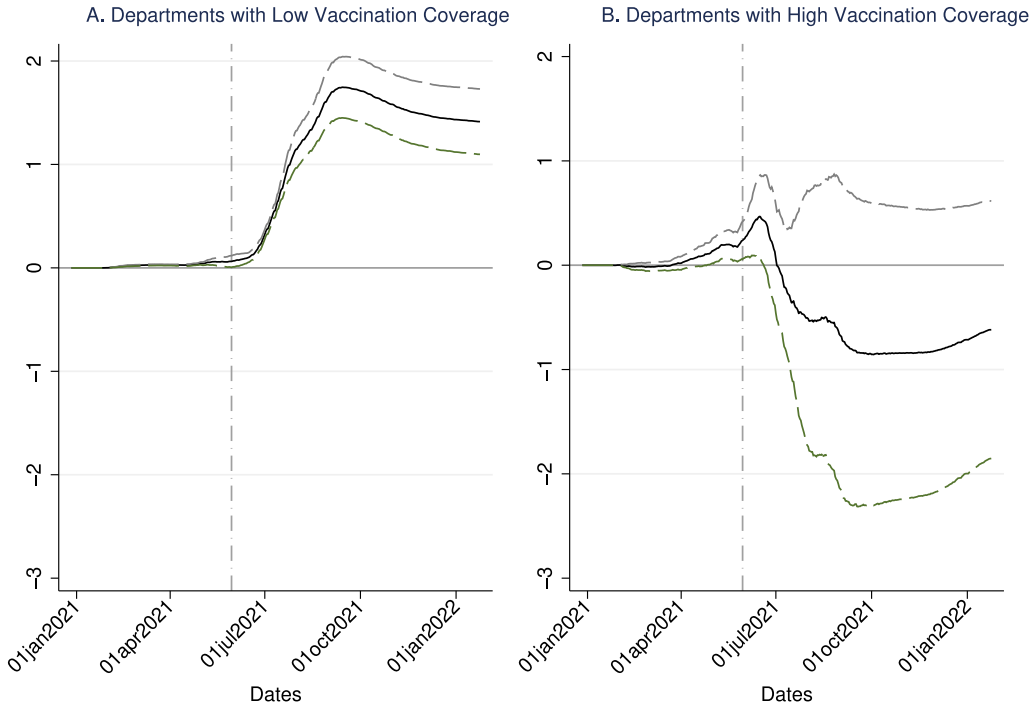


Fig. 2. Effect of $VaccinationCoverage^{50+}_{d,May302021}$ on $VaccinationCoverage^{18-49}_{d,t}$, date by date, across departments d.

infection or hospitalization incidence rates and future vaccination rates across age groups.

2.2. Data and empirical equation

We use the high-frequency "Vaccin Covid" database, administered by French Health Insurance, with data from health professionals performing vaccinations. Sant\'epubliqueFrance uses this information and makes it available to all at data.gouv.fr. This database enables the number of people who have received a COVID-19 vaccine injection to be counted on day 1. The availability of these new, reliable large datasets contributed to the increase in the amount of public information and support for the management of the COVID-19 vaccination campaign. The indicators record the number of people having received one, two or three doses, by date of injection, diet and age group.

We start with a simple regression analysis, where we regress, for any date t (from December 27, 2020, to January 24, 2022), the degree of vaccination coverage among those individuals aged $18-49$ years in department d on the degree of vaccination coverage among those individuals aged 50+ years on May 30, 2021 (date of vaccination introduction for the younger age group) in the same department.

Fig. 2 plots the coefficient date by date and provides this simple event graph according to department in terms of high and low degrees of vaccination coverage.[5] The vertical line shows the opening date of vaccination for the youngest group, i.e., May 30, 2021. Figs. 2A and 2B greatly differ. Regarding departments with low rates of vaccination coverage among elderly individuals at the start of the period, Fig. 2A shows a positive and significant effect that is more in the direction of a complementarity effect across age groups. These departments with low vaccination coverage rates, such as overseas departments, may have a higher rate of vaccination hesitancy. In this group, vaccination coverage rates among those individuals over 50 years of age at the date of vaccination introduction for the younger age groups have a significant and positive impact on vaccination coverage rates among the younger age groups in the short or long term. The timing of this effect is also slightly delayed. Regarding departments with high vaccination coverage rates, Fig. 2B shows a significantly positive and very short-term effect that fades in the longer term and becomes negative (though not significantly), which is more consistent with a substitution effect. In this group, vaccination among those individuals over 50 years of age at the date of vaccination introduction for the younger age groups may have had a negative impact on vaccination coverage rates among young people beginning in mid-September 2021. These two figures are, however, simplified, and further analysis is therefore needed. To refine this quasi-experimental framework, we estimate the following empirical equation:

$$\begin{aligned} VaccinationCoverage^{18-49}_{d,t} =& \alpha + \alpha_1 Post_{May302021} \\ & \times VaccinationCoverage^{50+}_{d,May302021} \\ & + \delta_d + \lambda_t + \Gamma \mathbf{X}_{d,t} + \epsilon \end{aligned} \tag{1}$$

where $VaccinationCoverage^{18-49}_{d,t}$ is the department (d) vaccination coverage rate (defined by those given a first dose plus a booster dose) among the 18-to-49 year age group at date t.[6]

$VaccinationCoverage^{50+}_{d,May302021}$ denotes the vaccination coverage rate among the 50+-year age group (defined by those given a first dose plus a booster dose) on May 30, 2021.[7] δ_d and λ_t are department and date fixed effects, respectively. We can either include or

[5] A department with a high degree of vaccination coverage is defined as a department with an average vaccination rate among the older age group on May 30, 2021, above the median (44.78%). The two figures thus split our sample into two groups.

[6] We note that the use of a restricted definition including only the 1st dose does not affect our results. Moreover, Santé publique France uses 4 age groups (18–24, 25–29, 30–39, and 40–49 years). We use an unweighted average for our 18-to-49 year group.

[7] Here, we also use an unweighted average from several age groups: 50–59, 60–64, 65–69, 70–74, 75–79, and 80+ years.

Table 1
Heterogeneous effect of elderly vaccination on young vaccination.
Source: SNDS.

	$VaccinationCoverage^{18-49}_{d,t}$	
	(1)	(2)
	OLS	IV
Post × $VaccinationCoverage^{50+}_{d,May30,2021}$ × High	−1.762**	−4.731*
	(0.534)	(1.986)
Post × $VaccinationCoverage^{50+}_{d,May30,2021}$	1.205***	1.450***
	(0.105)	(0.173)
Incidence Rate	−0.002***	−0.001
	(0.000)	(0.001)
Intercept	8.641**	–
	(2.753)	
R2	0.989	–
Observations	39,794	39,006
Dpt. FEs	Yes	Yes
Date FEs	Yes	Yes
Post × High	Yes	Yes

Note: The sample size is reduced by data constraints for the IV. Influenza vaccination rate over 65 yo in overseas departments is only available in Guadeloupe, Martinique, and Guyane. The results are clustered at the department level.

not include additional controls, such as hospitalization incidence[8] or infection incidence[9] through **X**. These additional controls do not affect our main results. Moreover, these controls may be endogenous to $VaccinationCoverage^{18-49}_{d,t}$. In addition, there may be some challenges related to the measurement of tests and the populations concerned. Indeed, Rozenfeld et al. (2020) point out that the availability and evolution of screening guidelines, individual factors or clinical judgments may affect who is tested. As a result, we present only the results controlling for incidence rates at the department level. The coefficient of interest is α_1 and provides the effect of vaccination coverage among the older age group *ex ante, i.e., on May 30, 2021* after vaccination introduction for the youngest group. Because the health pass was introduced in June 2021 and mostly generalized as of July 12, 2021, it is difficult to apply our test to the third vaccine doses, as different incentives were introduced to motivate individuals to get vaccinated. Finally, as we are interested in the differential (and nonlinear) results between departments with *ex ante low* (high) and *high* (low) vaccine hesitancy (coverage) rates, we interact our variables of interest with $High$, a dummy variable for departments above the median vaccination coverage rate among the older age group on May 30, 2021. The coefficient associated with this triple interaction term provides the average differential effect between "low" and "high" departments.

2.3. Ordinary least squares (OLS) and instrumental variable (IV) results

Our results are provided in Table 1. Our high-frequency database includes 101 departments (including 5 overseas departments) and 394 days, for a total of 39,794 observations.

Our OLS results (Column 1) confirm and refine the results from Fig. 2. The effects are oriented mainly toward a complement effect (e.g., vaccination coverage among individuals in the older group ex ante significantly increases vaccination coverage among those in the younger group after treatment). In other words, a higher proportion of older people getting vaccinated leads to higher vaccination coverage rate among younger individuals after treatment. However, this effect is significantly different in the "high" (compared to "low") vaccination coverage departments – where less vaccination hesitancy is observed *ex ante* among the old population – as shown by the coefficient on the triple interaction term. These heterogeneous effects show that the proportion of "antivaxxers" in the old population may be a crucial parameter, influencing vaccination coverage across generations non linearly. Our quasi-experiment, as defined earlier, assures that this effect is potentially causal. We also note that the department-specific incidence rate has a significant negative effect on vaccination coverage among young individuals but only in regression (1).

Potential selection bias and endogeneity concerns may threaten these results. First, overseas departments may be statistical outliers in our study and are included in the "high department" group. Although this is in fact a particularity we exploit here, unobserved characteristics such as history, culture, or religion could bias our results. At the department level, such factors should be accounted for by fixed effects. However, if department fixed effects capture important stable factors such as the relative size of populations, then they cannot control for increasingly varying characteristics such as the supply of vaccines or the political orientation of department leaders, which may have changed during the pandemic crisis. On the demand side, it is indeed possible that social differences and changes in vaccination practices may overlap with the social distribution and changes in vaccine reluctance, except, perhaps, in terms of gender differences (Bajos et al., 2022). On the supply side, social barriers hampering access to preventive practices, such as geographical distance from health centers (related to more or less urbanized areas), experiences of discrimination in the health system, or the availability of vaccines, are indeed important confounders. The vaccine strategy was complex and based on different vaccines that did not all arrive at the same time, which may have generated many sources of uncertainty. However, the scientific committee on COVID-19 and the Conseil d'orientation de la stratégie vaccinale[10] addressed specific regular points in terms of the vaccination strategy and overseas departments during the crisis. Even though testing capacity was discussed and the campaign started with a slight delay in overseas departments compared to that in the hexagon, there is no evidence that the supply of vaccines in overseas departments or within mainland France across departments has been strongly inequitable during the different phases of the campaign.

