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Incentives' Effect in Influenza Vaccination Policy

Dan Yamin
Department of Industrial Engineering and Management, Ben-Gurion University of the Negev,
Beer-Sheva 84105, Israel, yamind@bgu.ac.il

Arieh Gavious
Faculty of Business Administration, Ono Academic College, Kiryat Ono 55000, Israel; and
Department of Industrial Engineering and Management, Ben-Gurion University of the Negev,
Beer-Sheva 84105, Israel, ariehg@bgu.ac.il

In the majority of developed countries, the level of influenza vaccination coverage in all age groups is suboptimal. Hence, the authorities offer different kinds of incentives for people to become vaccinated such as subsidizing immunization or placing immunization centers in malls to make the process more accessible. We built a theoretical epidemiological game model to find the optimal incentive for vaccination and the corresponding expected level of vaccination coverage. The model was supported by survey data from questionnaires about people's perceptions about influenza and the vaccination against it. Results suggest that the optimal magnitude of the incentives should be greater when less contagious seasonal strains of influenza are involved and greater for the nonelderly population rather than the elderly, and should rise as high as $57 per vaccinated individual so that all children between the ages of six months and four years will be vaccinated.

Key words: influenza vaccination; game theory; incentive; SIR model; economic epidemiology
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1. Introduction

Influenza is the most common respiratory illness, leading to an annual infection rate of 5%–15% in developed countries. In the United States alone, more than 200,000 people are hospitalized every year due to influenza-related complications. Furthermore, about 1 in every 1,000 patients dies from the flu every year (Fiore et al. 2010). The disease is transferred from person to person, usually by coughing or sneezing. Healthy adults may infect others beginning one day before symptoms develop and up to five to seven days after the main symptoms disappear. On average, every eight years, as a result of a genetic shift in the virus, a more hazardous and contagious influenza type is reported.

In April 2009, a novel pandemic influenza A virus called H1N1, or swine flu, previously identified in pigs, was determined to be the cause of a respiratory illness that spread across North America and was identified in many areas of the world by May 2009. Deaths from influenza caused by the 2009 pandemic influenza were above seasonal baselines. This outbreak was considered the first pandemic since 1968.

The most efficient method for preventing influenza is through vaccination, which has an efficacy rate of 60%–90% (Fiore et al. 2010). Thus, in recent years, flu shots have been the focus of media attention and health service concerns. Vaccination protects against the most commonly expected types of influenza in the next season. Since influenza is a contagious disease, vaccination is vital in reducing mortality, not only for those who become vaccinated, but also for the entire population.

Lack of resources forces decision makers to prioritize those who should get vaccinated before others according to certain criteria. The U.S. Centers for Disease Control and Prevention (CDC) suggests that all individuals above the age of six months should get vaccinated, with the focus on high risk populations such as adults over 50 and children between six months and four years of age (Fiore et al. 2010). However, mathematical models show that different priorities based on age would improve results (Bansal et al. 2006, Funk et al. 2010, Galvani et al. 2007, Medlock and Galvani 2009, Miller et al. 2008, Patel et al. 2005, Tuite et al. 2010). Halloran and Longini (2006) suggested that immunization of just 20% of school children would do more in reducing overall mortality in adults over 65 years old than vaccinating 90% of these adults. Medlock and Galvani (2009) showed that in flu pandemics, there is a need to vaccinate the infants' parents as well. Accordingly, they suggest that an optimal influenza vaccination policy should also target individuals in the age range of 30 to 39.