Second, an alternative way in which to deliver facts about anti-vaccine attitudes in France consists of studying those pandemics that occurred before COVID-19. Indeed, by computing vaccination department coverage rates for other epidemics and by using them as an IV for the coverage rates of elderly individuals in the case of COVID-19, we can rule out many of the endogeneity concerns. For instance, one cannot pretend that the results are driven by the supply of COVID-19 vaccines. Our approach may even resolve the issue of unobserved characteristics at the department level. We thus use data on previous seasonal influenza vaccination campaigns. Specifically, we instrument the vaccination coverage rate of elderly individuals as of May 30, 2021, by that of elderly individuals for previous vaccination campaigns in response to previous epidemics, e.g., seasonal influenza (from https://www.snds.gouv.fr/SNDS/Accueil and those occurring in the winters of 2018–19 and 2019–20). The IV results are provided in Column (2) of Table 1 and reinforce our initial conclusions.

After having highlighted the nonnegligible effect of older individuals' vaccination behavior on that of younger individuals, we now develop a model that incorporates this feature and analyze how this intergenerational link may affect the dynamics of the disease.

[8] Daily number of new inpatients with COVID-19.

[9] Number of persons testing positive (RT-PCR and antigen test) for the first time in more than 60 days relative to population size.

[10] see, e.g., https://solidarites-sante.gouv.fr/IMG/pdf/avis_conseil_scientifique_covid-19_8_avril_2020.pdf or https://solidarites-sante.gouv.fr/IMG/pdf/avis_conseil_scientifique_26_fevrier_actualise_8_mars_2021.pdf or https://sante.gouv.fr/grands-dossiers/vaccin-covid-19/covid-19-la-strategie-vaccinale/article/les-avis-du-conseil-d-orientation-de-la-strategie-vaccinale .

3. Benchmark model

3.1. Population structure

We consider a discrete-time ($t = 0, 1, \ldots$) dynamic model in which each period t corresponds to a season (or a wave). As in our empirical test, and for simplicity's sake, this model includes two demographic groups: young (y) and old (o) individuals, with a constant population size of one for each generation.[11] In this model, individuals in the old population are assumed to be inactive, and thus, all their decisions are taken as given.[12] Individuals in the young generation are further divided into two preference groups, which we label *antivaxxers* and *vaxxers*, as defined in Bizzarri et al. (2023). Vaxxers exhibit stronger trust in the technology behind the vaccine than do antivaxxers. We are agnostic about the origin of the differences in opinions among individuals regarding vaccination (e.g., Bisin and Verdier (2001, 2011)).[13] To measure the aggregate level of beliefs or opinions about vaccines, we use the proportion of antivaxxers among the young adult population, denoted by q_t. The share of vaxxers among all young people is represented by $1 - q_t$.

At the beginning of each season, there is a proportion of healthy and infected people within each demographic group. Let $s_t^{s'}$ denote healthy susceptible people and $i_t^{s'}$ denote infected people, with superscript $s' = y$ representing young people and $s' = o$ representing old people. Thus, we have $2 = \sum_{s'} s_t^{s'} + \sum_{s'} i_t^{s'}$. As in Davin et al. (2021), we assume that susceptibility to infection does not depend on age. The numbers of adult and old agents being susceptible and infected are thus the same, meaning that $s_t^o = s_t^y = s_t$ and $i_t^o = i_t^y = i_t$. Therefore, at the beginning of the period, we have $2 = 2s_t + 2i_t$ of adult and old people, which is equivalent to $1 = s_t + i_t$, where i_t represents the share of infected people.

At a given point in time, once the proportion of unvaccinated old individuals (ρ) is known, young individuals undergo a two-step decision process. First, at the beginning of each period t, each agent decides whether or not to get vaccinated. Second, each active individual is involved in a socialization process with other individuals, as described in Section 4.1, during which his or her opinions or beliefs regarding vaccination may evolve.

3.2. Preferences and vaccination

We assume that vaccination is effective in the sense that once an individual is vaccinated in period t, he or she cannot be infected during that period. However, the efficacy of the vaccine is limited, which means that individuals have to choose again at the beginning of each period whether or not to get vaccinated.[14]

As previously mentioned, we consider the decision process of only the active population (young individuals).[15] Within the active population, there are two types of individuals: those who have high levels of trust in the technology behind the vaccine, whom we refer to as *vaxxers* (type v), and those who have low levels of trust in the vaccine, referred to as *antivaxxers* (type a). We assume that individuals align their actions with their opinions about vaccine, meaning that only individuals with a positive opinion about the vaccine choose to get vaccinated, while antivaxxers never get vaccinated.[16] At time t, the utilities of agents v and a are, respectively, given by the following:

$$V_t^v = \bar{u} + (1-\rho)\gamma - d \tag{2}$$

$$V_t^a = \bar{u} + \rho\gamma - \psi\beta i_t \frac{(q_t + \rho)}{2} \tag{3}$$

In Eqs. (2) and (3), $\bar{u}$ is the baseline component of the payoff corresponding to the value of a healthy life, which is constant over each season. We also assume an intergenerational peer effect such that vaxxers (antivaxxers) receive a payoff in proportion to how many other individuals among old individuals are vaccinated (nonvaccinated), and γ accounts for this intergenerational peer effect.[17] Bezin and Moizeau (2017) also model peer effects in the same way.[18] Additionally, d accounts for the disutility cost that an individual of type v incurs after vaccination. This cost represents vaxxers' perceived vaccine risks, which encompass both the perceived likelihood of adverse events and their perceived severity, as well as the long-term health impacts of the vaccine. Let us note that perceived vaccine risks may not necessarily reflect actual vaccine risks. ψ represents the agent's disutility of becoming infected. This utility loss increases linearly with their perceived probability of contracting the disease, expressed as $(q_t + \rho)\beta i_t/2$. This perception is influenced by the current disease prevalence rate (i_t), the proportions of unvaccinated young (q_t) and old (ρ) individuals, and the disease transmission rate (β).

4. Dynamics

Below, we elaborate on how opinions evolve when i_t remains fixed in Section 4.1, and in Section 4.2, we analyze infection dynamics when q_t remains fixed, before analyzing the joint evolution of infections and opinions in Section 4.3.

[11] Note that, our model is not an overlapping generations model where people live two periods; instead, we assume that the young remain young and the old stay old. This assumption seems reasonable for two reasons. Firstly, our aim is to model short-term dynamics rather than a long-run phenomenon. Secondly, in our model, each period t corresponds to a transmission season, which corresponds to 3–4 months. Thus, except at the margin, most young people will remain young.

[12] We relax this assumption in Appendix E, where we model old vaccination behavior explicitly. Then, we show that our results remain unchanged when we consider this extension.

[13] As becomes clearer later on, our objective is not to model how individuals form their opinions but, rather, to model how their opinions of vaccination evolve over time.

[14] This assumption is consistent with the spread of several diseases such as COVID-19 or seasonal flu. Studies such as that of Seow et al. (2020) have shown that COVID-19 antibodies decline rapidly in the human body and, thus, that regular vaccination against the virus is necessary for protection. Bizzarri et al. (2023) make a similar assumption.

[15] In our stylized example, young people are opening up to vaccination, while vaccination of the elderly has already exceeded 50% in most French departments. This could also be the case of a compulsory vaccination campaign targeting the elderly in particular. With this in mind, the parameter ρ captures the effectiveness of this vaccination policy. A lower value of ρ indicates greater effectiveness of vaccination of the elderly.

[16] This can be interpreted as an equilibrium situation, where antivaxxers experience a strong disutility in getting vaccinated, such that they never get vaccinated, whereas vaxxers have a low disutility in getting vaccinated, thereby motivating them to get vaccinated consistently.

[17] In fact, γ is the effect of injunctive social norms and measures the influence of the elderly generation or the effect of tradition on the young population. To generalize, note that the elderly could be considered as any *privileged* sub-group that would be perceived as a reference group influencing the young.

[18] We note that in this paper, we focus on intergenerational peer influence, rather than on intragenerational peer influence, as studied by Bezin and Moizeau (2017), the latter of which refers to how individuals within the same generation influence each other. In the field of network economics, researchers have often modeled conformity or peer effects as a disutility arising from deviating from the social norms of the majority group (Patacchini and Zenou, 2012; Itoh et al., 2021; Díaz and Patacchini, 2022; Olcina et al., 2017; Boucher et al., 2022; Liu et al., 2014). However, considering that vaccination choices are discrete in nature, this type of approach may not be entirely suitable for our framework.

4.1. Evolution of opinions

4.1.1. Socialization process

We use the socialization mechanism proposed by Besley (2017) (see also Besley and Ghatak (2016), Besley and Persson (2019a,b)) to model the dynamics of opinions of the vaccine. At each period t, each young agent meets another agent selected randomly from his or her demographic group. If two agents share the same opinions, then nothing happens, and the agent maintains his/her opinions or beliefs about the vaccine with a probability of one. Otherwise, the agent must choose between the two preference traits, which is based on a noisy comparison of the expected utilities associated with each opinion or belief. Formally, let $V^a\left(i_t,q_t\right)$ denote the utility of an individual with preference a and the utility difference between traits a and v by $\Delta V\left(i_t,q_t\right) \equiv V^a\left(i_t,q_t\right) - V^v\left(i_t,q_t\right)$; an individual of type a who meets an individual with an opposite preference chooses the antivaxxer preference (a) only if

$$V^a\left(i_t,q_t\right)+\varepsilon \geq V^v\left(i_t,q_t\right) \Leftrightarrow \Delta V\left(i_t,q_t\right)+\varepsilon \geq 0 \tag{4}$$

with ε denoting a 'noise' that follows a symmetric probability distribution with zero mean. Hence, denoting the cumulative distribution function of ε by $\Phi(.)$ and the density function corresponding to Φ by ϕ, the probability of an individual who meets another agent with different opinions adopting trait a equals $\Phi\left(\Delta V\left(i_t,q_t\right)\right)$, with $\phi\left(\Delta V\left(i_t,q_t\right)\right)>0$, $\Phi(0)=1/2$ and $\phi(0)=1/4$. The specification of the probability distribution is not important for our analysis (see, for instance, Touré (2021), Besley (2017), Besley and Persson (2019a), Baudin and Hiller (2019)), but we can use the example of a logistic distribution to explain how the probability works. When an individual encounters another person with different opinions, the probability of he or she adopting an antivaxxer trait by using a logistic distribution is as follows:

$$\Phi\left(\Delta V(i_t,q_t)\right)=\frac{\exp\left[\Delta V(i_t,q_t)\right]}{1+\exp\left[\Delta V(i_t,q_t)\right]}$$

When $\Delta V_t(i_t,q_t)=0$, this probability is $1/2$. Additionally, the derivative of the logistic function is always positive, and when $\Delta V_t(i_t,q_t)$ is 0, the value of the derivative is $1/4$.[19]

4.1.2. Opinion dynamics

By using this framework and denoting the probability of an agent j adopting preference j' at date t by $p^{jj'}$, we obtain the following transition probabilities:

$$\begin{array}{ll} p_t^{aa}=q_t+\left(1-q_t\right)\Phi\left(\Delta V\left(i_t,q_t\right)\right) & p_t^{av}=\left(1-q_t\right)\left(1-\Phi\left(\Delta V\left(i_t,q_t\right)\right)\right) \\ p_t^{vv}=\left(1-q_t\right)+q_t\left(1-\Phi\left(\Delta V\left(i_t,q_t\right)\right)\right) & p_t^{va}=q_t\Phi\left(\Delta V\left(i_t,q_t\right)\right) \end{array} \tag{5}$$

The above equation yields the following equation of the evolution of q_t:

$$q_{t+1}=q_t p_t^{aa}+\left(1-q_t\right)p_t^{va}=q_t^2+2q_t\left(1-q_t\right)\Phi\left(\Delta V\left(i_t,q_t\right)\right) \tag{6}$$

We can describe the right-hand side of the equation as follows. The first term q_t^2 represents the probability of an antivaxxer meeting another agent who shares the same opinions and thus remains an antivaxxer with certainty. The second term $2q_t(1-q_t)$ represents the probability of an antivaxxer meeting someone with different opinions of the vaccine. In this case, the probability of the latter staying an antivaxxer is determined by $\Phi\left(\Delta V\left(i_t,q_t\right)\right)$.