A vaccinated individual reduces the probability of the infection spreading to the rest of the population. However, the decision about whether or not to take the vaccination is personal and does not necessarily take into account the group perspective. Moreover, different interpretations and misunderstandings about the severity of the disease and the vaccination in different cultures lead to different decisions by individuals and the authorities (Gazmararian et al. 2010, Poland 2010). From an individual perspective, vaccination is an unpleasant procedure that takes time and, in countries in which the vaccination is not funded, money. The vaccination is administered in medical centers either by injection or as a nasal spray. Commonly, mild sores near the injection area and influenza-like symptoms are reported in the first 48 hours after vaccination (Fiore et al. 2010). Several other factors such as religious and personal beliefs regarding vaccinations, the limited efficacy of the vaccine, the perceived probability of catching the flu, and media criticism result in the vaccination being perceived as less than desirable (Blank et al. 2009). In the context of personal healthcare decisions, individuals make their decisions based on their perceptions about the situation rather than the reality of the situation (Janz and Becker 1984). Thus, in spite of the various recommendations presented above about who should get vaccinated, in the majority of developed countries, the level of vaccination coverage in all age groups is suboptimal (Blank et al. 2009, Fiore et al. 2010, Mereckiene et al. 2008).

To define a national policy, one must first study the individual's decision-making process regarding vaccination. Fine and Clarkson (1986) distinguished between two motivations for becoming vaccinated: self-interests and the interests of society. Self-interests motivate individuals to act to maximize their own utility. In contrast, vaccination coverage based on the interests of the group maximizes the overall utility of society at large. However, when rationality is assumed, Fine and Clarkson (1986) showed that in a variety of epidemic conditions, the level of vaccination coverage motivated by self-interests was less than the level of vaccination coverage motivated by the interests of the group. The reason for the difference was the free-rider phenomenon. The choice to free ride and exploit the vaccination behavior of others reduced self-interests to a relatively low level of vaccination coverage. In this context, game theory provides an analytical framework for predicting the outcome of the conflict about becoming vaccinated (Funk et al. 2010). Using a game theory model, Galvani et al. (2007) analyzed self-interests versus utilitarian interests in situations of epidemic and pandemic influenzas. Through simulation studies, they showed that the interests of the group should promote the vaccination of the nonelderly, who are responsible for much of the transmission of the flu. In contrast, it is in the self-interests of the elderly to get vaccinated.

In the current study, we will examine self-interests versus group interests as a motivation for becoming vaccinated. In practice, group interests refer to the interests of the healthcare provider (hereafter, HCP). We will show that the gap between coverage based on self-interests and the optimal level of vaccination coverage can be reduced by a tailored incentive scheme offered to vaccinated individuals. We define incentives as any action taken by the authorities that may lead to an increase in the level of vaccination coverage. In practice, the incentives can take the form of funding vaccinations, providing financial remuneration to a vaccinated individual, placing immunization centers in malls or near places of work to make the process of vaccination more accessible, reimbursing hospitalization fees only to vaccinated individuals, or any other action such as those suggested by the Advisory Committee on Immunization Practices (ACIP) (Fiore et al. 2010).

An early research offering a general theoretical framework of vaccination and incentives was introduced by Brito et al. (1991). However, this research does not consider heterogeneous populations or any data. In the context of influenza, whereas previous studies pointed out the need for subsidizing vaccinations to prevent outbreaks (e.g., Galvani et al. 2007, Shim et al. 2010), no epidemiological model has ever studied the impact of incentives on the decision to take the influenza vaccination or the effect of that decision for either the individual or the welfare of society as a whole.

The current study suggests what the magnitude of such incentives should be to achieve an optimal vaccination policy. Moreover, we will also offer an economic point of view as to how to implement an incentive policy. Under several issues we will challenge the CDC's recommendations and offer an optimal incentive policy that will increase the level of vaccination coverage and maximize the welfare of society as a whole.

This study has three main objectives. First, it will introduce a new concept to the field of epidemiology that is more informative and more practical to use than the term "herd immunity." Our new concept describes the marginal contribution generated by a single additional vaccinated individual and provides the authorities with a simple managerial tool that will support their determination of an influenza vaccination policy. Second, the study seeks to prove analytically that for the benefit of the public as well as for the HCP, providing incentives to encourage vaccination is inevitable. The third goal is to determine the optimal magnitude of the incentives authorities need to offer in a given seasonal or pandemic outbreak of the flu and the corresponding level of vaccination coverage per age group. To accomplish those goals, we have built a dynamic, two-stage game theory model with complete information. In the model, we first assume that healthcare authorities announce the incentive that will be provided to a vaccinated individual. Then, every individual decides whether to accept or reject the vaccination. The model is based on epidemic and game theory. Numeric results obtained by simulations based on data from a survey conducted for this study. The survey was administered among a representative sample of the Israeli population and includes questions related to perceptions about influenza and vaccinations.

Our findings suggest that the contribution of one additional vaccinated individual is greater in less contagious types of influenza than in more contagious types. Along the same lines, results suggest that the magnitude of the incentive offered should be higher in seasonal strains of influenza rather than in pandemic strains. Furthermore, we show that in most cases, subsidizing only the cost of the vaccination may not be sufficient to motivate individuals to take the vaccine, and that further incentives should be offered to increase the level of vaccination coverage. Our model also suggests that socially optimal incentives to the vaccinated individuals should be as high as \$57.[1] Contrary to the CDC's policy of focusing on incentives to populations at higher risk (Fiore et al. 2010), our results suggest that greater incentives should be offered to those who serve as spreaders of the disease. These groups include in particular all children between six months and four years of age. Although it may seem that such a policy does not favor the elderly, the elderly will be the first to benefit, because the probability of infection in this subgroup will decline dramatically.

2. The Model

Like Bauch et al. (2003), we consider a nonatomic population game where the size of the population is scaled to one unit, and the effect of a single individual (player) on the others is negligible. In the model, we assume that all individuals are identical and have the same preferences. In addition, we consider a unique player whom we term the "social planner" (hereafter, SP), who is interested in maximizing the social welfare. The SP may encourage individuals to get the vaccine by offering an incentive $\pi \geq 0$ to every vaccinated individual. The model assumes the rationality of all players in the game, an assumption that is supported by our survey data analyses and widely discussed as a issue in our discussion. The sequence of the game starts with the SP announcing the amount of the incentive π that will be given to every vaccinated individual. Then, every individual decides whether or not to get vaccinated. Thus, the SP's strategy is to determine $\pi \geq 0$, and the individual's strategies are $\{accept, reject\}$. We let the individual players use mixed strategies where a player may *accept* the vaccine with probability p or *reject* it with probability $1-p$. The proportion of the population who choose to get the vaccine is the level of vaccination coverage. Notice that if all individuals use the same mixed strategy (i.e., the same p), the level of vaccination coverage is p.

Let $\phi(p)$ be the probability of an individual becoming infected if he or she is not vaccinated as a function of the level of vaccination coverage p. In §2.1 we will find a specific structure for $\phi(p)$ based on epidemic modeling. Currently, we assume that $\phi(p)$ is strictly decreasing with p. Let D_s be the overall financial cost of being sick as perceived by an infected individual. The cost includes the inability to function normally and other costs associated with the disease's symptoms, including possible complications. We assume that individuals are risk neutral, so the expected payoff (disutility) for an individual who chooses to *reject* the vaccination is given by

$$U(reject; p) = -D_s\phi(p). \tag{1}$$

Let D_v be the overall perceived cost incurred by an individual due to vaccination. The cost may include the price of the vaccination itself (if the vaccination program is not funded), loss of time, the individual's perceived disutility from an intramuscular injection, and the vaccination's side effects. Let π represent the financial investment of the SP to encourage vaccination, and let $q(\pi)$ represent the individual's utility from π. As is common in the economics literature (see, e.g., Fudenberg and Tirole 1991), we assume that $q(0) = 0$, $dq(\pi)/d\pi \geq 0$, and $d^2q(\pi)/d^2\pi \leq 0$, namely, q is increasing and concave (presenting a diminishing marginal benefit from the incentives).[2]

Note that one possible type of incentive is to provide a financial grant to those who choose to be vaccinated. Hence, we demand that $dq(\pi = 0^+)/d\pi \geq 1$. The expected payoff for an individual who chooses the *accept* vaccination strategy, given that the population's level of vaccination coverage is p, is

$$U(accept; p) = -D_v + q(\pi) - (1-r)\phi(p)D_s, \tag{2}$$

where r is the efficacy of the vaccination (i.e., the probability that the vaccination will be effective).