By rearranging Eq. (6), we can obtain an equation that governs the evolution of q_t over time:[20]

$$\Delta q_t \equiv q_{t+1}-q_t=q_t\left(1-q_t\right)\left\{2\Phi\left(\Delta V\left(i_t,q_t\right)\right)-1\right\} \tag{7}$$

This equation corresponds to replicator dynamics, which are standard in evolutionary models. Let us highlight that the main point of departure between our framework and that considered in evolutionary game theory is that we consider that preference traits, rather than strategies, evolve over time. Thus, the direction of opinion change is determined by $\Phi\left(\Delta V\left(i_t,q_t\right)\right)\gtrless 1/2$ or the equivalent $\Delta V\left(i_t,q_t\right)\gtrless 0$. We know that vaxxers decide to get vaccinated, while antivaxxers decide not to get vaccinated, such that their utilities are given by (2) and (3), respectively. Therefore, the expected relative utility of an individual who chooses to remain an antivaxxer is as follows:

$$\Delta V\left(i_t,q_t\right)=\gamma(2\rho-1)-\psi\beta i_t\frac{(q_t+\rho)}{2}+d \tag{8}$$

Thus, by combining this expression of $\Delta V\left(i_t,q_t\right)$ with the expression of the law of motion of q_t (Eq. (7)), we obtain the following:

$$\Delta q_t=q_t\left(1-q_t\right)\left\{2\Phi\left(\gamma(2\rho-1)-\psi\beta i_t\frac{(q_t+\rho)}{2}+d\right)-1\right\} \tag{9}$$

Let us define by $\bar{i}(q_t)$ the threshold i_t for which $\Phi(.)=1/2$:

$$\frac{2\left(\gamma(2\rho-1)+d\right)}{\beta\psi(q_t+\rho)}\equiv\bar{i}(q_t)$$

To ensure that this threshold is always positive, we assume that parameter d is such that

Assumption 1. $d>\gamma$

Under this assumption, we can summarize the properties of the opinion dynamics for a given i_t in the following lemma:

Lemma 1. *Under Assumption 1 and fixing $i_t=i\in[0,1]$, we have the following:*

1. *if $i<\bar{i}(q_t)$, then $\Delta q_t>0$: antivaxxers opinions spread within the population over time, and*
2. *if $i>\bar{i}(q_t)$, then $\Delta q_t<0$: vaxxers opinions spread within the population over time*

Proof. See Appendix A. ■

The intuition behind this result is as follows: if $i>\bar{i}(q_t)$, then the level of infection or the likelihood of being infected is too high such that the utility from becoming a vaxxer is higher relative to that from remaining an antivaxxer. This favors the expansion of vaxxer opinions within the economy, and q_t decreases over time. However, when the likelihood of being infected is too low $\left(i<\bar{i}(q_t)\right)$, antivaxxer opinions within the population increase over time. Interestingly, the threshold $\bar{i}(q_t)$ is also decreasing in q_t, meaning that the minimal level of i above which vaxxer opinions spread within the population is decreasing in the proportion q_t of antivaxxers. This finding reflects the existence of

[19] It is straightforward to allow for opinion bias (nonzero mean shock) with the following:

$$\Phi\left(\Delta V_t(i_t,q_t)\right)=\frac{\exp\left[\varsigma+\Delta V_t(i_t,q_t)\right]}{1+\exp\left[\varsigma+\Delta V_t(i_t,q_t)\right]}$$

where $\varsigma>0$ represents a bias toward antivaxxer beliefs and $\varsigma<0$ represents a bias against such beliefs. In this case, when the shock has a positive mean (negative mean), the proportion of antivaxxers in the long run is larger (smaller) than that when $\varsigma=0$.

[20] Lieu et al. (2015) find that people with antivaccine beliefs tend to talk more to others who share their views than to those who do not. We can extend the model to account for this situation by assuming that people in both groups have a probability, h, of meeting someone from their own group and a probability, $1-h$, of meeting someone randomly (Bizzarri et al. 2023). Based on this assumption, we can describe the evolution of opinions as follows:

$$\Delta q_t=q_t(1-q_t)(1-h)\left\{2\Phi\left(\Delta V\left(i_t,q_t\right)\right)-1\right\}$$

Therefore, we see that the existence of homophily in the socialization process does not affect our qualitative results regarding opinion evolution for all $h\neq 1$.

substitutability between q_t and i_t. Indeed, when antivaxxer opinions increase within the population, the risk of becoming infected increases, making it easier to become a vaxxer.

4.2. Evolution of infections

We consider a simple SIS model, where the virus is transmitted by direct contact between individuals (Day and Gandon, 2007; Hethcote, 2000). Let us recall that within the population, there are healthy hosts (s_t), potentially susceptible hosts, and infected hosts (i_t) who can transmit the disease. Infection occurs if an infected individual meets a healthy individual and the virus is transmitted during this process. As in Goenka and Liu (2012), Goenka et al. (2014), and Prieur et al. (2022), we abstract from disease-related mortality, such that infected individuals recover and become healthy and therefore reinfectable. Let us denote by β the transmission rate, i.e., the rate at which healthy individuals become infected,[21] and by δ the cure rate. From there, we can then determine the dynamics of the evolution of infected individuals as follows:

$$\Delta i_t \equiv i_{t+1} - i_t = (\beta s_t - \delta) i_t \tag{10}$$

$s_t = \frac{q_t+\rho}{2}(1 - i_t)$ represents the set of agents who are neither vaccinated nor infected and are therefore susceptible to being infected by other infected agents. In our SIS framework with vaccination, vaccination tends to decrease the pool of susceptible people.[22]

For a fixed value of $q_t = q \in [0, 1]$, the disease dynamics described in (10) display two stationary equilibria: a trivial steady state without any infected people,

$$\tilde{i} = 0 \qquad \text{and} \qquad \tilde{s} = \frac{q+\rho}{2}, \tag{11}$$

and another endemic steady state characterized by a positive level of infected people at equilibrium:

$$\hat{i}(q) = 1 - \frac{2\delta}{\beta(q+\rho)} \qquad \text{and} \qquad \hat{s} = \frac{\delta}{\beta}. \tag{12}$$

The convergence toward one or the other of these equilibria depends on the R_0, also called the basic reproductive rate of a virus. R_0 measures the average number of secondary infections due to the presence of an infectious individual in a population of healthy hosts. If the value of R_0 is greater than 1, then we converge to an endemic equilibrium; otherwise, we converge to an equilibrium without any infected people. Given that the duration of the infection of an individual is $1/\delta$ and that during the infectious period, the individual can meet $\tilde{s} = (q+\rho)/2$ healthy individuals with a transmission rate, β, R_0 is written as follows:

$$R_0 = \frac{\beta(q+\rho)}{2\delta} \tag{13}$$

It is easy to see that the reproduction rate of the virus, i.e., the average number of new cases of infection that an infected person generates, on average, increases with the proportion of antivaxxers. In other words, the higher the number of antivaxxers is, the higher the number of people that are infected by a contagious individual. In our framework, we see that $\hat{i}(q) > 0$ if $R_0 > 1$, meaning that we converge toward the endemic steady state when an infected individual causes, on average, more than one secondary infection. From this, we can define the proportion of individuals with antivaxxer beliefs within the economy, denoted by $\bar{q} \equiv (2\delta - \beta\rho)/\beta$, above which the economy converges toward endemic equilibrium. To ensure that the threshold $\bar{q}$ is always positive, we assume that the parameter δ is large enough such that the following holds:[23]

Assumption 2. $2\delta > \beta\rho$

Under this last assumption, we claim the following:

Lemma 2. *Under Assumptions 1–2 and fixing $q_t = q \in [0, 1]$, the dynamic Eq. (10) exhibits two steady states:*

1. *if $q > \bar{q}$, then the economy converges to the endemic equilibrium $\hat{i}(q_t)$, and*
2. *if $q < \bar{q}$, then the economy converges to the trivial equilibrium $\tilde{i}$.*

Proof. See Appendix B. ■

Lemma 2 states that for a given q such that $q < \bar{q}$, the proportion of antivaxxers is low enough that a sick person infects, on average, less than one person, and thus, in the long run, the number of infected individuals converges to 0. However, if $q > \bar{q}$, then symmetric reasoning applies, and i_t converges to $\hat{i}(q)$. Interestingly, the level $\hat{i}(q)$ increases with q, meaning that the steady-state level of infections increases with the proportion of antivaxxers, which reflects the existence of complementarity between antivaxxer values and long-term infection levels.

4.3. Dynamics of the economy

Joint dynamics of preferences and infections. As discussed in Sections 4.1 and 4.2, the level of infection affects people's attitudes: if the level of infection is too high, then people tend to get vaccinated, but when the level of infection is too low, the risk of being infected is quite low, and people do not get vaccinated. This link between the level of infection and people's preferences is, in fact, bidirectional because the higher the number of vaxxers within the population is, the fewer infected people there are. We utilize Lemmas 1 and 2 and define the following four sets:

$$\begin{aligned}
\Omega_1 &= \{ i_t \in \mathbb{R}_+ : \ i_t \le \hat{i}(q_t) \quad \text{and} \quad i_t \le \bar{i}(q_t) \ \} \\
\Omega_2 &= \{ i_t \in \mathbb{R}_+ : \ i_t \le \hat{i}(q_t) \quad \text{and} \quad i_t \ge \bar{i}(q_t) \ \} \\
\Omega_3 &= \{ i_t \in \mathbb{R}_+ : \ i_t \ge \hat{i}(q_t) \quad \text{and} \quad i_t \ge \bar{i}(q_t) \ \} \\
\Omega_4 &= \{ i_t \in \mathbb{R}_+ : \ i_t \ge \hat{i}(q_t) \quad \text{and} \quad i_t \le \bar{i}(q_t) \ \}
\end{aligned}$$

Then, we can state the following proposition:

Proposition 1. *Under Assumptions 1–2, the joint dynamics of i_t and q_t lead to the emergence of oscillations.*

An intuitive representation of this dynamic result can be highlighted by a phase diagram. This diagram, presented in Fig. 3, incorporates the stationary loci of i_t ($\tilde{i}$ and $\hat{i}(q_t)$) and q_t ($\bar{i}(q_t)$).[24] The crossing point between the $\hat{i}(q_t)$ locus and $\bar{i}(q_t)$ locus, denoted as E, represents the

[21] Recent empirical evidence (e.g., Au (2022), Paetzold et al. (2022), and Kim and Lee (2022)) suggests that the transmission rate decreases with the vaccination rate. If we had made this assumption, it may have strengthened our results by introducing an additional channel through which beliefs about vaccines affect disease dynamics. Other studies have also linked the transmission rate to economic activity. For example, Baril-Tremblay et al. (2021) and Fabbri et al. (2023) propose a model where the transmission rate depends on individuals' mobility decisions, while Davin et al. (2021) assume that the transmission rate decreases with an increase in the amount of public expenditure on health care, such as masks, tests, emergency services, and research for treatments.

[22] We note that without vaccination ($q_t = \rho = 1$), the proportion of individuals susceptible to infection is $s_t = 1 - i_t$, as in the standard SIS model.

[23] Assumption 2 guarantees the existence of a steady state where there are no infections. However, in Section 4.3, we demonstrate that even though this steady state exists, the interplay between the dynamics of people's opinions regarding vaccination and the level of infection can lead to enhanced disease persistence.

[24] The shape of these various loci can be easily derived from the analysis developed in Sections 4.1 and 4.2.

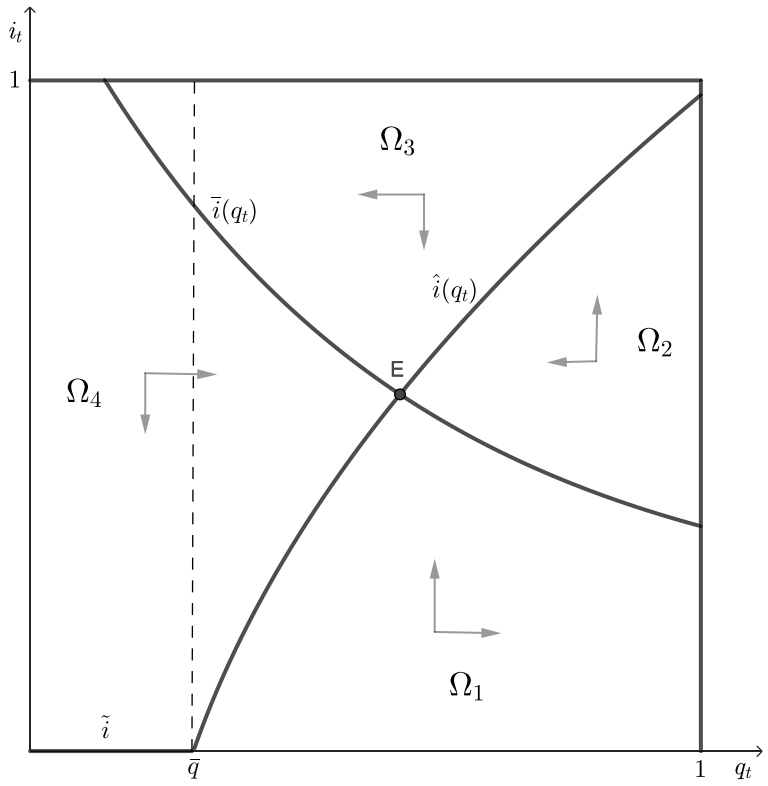


Fig. 3. Joint dynamics of q_t and i_t.

steady-state equilibrium of the joint dynamics of (i_t, q_t), the expressions of which are given as follows:

$$q^* = \frac{2(2\gamma\rho + d - \gamma) + \psi(2\delta - \beta\rho)}{\beta\psi} \tag{14}$$

$$i^* = \frac{2\gamma\rho + d - \gamma}{2\gamma\rho + d - \gamma + \delta\psi} \tag{15}$$

Let us consider an economy initially in Ω_1. In this region, the likelihood of being infected is low enough that the utility of an antivaxxer is higher than that of a vaxxer, leading to an increase in the proportion of antivaxxers within the population over time. However, in this configuration, since the proportion of vaxxers is too low, on average, an infected individual infects more than one other individual, resulting in an increase in the number of infections. This increase is reinforced by the rise in the proportion of antivaxxers, leading the economy to transition to Ω_2.

In Ω_2, the level of infection is higher, making the probability of being infected quite high. As a result, the utility of a vaxxer becomes higher than that of an antivaxxer, leading to an increase in the prevalence of vaxxer opinions within the population. However, these decreases in the proportion of antivaxxers alone are not sufficient for altering the increases in the number of infected individuals, and the economy eventually transitions to Ω_3. In this regime, the decrease in the proportion of antivaxxers is now significant enough, resulting in a decrease in the number of infected individuals. Once this decrease in the number of infected individuals is quite important, the economy enters the Ω_4 regime, where the proportion of antivaxxers increases because, for this level of infection, the utility of antivaxxers becomes higher than that of vaxxers. However, in this region, the level of infection continues to decline because the proportion of vaxxers is quite high; then, the economy returns to Ω_1. We therefore observe that our economy is characterized by endogenous cycles, where the economy goes through periods of high and low infections. The emergence of oscillations in our model is closely related to the process of complementarity and substitutability dynamics between i_t and q_t. When the dynamics of these two variables are examined separately, each of them converges to a unique and globally stable steady state, as demonstrated in Sections 4.1 and 4.2. Therefore, our model highlights a new mechanism that can cause an epidemic to persist through the oscillatory dynamics related to the joint interplay between opinions and infections.

This finding supports the conclusions of Oster (2018), who highlights that vaccination can suffer from the paradoxical effect of its own success. As the level of disease incidence decreases with widespread vaccination, the benefits of vaccination become less apparent, leading to a decrease in public awareness of the importance of vaccination. This, in turn, can result in a reduction in the level of vaccination coverage, which may ultimately lead to disease resurgence (see also (Larson et al., 2018; Dubé et al., 2015; MacDonald et al., 2015)). In the specific context of COVID-19, Schwarzinger et al. (2021) find that the reduction in disease incidence due to successful vaccination campaigns can lead to a false sense of security and reduced vaccine uptake levels.

Local stability. The coevolution of infections and opinions has been shown to give rise to periodic cycles due to the intricate feedback effects between these two variables. A crucial issue is whether such oscillatory behavior converges toward a stable equilibrium as time goes to ∞. To address this question, we conduct a stability analysis of the steady state, denoted as E, in Fig. 3. More formally, by using Eqs. (9) and (10), we can rewrite q_{t+1} and i_{t+1} as a function of their lagged past values as follows:

$$\begin{cases} q_{t+1} = f(q_t, i_t) \\ i_{t+1} = g(q_t, i_t) \end{cases}$$

By differentiating these two equations in the neighborhood of the steady state E, we obtain the following:

$$\begin{pmatrix} q_{t+1} - q^* \\ i_{t+1} - i^* \end{pmatrix} = J \begin{pmatrix} q_t - q^* \\ i_t - i^* \end{pmatrix} \quad \text{with } J = \begin{pmatrix} f'_q(i^*, q^*) & f'_i(i^*, q^*) \\ g'_q(i^*, q^*) & g'_i(i^*, q^*) \end{pmatrix}$$

(16)

where J is the Jacobian matrix and the elements of the associated Jacobian matrix at the steady state are as follows:

$$f'_q(i^*, q^*) = 1 - \psi\beta i^* q^* \left(1 - q^*\right) \phi\left(\Delta V_t(i^*, q^*)\right) \tag{17}$$

$$f'_i(i^*, q^*) = -\psi\beta q^* \left(1 - q^*\right)(q^* + \rho)\phi\left(\Delta V_t(i^*, q^*)\right) \tag{18}$$

$$g'_q(i^*, q^*) = \frac{\beta i^*}{2}(1 - i^*) \tag{19}$$

$$g'_i(i^*, q^*) = 1 - \frac{\beta i^*}{2}(q^* + \rho) \tag{20}$$

The local stability properties of the model are determined by the eigenvalues of the Jacobian matrix J (or, equivalently, by its trace T and determinant D).[25] From there, we can easily obtain the following:

Proposition 2. *Under Assumptions 1–2, the steady state (E) of the joint dynamics of i_t and q_t is always stable.*

Proof. See Appendix C. ■

This proposition establishes that the economy, regardless of its initial state, ultimately reaches a steady state, denoted as E. Consequently, the current model assumptions imply that epidemics persist and do not collapse in the long run, as they eventually reach a stable endemic steady state. The intuition behind this result is that the joint dynamics of infection rates (i_t) and vaccination coverage (q_t) lead to the emergence of endogenous cycles, as illustrated in Fig. 3. However, it is evident from the figure that changes in infection rates and vaccination opinions are not perfectly synchronized due to threshold effects. For instance, let us consider the case where the economy is in zone Ω_1. Despite an increase in the degree of risk of infection due to an increase in i_t, the proportion of antivaxxers continues to rise because the degree of risk of infection is not large enough to induce a change in opinions vaccination. Therefore, there is a delay before individuals start changing their vaccination preferences based on infection levels. This delay causes the oscillations in the system to shift in terms of their timing. As time approaches infinity, this delay causes the cycles to dampen and stabilize around a certain level of infection and vaccination coverage. This result is consistent with those of previous studies on the dynamics of infectious diseases and their control. For example, Viboud et al. (2006) analyzed the dynamics of influenza outbreaks and found that epidemics tend to stabilize over time around a certain level of infections due to various factors, including immunity and behavioral changes.