The SP is interested in minimizing its overall financial losses that result from the individuals' decisions. Alternatively, the SP may be a healthcare provider

[1] Hereafter, all prices are in U.S. dollars.

[2] Observe that $q(\pi)$ may be interpreted as an individual's risk aversion with respect to incentives.

interested in minimizing the overall costs associated with the flu. Let S_v and S_s represent the overall financial costs to the SP due to vaccinations and the illness of an individual, respectively. The expected payoff for the SP is defined as the overall financial costs due to vaccinations, illness, and the incentive granted to vaccinated individuals. Recall that p is also the vaccination coverage, and thus, scaling the population size to one unit, the SP's expected payoff is given by

$$U^{SP} = -p[S_v + \pi + (1-r)\phi(p)S_s] - (1-p)[\phi(p)S_s]. \quad (3)$$

We also define the overall social welfare utility U^{SW}, which is obtained by substituting $S_v = D_v$, $S_s = D_s$, and $\pi = 0$ in (3), reflecting the overall influenza burden to society, giving us

$$U^{SW} = -p[D_v + (1-r)\phi(p)D_s] - (1-p)[\phi(p)D_s]. \quad (4)$$

2.1. $\phi(p)$ and the Contribution of Vaccinations

In the current study, we use $\phi(p)$, which is obtained as a solution of the basic, susceptible-infected-recovered (SIR) epidemic model (e.g., Diekmann and Heesterbeek 2000). Let $S(t)$, $I(t)$, and $R(t)$ be the proportion at time t of susceptible, infectious, and recovered individuals, respectively, where $S(t)+I(t)+R(t)=1$. The model is given by the system of the three differential equations:

$$\begin{aligned}\frac{dS(t)}{dt} &= -\beta S(t)I(t),\\ \frac{dI(t)}{dt} &= \beta S(t)I(t) - \gamma I(t),\\ \frac{dR(t)}{dt} &= \gamma I(t),\end{aligned} \quad (5)$$

where β and γ represent the infectious and recovery rates, respectively. Note that in the basic SIR model, β/γ is equal to R_0, the number of secondary cases caused by a single infected case in a completely susceptible population (Diekmann and Heesterbeek 2000). For a susceptible individual, effective vaccination will progress the individual to the recovered compartment. The initial conditions are given by

$$\begin{aligned} S(0) &= 1 - i_0 - rp,\\ I(0) &= i_0,\\ R(0) &= rp,\end{aligned} \quad (6)$$

where i_0 represents the initial number of infected individuals.

Proposition 1. *The probability of a nonvaccinated individual becoming infected, $\phi(p)$, is given by*

$$\phi(p) = \begin{cases} 1 - \dfrac{\gamma}{\beta(-1+i_0+rp)} W\left(-\dfrac{\beta}{\gamma}(1-rp-i_0)e^{-(\beta/\gamma)(1-rp)}\right), \\ \qquad 0 \le p < 1-p-i_0; \\ 0, \quad \textit{otherwise}, \end{cases}$$

where $W(x)$ is the Lambert W function defined by the implicit function $x = We^W$.

Proof. See Appendix A. □

Corollary 1. *The probability of an individual becoming infected, $\phi(p)$ is monotonously decreasing, and for $R_0 > 1$ in a completely susceptible population, $\phi(p)$ has a single saddle point turning from concavity to convexity.*

Proof. By differentiation of $\phi(p)$ we find that the derivative is negative. A second differentiation and some algebraic manipulations yield the second result. □

In mathematical epidemiology, it is common to use the term *herd immunity threshold*, which represents the critical level of vaccination coverage needed to eradicate the disease (Diekmann and Heesterbeek 2000) and is given by[3]

$$p_{\text{herd}} = \frac{R_0 - 1}{rR_0}. \quad (7)$$

In practice, the level of influenza vaccination coverage worldwide is below the "herd immunity" level. Therefore, decision makers should determine the marginal contribution of a vaccinated individual given a particular level of vaccination coverage, rather than the level of vaccination coverage above which the marginal contribution of a vaccinated individual will be close to zero (i.e., herd immunity). Since the cost of incentives should be bounded by their benefits, knowing this contribution can be helpful in determining a cost-effective incentive policy.

To that end, we introduce a new parameter called the NIS, the number of individuals saved from becoming infected as a result of a single additional immunized individual. The NIS due to the first vaccinated individual is different from the NIS of those vaccinated later on, because the NIS depends on the proportion of the population that already took the vaccine. To find the NIS, we calculate the number of infected people when a single additional individual is vaccinated minus the number of infected people without the additional vaccinated individual. The NIS[4] is defined by

$$\begin{aligned}\text{NIS}(p) &= -\lim_{\Delta p \to 0} \frac{\phi(p+\Delta p)[1-i_0-r(p+\Delta p)] - \phi(p)(1-i_0-rp)}{\Delta p}\\ &= -\frac{d\phi(p)}{dp}(1-i_0-rp) + \phi(p)r.\end{aligned} \quad (8)$$

[3] If $p \ge p_{\text{herd}}$, the disease will be eradicated.

[4] In mathematical epidemiology, the term *attack rate* represents the total number of infected people (Diekmann and Heesterbeek 2000). The NIS can be also defined as the derivative with respect to p of the attack rate.

The NIS is composed of the sum of two components: the self-interest component $\phi(p)r$ and the altruistic component $(-d\phi(p)/dp)(1-i_0-rp)$. Both can be written in terms of the Lambert W function. The component $\phi(p)r$ in (8) represents the marginal contribution of a vaccinated individual in reducing the probability of becoming infected himself, whereas $(-d\phi(p)/dp)(1-i_0-rp)$ represents the marginal contribution to the entire population. From (8), we see that the self-interest component declines with p, whereas the altruistic component might increase. This is why the free-rider phenomenon is common and incentives for vaccination are necessary. Along the same lines, numeric simulations presented later suggest that the higher the level of vaccination coverage, the greater the marginal contribution, and therefore the greater the incentive should be for vaccination. Numeric simulations presented later emphasize that the incentive policy should depend not only on the virulence of the influenza strain, but also on the predicted level of vaccination coverage in the region. Results demonstrate that greater incentives should be provided in regions where the level of vaccination coverage is higher. This finding contradicts the approach that does not distinguish between states with regard to their incentive policy. For example, the ACIP publishes the same recommendations to cope with flu outbreaks for all of the states in the United States (Fiore et al. 2010).

3. Equilibrium and Optimal Outcomes for Society

In this section, we show analytically that providing incentives to vaccinated individuals will always improve the individual's utility, the welfare of society in general, and the healthcare provider's utility regardless of the parameters of the influenza epidemic.

We start with the case in which no incentive is provided, namely, $\pi = 0$, which leads to $q(0) = 0$, and find the level of vaccination coverage in equilibrium. Given that all individuals have the same payoff function, we look for a symmetric equilibrium in which all players take the vaccine with the same probability p. If a relatively small proportion of the population is vaccinated, the probability of infection will be high, so an individual will be motivated to get vaccinated. On the other hand, if a relatively large proportion of the population gets vaccinated, individuals have less motivation to become vaccinated. We look for a level of vaccination coverage, p_{eq}, in which individuals will be indifferent as to whether to accept or reject the vaccination. That level of vaccination coverage is also the mixed strategies Nash equilibrium in the game.