Overall, our findings suggest that while the disease may persist in the long run, it eventually reaches an equilibrium, and the characteristics of this equilibrium depend on the structural parameters of the economy.[26]

Comparative statics. The findings of our study, as presented in Section 2, indicate a strong positive association between the vaccination behaviors of young and old individuals in departments which are characterized by high levels of antivaxxers. This association is consistent with the research conducted by Gauri and Khaleghian (2002), which highlights the influential role played by elderly individuals in promoting healthy behaviors, including vaccination. Acknowledging the significance of elderly individuals in encouraging vaccination practices can assist policy-makers and health care providers in developing more effective strategies through which to promote vaccination and to improve public health outcomes in developing societies, where vaccination coverage is generally low. This finding suggests that the successful implementation of the initial phase of vaccination, which caters to the most high-priority populations, such as elderly individuals, may be of great significance in achieving the optimal control of an epidemic.

In the comparative static exercises proposed here, we analyze the impact of an increase in the degree of vaccination coverage of elderly individuals on the joint dynamics of infections and beliefs about vaccination. In our setup, the impact of these measures can be captured by an exogenous decrease in the value of ρ on the steady-state level of i_t and q_t.

Let us first recall that the endemic equilibrium in our model is stable, irrespective of the parameter values, such that $(i^*, q^*) \in [0, 1]^2$. Then, under the current model assumptions, an increase in the vaccination rate among elderly individuals affects the long-term dynamics of our model through two main channels. The first channel operates through the utility function, and the second channel operates through the epidemic part of the model. A simple inspection of (14) and (15) brings us to the conclusion that the impact of ρ on the steady-state level of infections and opinions depends on the structural parameters of the model. Indeed, when γ is large enough $(4\gamma > \beta\psi)$, meaning that the influence of the elderly generation on the young population is high, when vaccination coverage among elderly individuals increases, via intergenerational peer effects, the utility of antivaxxers decreases and that of vaxxers increases, resulting in a downward shift in the $\hat{i}(q_t)$ curve. Thus, at a given $\hat{i}(q_t)$ value, the proportion of infected individuals and antivaxxers decreases at equilibrium. However, this reduction is reinforced by a second mechanism operating through the epidemic part of the model. Indeed, when ρ decreases, the size of the pool of susceptible individuals decreases, resulting in a downward shift in the $\hat{i}(q_t)$ curve. Combined, these two effects can lead to a considerable improvement in the endemic situation at the steady state. However, when γ is too low $(4\gamma < \beta\psi)$, individuals place more value on the risk of being infected. As a result, when ρ decreases, the probability of being infected decreases such that the relative benefit of being vaccinated compared to that of not being vaccinated becomes relatively weaker, leading to a higher proportion of antivaxxers in the long term so that a decrease in ρ is likely to have essentially moderate effects on reducing the steady-state level of infections.[27]

These results provide a rationale for the mixed findings regarding the impact of vaccination behavior among the older generation on that of the younger generation, as highlighted in Section 2. Specifically, in regions/areas where individuals may attach great importance to the choices of elderly individuals, an increase in the vaccination coverage rate of elderly individuals may lead to an increase in that of young individuals such that the steady-state level of infections is low. This result highlights the critical importance of early-phase vaccination behaviors in controlling epidemic diseases, especially in areas with low vaccination coverage rates.

5. Conclusions

Various economic models have been developed to examine the impact of individual actions and decisions on the transmission of COVID-19 when considering age heterogeneity. However, few studies have explored the relationship between vaccination decisions and individuals' opinions of vaccines, as well as how these opinions interact with epidemic dynamics. We fill this gap by proposing a simple theoretical framework, where there is an interplay between opinions of vaccines and infection dynamics. Our findings reveal that there is a mutual interplay between individuals' opinions of vaccination and the number of infections, which can lead to the emergence of endogenous

[25] See the technical Appendix of De La Croix and Michel (2002).

[26] Note that, when young and old have the same preferences, the model would not change, since in this configuration we could just aggregate the fraction of antivaxxers of the two demographic groups. Consequently, the evolution of opinions would be the same as the one obtained in (9), leading to the emergence of converging oscillations towards the endemic steady state. Thus, our results do not depend on the particular assumptions concerning the two generations and the intergenerational transmission of opinions.

[27] See Appendix D for graphical illustrations.

cycles. These cycles gradually dampen and stabilize over time around certain levels of infection and vaccination coverage.

Our contribution can thus be summarized in two main points. Firstly, endogenous views on vaccination can generate endemic disease, and secondly, the vaccination level of the elderly (or any other reference group) can be a variable used to adjust public policy, thus contributing to the debate on targeted epidemic control. Starting with the observation that the vaccination behaviors of young and old individuals appear to be interconnected in certain French departments, particularly in those with higher levels of vaccine hesitancy *ex-ante*, we investigate the impact of an increase in the proportion of vaccinated sub-groups as a policy choice. Our findings suggest that increasing this proportion (i.e. targeting the elderly) may have a greater impact on reducing the steady-state level of infections, highlighting the critical importance of early-phase vaccination behaviors in controlling epidemic diseases, especially in areas with low levels of vaccination coverage. Our model can also be interpreted as much more general and "externally valid" if we consider the elderly group as any "privileged" sub-group that would be perceived as a reference group and could be targeted by policies. Similarly, Verdier and Zenou (2015, 2018), consider other socialization agents or cultural leaders and their role in the transmission of preferences. Our results may also be valid for other infectious diseases for which vaccination at different ages is necessary, such as seasonal flu.

CRediT authorship contribution statement

Josselin Thuilliez: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing, Supervision. **Nouhoum Touré:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data are already open access.

Appendix A. Proof of Lemma 1

When $i_t < \bar{i}(q_t)$, according to Eq. (8), $\Delta V(i_t, q_t) > 0$ such that $\Phi\left(\Delta V(i_t, q_t)\right) > 1/2$. It directly follows from Eq. (9) that $\Delta q_t > 0$. When $i_t > \bar{i}(q_t)$, according to Eq. (8) and by definition of $\bar{i}(q_t)$, $\Delta V(i_t, q_t) < 0$ such that $\Phi\left(\Delta V(i_t, q_t)\right) < 1/2$. It directly follows from Eq. (9) that in this case, $\Delta q_t < 0$.

Appendix B. Proof of Lemma 2

To obtain this result, we set the right-hand side of the dynamic equation stated in (10) to zero and solve for i_t considering that $s_t = \frac{q_t+\rho}{2}(1 - i_t)$.

$$0 = \left(\beta\left(\frac{q_t+\rho}{2}(1-i_t)\right) - \delta\right) i_t \tag{B.1}$$

Eq. (B.1) admits two roots:

$$\begin{aligned} \tilde{i} &= 0 \\ \hat{i}(q_t) &= 1 - \frac{2\delta}{\beta(q_t+\rho)} \end{aligned}$$

It is easy to verify that $\Delta i_t < 0$ when $i_t > \hat{i}(q_t)$ and that $\Delta i_t > 0$ when $i_t < \hat{i}(q_t)$. Thus, $\hat{i}(q_t)$ is a globally stable steady state. Notably, $\hat{i}(q_t) < 0$ when $q_t < \bar{q}$ and $\hat{i}(q_t) > 0$ when $q_t > \bar{q}$. Therefore, if $q_t > \bar{q}$, then i_t converges to $\hat{i}(q_t)$, while if $q_t < \bar{q}$, then the economy converges to $\tilde{i}$.

Appendix C. Proof of Proposition 2

This proof is performed in two steps. First, we demonstrate that there exists a set of parameter values for which $\hat{i}(q_t)$ and $\bar{i}(q_t)$ cross at least once. Then, we analyze the local stability of the equilibrium in that case and prove that E is stable.

Points that are potential candidates to be a steady state. Simple inspection shows that the curve $\bar{i}(q_t)$ is decreasing and convex, while the curve $\hat{i}(q_t)$ is increasing and concave, implying that the two curves intersect at least once. The steady-state values of q_t that are candidates to be a crossing point between $\hat{i}(q_t)$ and $\bar{i}(q_t)$ might be obtained by equalizing $\hat{i}(q_t)$ and $\bar{i}(q_t)$; then, we obtain the following:

$$\psi\left(\beta(q_t+\rho) - 2\delta\right) - 2\left(\gamma(2\rho - 1) + d\right) = 0$$

The value of the q_t solution to this equation is as follows:

$$q^* = \frac{2(2\gamma\rho + d - \gamma) + \psi(2\delta - \beta\rho)}{\beta\psi}$$

with $q^* > 0$ under Assumptions 1–2. This root is associated with a steady-state level of infections that might be obtained by replacing q_t by q^* in the expression of $\hat{i}(q_t)$ or $\bar{i}(q_t)$. After some calculations, the expressions of i_* are reduced to the following:

$$i^* = \frac{2\gamma\rho + d - \gamma}{2\gamma\rho + d - \gamma + \delta\psi}$$

with $i^* > 0$ under Assumptions 1–2.

Local stability analysis. The stability properties of the steady state E can be analyzed by using the trace and determinant of the Jacobian matrix since the eigenvalues λ_1 and λ_2 are the roots of the following characteristic polynomial:

$$P(\lambda) = \lambda^2 - T\lambda + D = 0$$

where $T = f'_q(i^*, q^*) + g'_i(i^*, q^*)$ and $D = T = f'_q(i^*, q^*)g'_i(i^*, q^*) - f'_i(i^*, q^*)g'_q(i^*, q^*)$ are the trace and determinant, respectively, of the Jacobian matrix J.

In the continuous-time model, a sufficient condition for the local stability of a steady state is that the real parts of the eigenvalues for the Jacobian matrix be negative; and one sufficient condition for that in a 2×2 matrix is that $T < 0$ and $D > 0$ (see Meiss 2007, ch 2). However, in discrete-time models (as in this paper), the stability conditions are explained in terms of the modulus of the aforementioned eigenvalues. As stated in Medio and Lines (2001, p. 52),[28] we know that all eigenvalues of a 2×2 Jacobian matrix are lower than 1 in modulo provided that the following three conditions are satisfied:

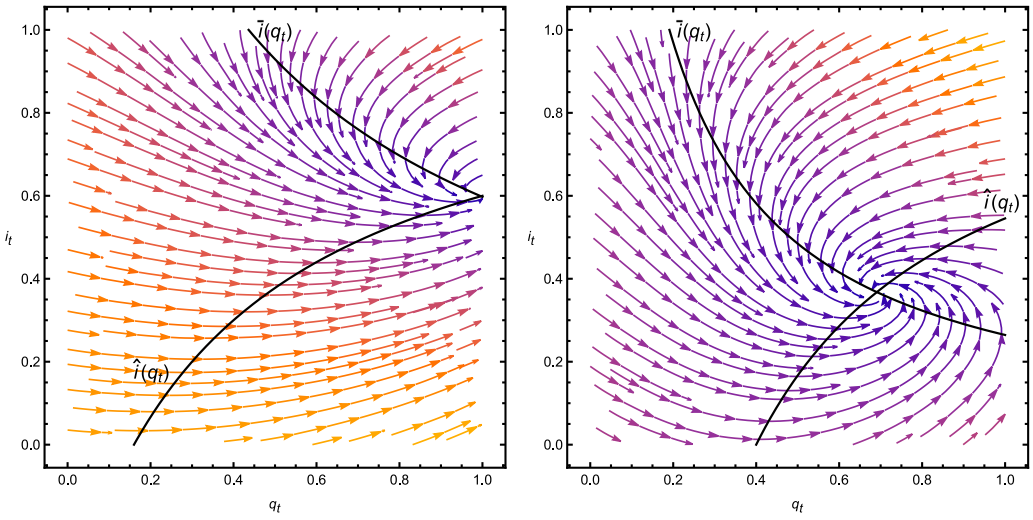
(i) $P(-1) > 0 \Leftrightarrow 1 + T + D > 0$
(ii) $P(1) > 0 \Leftrightarrow 1 - T + D > 0$
(iii) $1 - D > 0$

- Regarding the first condition, we have that

$$T = 2 - \beta i^* \frac{q^* + \rho}{2} - \psi\beta i^* q^*(1 - q^*)\phi(0) > 0 \tag{C.1}$$

$$D = \left\{1 - \psi\beta i^* q^*(1 - q^*)\phi(0)\right\} \times \left(1 - \beta i^* \frac{q^* + \rho}{2}\right)$$

[28] See also Croix and Michel (2002, pp. 321–322) and Galor (2007, pp. 87–91).