Proposition 2. *When no incentive is offered, there is a unique, symmetric Nash equilibrium given by*

$$p_{eq} = \begin{cases} \phi^{-1}\left(\dfrac{D_v}{rD_s}\right), & \phi(0) > \dfrac{D_v}{rD_s}; \\ 0, & \text{otherwise}, \end{cases} \tag{9}$$

where ϕ^{-1} is the inverse function of ϕ.

Proof. In a mixed strategies equilibrium, a player is indifferent about alternatives, and thus $U(accept; p_{eq}) = U(reject; p_{eq})$. Substituting $q = 0$ and solving for p_{eq} yields the result. Since $\phi(p)$ is a monotonically decreasing function with p, and the expression D_v/rD_s is constant, if there exists p in which $\phi(p) = D_v/rD_s$, it is necessarily unique. Otherwise, $p_{eq} = 0$, meaning that players will play the pure strategy *reject*. □

It is worthwhile stating some of the characteristics of p_{eq}.

Corollary 2. *The equilibrium vaccination coverage p_{eq} increases with the vaccine's efficacy r and the cost of the disease D_s, and decreases with the cost of the vaccine D_v.*

Proof. Since $\phi(x)$ is a monotonically decreasing function and D_v/rD_s decreases with r and D_s and increases with D_v, the result follows from (9). □

After finding the equilibrium vaccination coverage, p_{eq}, we look for the socially optimal vaccination coverage, p_{opt}, that maximizes the social welfare utility U^{SW} given in (4).

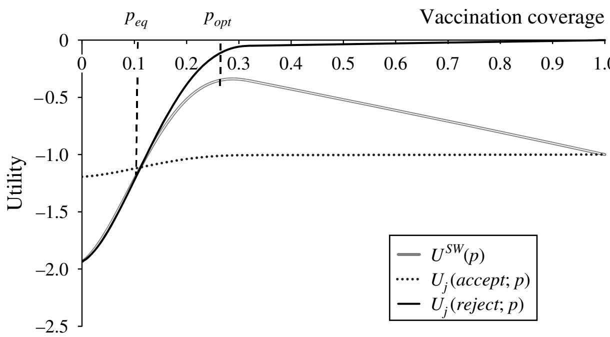
Proposition 3. *If $p_{eq} > 0$, then $p_{opt} > p_{eq}$.*

Proof. See Appendix B. □

Note from Corollary 2 that a necessary condition for $p_{eq} > 0$ is that $D_v < D_s$. In other words, the perceived costs due to vaccination are less than the perceived costs due to infection. This assumption is supported by the vast majority of our interviewees and the litrature (e.g., Armstrong et al. 2001, Fisher et al. 2011, Steiner et al. 2002, Blank et al. 2009, Kee et al. 2007). Later we will discuss the issues of this assumption.

Figure 1 demonstrates the result in Proposition 3. In the figure, the point at which U^{SW} reaches its maximum represents the optimal payoff for society when the optimal level of vaccination coverage, p_{opt}, is achieved. The intersection of the three functions represents the payoff when the level of vaccination coverage in equilibrium, p_{eq}, is achieved. Observe that indeed $p_{eq} < p_{opt}$. The simulations presented below show that the gap in vaccination coverage between self-interests (p_{eq}) and group interests (p_{opt}) can range from 7.5% to 38%. The gap is wider when dealing with less contagious and less hazardous types of influenza.