(a) When $\rho = 0.4$ (b) When $\rho = 0.2$ is low

Fig. D.1. Impact of ρ on the joint dynamics of q_t and i_t when $4\gamma > \beta\psi$. For the illustrations, we use $d = 0.55$, $\gamma = 0.50$, $\psi = 1.1$, $\delta = 0.4$, and $\beta = 1$.

$$+\frac{\beta}{2}(1-i^*)i^*\left\{\psi\beta(q^*+\rho)q^*(1-q^*)\phi(0)\right\} > 0 \tag{C.2}$$

Since $T > 0$ and $D > 0$, $P(-1) > 0$, implying that condition (i) is satisfied.

- We now have to check for the sign of $P(1) = 1 - T + D$. After some calculations, we obtain the following:

$$P(1) = \frac{\beta^2 i}{2} q^*(1-q^*)\psi(q^*+\rho)\phi(0) > 0$$

This condition holds under our current assumptions .

- Since $P(1) > 0$ and $P(-1) > 0$, the steady state is unstable when $D > 1$ or stable when $D < 1$. D is given by Eq. (C.2). Once this expression is developed, we obtain the following:

$$D = 1 - \frac{\beta}{2} i^*(q^*+\rho) - \beta\psi i^* q(1-q)\phi(0)\left\{\frac{2-\beta(q^*+\rho)}{2}\right\} < 1$$

It is straightforward to see that condition (iii) holds.

Given that conditions (i)-(iii) are satisfied, all eigenvalues of the Jacobian matrix are less than 1 in modulo so that the equilibrium (E) is stable. Moreover, those conditions also guarantee that no eigenvalue equals 1 in modulo and, thus, the hyperbolicity of the equilibrium.

Appendix D. Comparative statics: Graphical illustrations

See Figs. D.1 and D.2.

Appendix E. Elderly individuals' vaccination behaviors

Instead of assuming that ρ is exogenous, here, we model the vaccination behavior of elderly individuals. We assume that elderly people weigh the tradeoff between paying a fixed cost for vaccination (d^o), which represents their opinions/beliefs, and refusing to get vaccinated and thereby incurring a utility loss, denoted as ψ, in the event of infection. For young people, this utility loss increases linearly with their perceived probability of contracting the disease, expressed as $(q_t + \rho_t)\beta i_t/2$. We assume that the cost of vaccination for elderly individuals follows a uniform distribution, i.e., that $d^o \sim U[0, 1/k]$. When d^o is close to 0, the individual has positive opinions of vaccination, and when d^o is high, the individual is an antivaxxer. k represents the parameter characterizing the distribution of vaccination costs within the population. A higher k value implies lower vaccination costs, while a lower k value implies higher vaccination costs. Consequently, elderly individuals with a vaccination cost, $d^o > \beta\psi i_t(\rho_t + q_t)/2$, choose not to get vaccinated, whereas those with $d^o < \beta\psi i_t(\rho_t + q_t)/2$ opt for vaccination. Thus, we have that

$$\rho_t = 1 - F\left(1 - \frac{\beta\psi i_t(\rho_t + q_t)}{2}\right) \tag{E.1}$$

From this equation, we can determine the proportion of elderly individuals who remain unvaccinated:

$$\rho_t = \frac{2 - k\beta\psi i_t q_t}{2 + k\beta\psi i_t} \tag{E.2}$$

To ensure that $\rho_t \geq 0$ for any value of i_t and q_t, we assume that the parameter k is low enough:

Assumption 3. $k \leq 2/\psi\beta$

The proportion of vaccinated elderly individuals increases with the increases in the disease transmission rate (β), proportion of unvaccinated young people (q_t), and disease prevalence rate (i_t). Furthermore, when k increases, meaning that the perception of the cost of vaccination for elderly individuals decreases, ρ_t increases.

By using (9) and (10), we can now characterize the dynamic system that describes the joint dynamics of i_t and q_t when ρ_t is endogenous as follows:

$$\Delta q_t = q_t(1-q_t)\left\{2\Phi\left(\frac{2(d+\gamma) - \beta\psi i_t\left(1 + q_t + k(\gamma - d + 2q_t\gamma)\right)}{2 + k\beta\psi i_t}\right) - 1\right\} \tag{E.3}$$

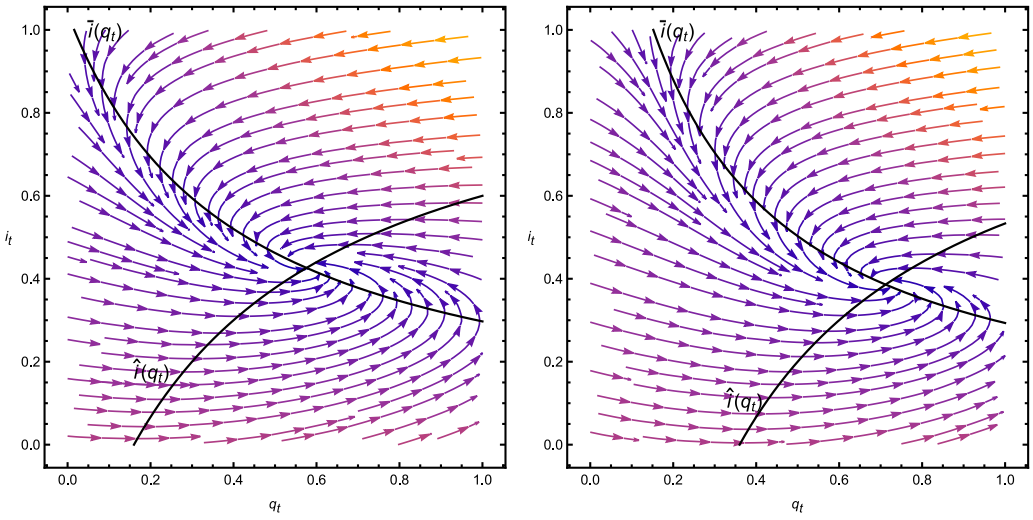
$$\Delta i_t = i_t\left(\frac{\beta\left((1+q_t)(1-i_t) - i_t k\delta\psi\right) - 2\delta}{2 + k\beta\psi i_t}\right) \tag{E.4}$$

A simple inspection of (E.3) and (E.4) brings us to the conclusion that this dynamic system has the same dynamic properties as those of the system we obtained in the core of the paper. Indeed, as in the baseline model, steady-states of the joint dynamics of i_t and q_t are given by the intersections of stationarity loci of these two variables.

(i) From (E.3), the proportion of antivaxxers is constant for $q_t = 0$, $q_t = 1$ or $i_t = \bar{i}(q_t)$ with $\bar{i}(q_t)$ now given in this extended framework by:

$$\bar{i}(q_t) = \frac{2(d+\gamma)}{\beta\psi\left\{1 - (d-\gamma) + q_t(1+2k\gamma)\right\}}$$

which is a decreasing and convex function of q_t. Moreover, if $i_t < \bar{i}(q_t)$, then $\Delta q_t > 0$: antivaxxers opinions spread within the population over time, and if $i_t > \bar{i}(q_t)$, then $\Delta q_t < 0$: vaxxers opinions spread within the population over time.



(a) When $\rho = 0.4$ (b) When $\rho = 0.2$

Fig. D.2. Impact of ρ on the joint dynamics of q_t and i_t when $4\gamma < \beta\psi$. For the illustrations, we use $d = 0.55$, $\gamma = 0.20$, $\psi = 2.5$, $\delta = 0.4$, and $\beta = 1$.

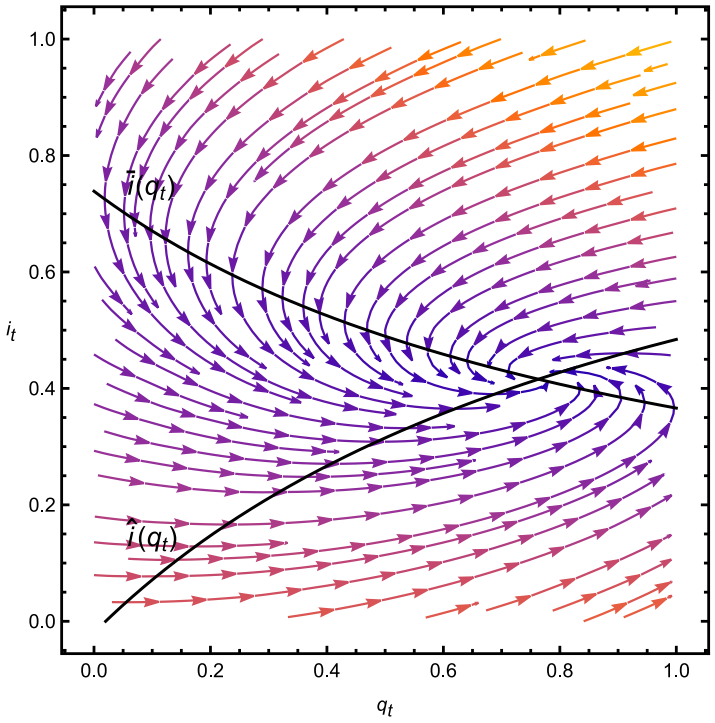


Fig. E.1. Joint dynamics of q_t and i_t when ρ is endogenous. For the illustration, we use $d = 0.20$, $\gamma = 0.15$, $\psi = 0.95$, $\delta = 0.51$, $\beta = 1$ and $k = 0.05$.

(ii) And from (E.4) it follows that, the proportion of infected people (i_t) remains invariant if $i_t = \tilde{i} = 0$ or $i_t = \hat{i}(q_t)$ with $\hat{i}(q_t)$ now given by:

$$\hat{i}(q_t) = \frac{\beta(1+q_t) - 2\delta}{\beta(1+q_t+k\gamma\psi)}$$

which is increasing and concave in q_t. From this, we can define the proportion of antivaxxer within the economy, denoted by $\bar{q} \equiv (2\delta - \beta)/\beta$ such that if $q_t > \bar{q}$, then $\Delta i_t > 0$: i_t converges to $\hat{i}(q_t)$ (endemic equilibrium) and if $q_t < \bar{q}$, then $\Delta i_t < 0$: i_t converges to $\tilde{i} = 0$.

In this extended framework, $\bar{i}(q_t)$ is decreasing and convex, while $\hat{i}(q_t)$ is increasing and concave. This implies that the two curves intersect at least once, allowing the joint dynamics of i_t and q_t to admit at least one steady state. Moreover, it follows from point (i) that when the level of infection is too high, people tend to get vaccinated, but when the level of infection is too low, the risk of being infected is quite low, and people do not get vaccinated (this result echoes Lemma 1). On the other hand, from point (ii), the higher the number of vaccinated individuals within the population, the fewer infected people there are (this result echoes Lemma 2). Therefore, as in the basic model, the joint dynamics of i_t and q_t lead to the emergence of oscillations. An intuitive representation of this dynamic result is highlighted in Fig. E.1.[29]

[29] The parameter values are selected to align with the model assumptions.

Hence, the results obtained in Propositions 1 and 2 hold unchanged, when we consider endogenous vaccination behaviors of the elderly population rather than the exogenous vaccination behaviors.

References

Acemoglu, D., Chernozhukov, V., Werning, I., Whinston, M.D., 2021. Optimal targeted lockdowns in a multigroup SIR model. Am. Econ. Rev. Insights 3 (4), 487–502.

Adhvaryu, A., 2014. Learning, misallocation, and technology adoption: Evidence from new malaria therapy in Tanzania. Rev. Econom. Stud. rdu020.

Alfano, V., Guarino, M., 2023. The effect of self-esteem on the spread of a pandemic. A cross-country analysis of the role played by self-esteem in the spread of the COVID-19 pandemic. Soc. Sci. Med. 324, 115866.

Amir, R., Boucekkine, R., 2022. Introduction to the special issue on new insights into economic epidemiology: Theory and policy. J. Public Econ. Theory 24 (5), 861–872.

Attema, A.E., L'Haridon, O., Raude, J., Seror, V., The COCONEL Group, Peretti-Watel, P., Seror, V., Cortaredona, S., Launay, O., Raude, J., Verger, P., Alleaume, C., Fressard, L., Beck, F., Legleye, S., L'Haridon, O., Ward, J., 2021. Beliefs and risk perceptions about COVID-19: Evidence from two successive French representative surveys during lockdown. Front. Psychol. 12.

Au, J., 2022. Higher vaccination rates predict reduction in SARS-CoV-2 transmission across the United States. Infection 50 (5), 1255–1266.

Auld, M.C., 2003. Choices, beliefs, and infectious disease dynamics. J. Health Econ. 22 (3), 361–377.

Bajos, N., Spire, A., Silberzan, L., Sireyjol, A., Jusot, F., Meyer, L., Franck, J.-E., Warszawski, J., The EpiCov study group, Bajos, N., Warszawski, J., Bagein, G., Counil, E., Jusot, F., Lydie, N., Martin, C., Meyer, L., Raynaud, P., Rouquette, A., Pailhé, A., Rahib, D., Sillard, P., Slama, R., Spire, A., 2022. When lack of trust in the government and in scientists reinforces social inequalities in vaccination against COVID-19. Front. Public Health 10.

Barber, A., West, J., 2022. Conditional cash lotteries increase COVID-19 vaccination rates. J. Health Econ. 81, 102578.

Bargain, O., Aminjonov, U., 2020. Trust and compliance to public health policies in times of COVID-19. J. Public Econ. 192, 104316.

Baril-Tremblay, D., Marlats, C., Ménager, L., 2021. Self-isolation. J. Math. Econom. 93, 102483, The economics of epidemics and emerging diseases.

Baudin, T., Hiller, V., 2019. On the dynamics of gender differences in preferences. Oxf. Econ. Pap. 71 (3), 503–527.

Benoit, S.L., Mauldin, R.F., 2021. The "anti-vax" movement: a quantitative report on vaccine beliefs and knowledge across social media. BMC Public Health 21 (1), 1–11.

Besley, T., 2017. Aspirations and the Political Economy of Inequality. Oxf. Econ. Pap. 69 (1), 1–35.

Besley, T., Ghatak, M., 2016. Market incentives and the evolution of intrinsic motivation. Unpublished manuscript. London School of Economics, London.

Besley, T., Ghatak, M., 2018. Prosocial motivation and incentives. Annu. Rev. Econ. 10, 411–438.

Besley, T., Persson, T., 2019a. Democratic values and institutions. Am. Econ. Rev. Insights 1 (1), 59–76.

Besley, T., Persson, T., 2019b. The dynamics of environmental politics and values. J. Eur. Econom. Assoc. 17 (4), 993–1024.

Betsch, C., Böhm, R., Chapman, G.B., 2015. Using behavioral insights to increase vaccination policy effectiveness. Policy Insights Behav. Brain Sci. 2 (1), 61–73.

Bezin, E., Moizeau, F., 2017. Cultural dynamics, social mobility and urban segregation. J. Urban Econ. 99, 173–187.

Bisin, A., Rubin, J., Seror, A., Verdier, T., 2021. Culture, Institutions & the Long Divergence. Technical Report, National Bureau of Economic Research.

Bisin, A., Verdier, T., 2001. The economics of cultural transmission and the dynamics of preferences. J. Econ. Theory 97 (2), 298–319.

Bisin, A., Verdier, T., 2011. The economics of cultural transmission and socialization. In: Handbook of Social Economics, vol. 1, Elsevier, pp. 339–416.

Bizzarri, M., Panebianco, F., Pin, P., 2023. Homophily and infections: static and dynamic effects.

Boucekkine, R., Carvajal, A., Chakraborty, S., Goenka, A., 2021. The economics of epidemics and contagious diseases: An introduction. J. Math. Econom. 93, 102498.

Boucher, V., Rendall, M., Ushchev, P., Zenou, Y., 2022. Toward a general theory of peer effects.

Brewer, N.T., DeFrank, J.T., Gilkey, M.B., 2016. Anticipated Regret and Health Behavior: A Meta-Analysis. Health Psychol. Off. J. Div. Health Psychol. Am. Psychol. Assoc. 35 (11), 1264–1275.

Brotherhood, L.M., Kircher, P., Santos, C., Tertilt, M., et al., 2021. An Economic Model of the Covid-19 Pandemic with Young and Old Agents: Behavior, Testing and Policies. Technical Report, CORE.

Cadeddu, C., Sapienza, M., Castagna, C., Regazzi, L., Paladini, A., Ricciardi, W., Rosano, A., 2021. Vaccine hesitancy and trust in the scientific community in Italy: comparative analysis from two recent surveys. Vaccines 9 (10), 1206.

Caserotti, M., Girardi, P., Rubaltelli, E., Tasso, A., Lotto, L., Gavaruzzi, T., 2021. Associations of COVID-19 risk perception with vaccine hesitancy over time for Italian residents. Soc. Sci. Med. 272, 113688.

Chevallier, C., Hacquin, A.-S., Mercier, H., 2021. COVID-19 vaccine hesitancy: Shortening the last mile. Trends in Cognitive Sciences 25 (5), 331–333.

Chodick, G., Tene, L., Rotem, R.S., Patalon, T., Gazit, S., Ben-Tov, A., Weil, C., Goldshtein, I., Twig, G., Cohen, D., Muhsen, K., 2021. The effectiveness of the TWO-DOSE BNT162b2 vaccine: analysis of real-world data. Clin. Infect. Dis. (ciab438).

Croix, D.d.l., Michel, P., 2002. A Theory of Economic Growth: Dynamics and Policy in Overlapping Generations. Cambridge University Press, Google-Books-ID: jrA4FjgsPxkC.

d'Albis, H., Etner, J., Thuilliez, J., 2022. Vaccination under pessimistic expectations in clinical trials and immunization campaigns. J. Public Econ. Theory.

Davin, M., Fodha, M., Seegmuller, T., 2021. Environment, public debt, and epidemics. J. Public Econ. Theory.

Day, T., Gandon, S., 2007. Applying population-genetic models in theoretical evolutionary epidemiology. Ecol. Lett. 10 (10), 876–888.

De La Croix, D., Michel, P., 2002. A Theory of Economic Growth: Dynamics and Policy in Overlapping Generations. Cambridge University Press.

Díaz, C., Patacchini, E., 2022. Parents, neighbors and youth crime. Rev. Econ. Househ. 1–20.

Du, E., Chen, E., Liu, J., Zheng, C., 2021. How do social media and individual behaviors affect epidemic transmission and control? Sci. Total Environ. 761, 144114.

Dubé, E., Vivion, M., MacDonald, N.E., 2015. Vaccine hesitancy, vaccine refusal and the anti-vaccine movement: influence, impact and implications. Expert Rev. Vaccines 14 (1), 99–117.

Dupas, P., Miguel, E., 2017. Chapter 1 - Impacts and determinants of health levels in low-income countries. In: Banerjee, A.V., Duflo, E. (Eds.), In: Handbook of Economic Field Experiments, vol. 2, North-Holland, pp. 3–93.

Fabbri, G., Federico, S., Fiaschi, D., Gozzi, F., 2023. Mobility decisions, economic dynamics and epidemic. Econom. Theory 1–37.

Galor, O., 2007. Discrete Dynamical Systems. Springer Science & Business Media.

Gauri, V., Khaleghian, P., 2002. Immunization in developing countries: its political and organizational determinants. World Dev. 30 (12), 2109–2132.

Geoffard, P.-Y., Philipson, T., 1997. Disease eradication: private versus public vaccination. Am. Econ. Rev. 222–230.

Gersovitz, M., Hammer, J.S., 2004. The economical control of infectious diseases*. Econ. J. 114 (492), 1–27.

Giulietti, C., Vlassopoulos, M., Zenou, Y., 2023. When reality bites: Local deaths and vaccine take-up. Eur. Econ. Rev. 156, 104463.

Goenka, A., Liu, L., 2012. Infectious diseases and endogenous fluctuations. Econom. Theory 50, 125–149.

Goenka, A., Liu, L., Nguyen, M.-H., 2014. Infectious diseases and economic growth. J. Math. Econom. 50, 34–53.

Gollier, C., 2020a. Cost–benefit analysis of age-specific deconfinement strategies. J. Public Econ. Theory 22 (6), 1746–1771.

Gollier, C., 2020b. If the objective is herd immunity, on whom should it be built? Environ. Resour. Econ. 76 (4), 671–683.

Greenwood, J., Kircher, P., Santos, C., Tertilt, M., 2019. An equilibrium model of the African HIV/AIDS epidemic. Econometrica 87 (4), 1081–1113.

Haas, E.J., Angulo, F.J., McLaughlin, J.M., Anis, E., Singer, S.R., Khan, F., Brooks, N., Smaja, M., Mircus, G., Pan, K., Southern, J., Swerdlow, D.L., Jodar, L., Levy, Y., Alroy-Preis, S., 2021. Impact and effectiveness of mRNA BNT162b2 vaccine against SARS-CoV-2 infections and COVID-19 cases, hospitalisations, and deaths following a nationwide vaccination campaign in Israel: an observational study using national surveillance data. Lancet 397 (10287), 1819–1829.

Hethcote, H.W., 2000. The mathematics of infectious diseases. SIAM Rev. 42 (4), 599–653.

Hiller, V., Wu, J., Zhang, H., 2022. Marital preferences and stable matching in cultural evolution. Available at SSRN 4327871.

Hirani, J.L.-J., 2021. Inattention or reluctance? Parental responses to vaccination reminder letters. J. Health Econ. 76, 102439.

Horne, Z., Powell, D., Hummel, J.E., Holyoak, K.J., 2015. Countering antivaccination attitudes. Proc. Natl. Acad. Sci. 112 (33), 10321–10324.

Itoh, R., Sato, Y., Zenou, Y., 2021. Intergenerational assimilation of minorities: The role of the majority group.

Khan, H., Dabla-Norris, M.E., Lima, F., Sollaci, A., 2021. Who Doesn't Want to Be Vaccinated? Determinants of Vaccine Hesitancy During COVID-19. International Monetary Fund.

Kim, D., Lee, Y.J., 2022. Vaccination strategies and transmission of COVID-19: Evidence across advanced countries. J. Health Econ. 82, 102589.

Larson, H.J., Clarke, R.M., Jarrett, C., Eckersberger, E., Levine, Z., Schulz, W.S., Paterson, P., 2018. Measuring trust in vaccination: A systematic review. Hum. Vaccines Immunother. 14 (7), 1599–1609.

Lieu, T.A., Ray, G.T., Klein, N.P., Chung, C., Kulldorff, M., 2015. Geographic clusters in underimmunization and vaccine refusal. Pediatrics 135 (2), 280–289.

Liu, X., Patacchini, E., Zenou, Y., 2014. Endogenous peer effects: local aggregate or local average? J. Econ. Behav. Organ. 103, 39–59.

Luo, S., Xin, M., Wang, S., Zhao, J., Zhang, G., Li, L., Li, L., Lau, J.T.-f., 2021. Behavioural intention of receiving COVID-19 vaccination, social media exposures and peer discussions in China. Epidemiol. Infect. 149.

MacDonald, N.E., et al., 2015. Vaccine hesitancy: Definition, scope and determinants. Vaccine 33 (34), 4161–4164.
Medio, A., Lines, M., 2001. Nonlinear Dynamics: A Primer. Cambridge University Press.
Meiss, J.D., 2007. Differential Dynamical Systems. SIAM.
Milman, O., Yelin, I., Aharony, N., Katz, R., Herzel, E., Ben-Tov, A., Kuint, J., Gazit, S., Chodick, G., Patalon, T., Kishony, R., 2021. Community-level evidence for SARS-CoV-2 vaccine protection of unvaccinated individuals. Nature Med. 1–3.
Neumann-Böhme, S., Varghese, N.E., Sabat, I., Barros, P.P., Brouwer, W., van Exel, J., Schreyögg, J., Stargardt, T., 2020. Once we have it, will we use it? A European survey on willingness to be vaccinated against COVID-19. Eur. J. Health Econ. 21, 977–982.
Olcina, G., Panebianco, F., Zenou, Y., 2017. Conformism, social norms and the dynamics of assimilation.
Oster, E., 2018. Does disease cause vaccination? Disease outbreaks and vaccination response. J. Health Econ. 57, 90–101.
Paetzold, J., Kimpel, J., Bates, K., Hummer, M., Krammer, F., von Laer, D., Winner, H., 2022. Impacts of rapid mass vaccination against SARS-CoV2 in an early variant of concern hotspot. Nature Commun. 13 (1), 612.
Patacchini, E., Zenou, Y., 2012. Juvenile delinquency and conformism. J. Law Econ. Organ. 28 (1), 1–31.
Paul, E., Fancourt, D., 2022. Predictors of uncertainty and unwillingness to receive the COVID-19 booster vaccine: An observational study of 22,139 fully vaccinated adults in the UK. Lancet Reg. Health - Europe 14, 100317.
Peretti-Watel, P., Verger, P., Raude, J., Constant, A., Gautier, A., Jestin, C., Beck, F., 2013. Dramatic change in public attitudes towards vaccination during the 2009 influenza A(H1N1) pandemic in France. Eurosurveillance 18 (44), 20623.
Philipson, T., 1996. Private vaccination and public health: An empirical examination for U.S. measles. J. Hum. Resour. 31 (3), 611–630.
Piedrahita-Valdés, H., Piedrahita-Castillo, D., Bermejo-Higuera, J., Guillem-Saiz, P., Bermejo-Higuera, J.R., Guillem-Saiz, J., Sicilia-Montalvo, J.A., Machío-Regidor, F., 2021. Vaccine hesitancy on social media: Sentiment analysis from June 2011 to April 2019. Vaccines 9 (1), 28.
Prieur, F., Ruan, W., Zou, B., 2022. Optimal lockdown and vaccination policies to contain the spread of a mutating infectious disease.
Pritchard, E., Matthews, P.C., Stoesser, N., Eyre, D.W., Gethings, O., Vihta, K.-D., Jones, J., House, T., VanSteenHouse, H., Bell, I., Bell, J.I., Newton, J.N., Farrar, J., Diamond, I., Rourke, E., Studley, R., Crook, D., Peto, T.E.A., Walker, A.S., Pouwels, K.B., 2021. Impact of vaccination on new SARS-CoV-2 infections in the United Kingdom. Nature Med. 1–9.
Raude, J., Lecrique, J.-M., Lasbeur, L., Leon, C., Guignard, R., du Roscoät, E., Arwidson, P., 2020. Determinants of preventive behaviors in response to the COVID-19 pandemic in France: Comparing the sociocultural, psychosocial, and social cognitive explanations. Front. Psychol. 11.
Reich, J.A., 2020. "We are fierce, independent thinkers and intelligent": Social capital and stigma management among mothers who refuse vaccines. Soc. Sci. Med. 257, 112015.
Rozenfeld, Y., Beam, J., Maier, H., Haggerson, W., Boudreau, K., Carlson, J., Medows, R., 2020. A model of disparities: risk factors associated with COVID-19 infection. Int. J. Equity Health 19 (1), 126.
Saied, S.M., Saied, E.M., Kabbash, I.A., Abdo, S.A.E.-F., 2021. Vaccine hesitancy: Beliefs and barriers associated with COVID-19 vaccination among Egyptian medical students. J. Med. Virol. 93 (7), 4280–4291.
Salali, G.D., Uysal, M.S., 2022. COVID-19 vaccine hesitancy is associated with beliefs on the origin of the novel coronavirus in the UK and Turkey. Psychol. Med. 52 (15), 3750–3752.
Salmon, D.A., Dudley, M.Z., Glanz, J.M., Omer, S.B., 2015. Vaccine hesitancy: Causes, consequences, and a call to action. Vaccine 33, D66–D71.
Schwarzinger, M., Watson, V., Arwidson, P., Alla, F., Luchini, S., 2021. COVID-19 vaccine hesitancy in a representative working-age population in France: a survey experiment based on vaccine characteristics. Lancet Public Health 6 (4), e210–e221.
Seow, J., Graham, C., Merrick, B., Acors, S., Pickering, S., Steel, K.J., Hemmings, O., O'Byrne, A., Kouphou, N., Galao, R.P., et al., 2020. Longitudinal observation and decline of neutralizing antibody responses in the three months following SARS-CoV-2 infection in humans. Nat. Microbiol. 5 (12), 1598–1607.
Shim, E., Chapman, G.B., Townsend, J.P., Galvani, A.P., 2012. The influence of altruism on influenza vaccination decisions. J. R. Soc. Interface 9, 2234–2243.
Touré, N., 2021. Culture, institutions and the industrialization process. J. Econ. Behav. Organ. 186, 481–503.
Tyson, R.C., Hamilton, S.D., Lo, A.S., Baumgaertner, B.O., Krone, S.M., 2020. The timing and nature of behavioural responses affect the course of an epidemic. Bull. Math. Biol. 82 (1), 14.
Verdier, T., Bisin, A., 2023. Advances in the economic theory of cultural transmission. Annu. Rev. Econ..
Verdier, T., Zenou, Y., 2015. The role of cultural leaders in the transmission of preferences. Econom. Lett. 136, 158–161.
Verdier, T., Zenou, Y., 2018. Cultural leader and the dynamics of assimilation. J. Econom. Theory 175, 374–414.
Viboud, C., Bjørnstad, O.N., Smith, D.L., Simonsen, L., Miller, M.A., Grenfell, B.T., 2006. Synchrony, waves, and spatial hierarchies in the spread of influenza. Science 312 (5772), 447–451.
Ward, C.J., 2014. Influenza vaccination campaigns: Is an ounce of prevention worth a pound of cure? Am. Econ. J. Appl. Econ. 6 (1), 38–72.
Wong, L.P., Alias, H., Danaee, M., Ahmed, J., Lachyan, A., Cai, C.Z., Lin, Y., Hu, Z., Tan, S.Y., Lu, Y., et al., 2021. COVID-19 vaccination intention and vaccine characteristics influencing vaccination acceptance: a global survey of 17 countries. Infect. Dis. Poverty 10 (1), 1–14.
Wooten, K.G., Wortley, P.M., Singleton, J.A., Euler, G.L., 2012. Perceptions matter: beliefs about influenza vaccine and vaccination behavior among elderly white, black and Hispanic Americans. Vaccine 30 (48), 6927–6934.
Yousefinaghani, S., Dara, R., Mubareka, S., Papadopoulos, A., Sharif, S., 2021. An analysis of COVID-19 vaccine sentiments and opinions on Twitter. Int. J. Infect. Dis. 108, 256–262.