Figure 1 Curves Depicting $U(reject; p)$, $U(accept; p)$, and U^{SW} as a Function of Vaccination Coverage p



We continue with the more general case in which the SP can offer incentives to vaccinated individuals who took the vaccine. We let the SP's utilities diverge from the private case in which the payoff is U^{SW} presented in (4) to the general case in which the payoff is U^{SP} presented in (3). We look for an optimal incentive policy that maximizes the SP's utility and the corresponding level of vaccination coverage. Recall that the game starts with the SP announcing the magnitude of the incentive that will be given to an individual who decides to take the vaccine. Then, every individual chooses whether or not to accept the offer. Thus, the model is described as a dynamic, two-stage game with complete information. One can predict the game's results by finding the subgame perfect Nash equilibrium (π^*, p_{SGP}), where π^* is the planner's optimal incentive given that all individuals play according to $p_{SGP} = p_{SGP}(\pi)$, which is the individual's best response in mixed strategies given an incentive π.

Proposition 4. *There exists a symmetric subgame perfect Nash equilibrium $(\pi^*, p_{SGP}(\pi))$, where*

$$p_{SGP}(\pi)=\begin{cases}\phi^{-1}\left(\dfrac{D_v-q(\pi)}{rD_s}\right), & r\phi(0)D_s>D_v-q(\pi);\\ 0, & \text{otherwise.}\end{cases}$$

Proof. We solve by backward induction (e.g., Fudenberg and Tirole 1991). Given any incentive π, the level of vaccination coverage in equilibrium, $p_{SGP}(\pi)$, is found using a procedure similar to that used in Proposition 2. For all possible values of π, π^* optimizes the SP's utility function U^{SP}. □

Given that there is no analytic solution for $(\pi^*, p_{SGP}(\pi))$ and $q(\pi)$ is unknown, the next step is to find the conditions in which the optimal incentive is a positive value, (i.e., $\pi^* > 0$) for any set of realistic parameters. Those conditions are related to the ratio of costs and of effective vaccination coverage as follows:

Corollary 3. *If $D_v > S_v$ and $rp_{eq}/(1-rp_{eq}) < S_s/D_s$, then $p_{SGP} > p_{eq}$ and $\pi^* > 0$.*

Proof. See Appendix C. □

Table 1 Parameters Used in the Simulation Analyses

Symbol	Meaning	Range checked	Justification
R_{eff}	Effective basic reproductive ratio	1–1.8	Fraser et al. (2009), McCaw et al. (2009), and Barnea et al. (2011)
i_0	Initial fraction of infectious	10^{-4}–10^{-3}	Galvani et al. (2007)
s_0	Initial fraction of susceptibility	0.3–1	Estimated using Pitzer et al. (2007), Katriel et al. (2010), and Huppert et al. (2012)
r	Efficacy of vaccination	0.5–0.9	Fiore et al. (2010)
D_s	Perceived financial costs due to illness	\$100–\$150	Appendix D
D_v	Perceived financial costs due to vaccination	\$20–\$50	Appendix D
S_s	Financial loss to HCP due to illness	\$200–\$240	Ryan et al. (2006)
S_v	Financial loss to HCP due to vaccination	\$15–\$25	Burch et al. (2009)
a	Relative risk aversion	0–0.4	This paper

When estimating the parameters for the HCP (see Table 1), we find that $D_v > S_v$ and $S_s > D_s$ and that the effective level of vaccination coverage is less than 50%. These empirical results satisfy the two conditions. From Corollary 3 we can infer that offering incentives is essential in order to increase the HCP's utility. In addition, such incentives will increase the level of vaccination coverage, improve the utility of those motivated by self-interests, and benefit society at large. Simulation studies (see §4) conducted among a vast array of different strains of influenza show that up to 70% of the gap in vaccination coverage between those motivated by self-interests and the optimal social welfare can be overcome by providing the optimal incentives.

4. Data Set and Simulation Analysis

In this section, we present the results obtained in the simulation studies based on the model suggested above. The model includes epidemic parameters as well as economic parameters. Both were estimated based on the relevant literature and a survey conducted for the current study. First, we present the survey and the parameters used in the analysis of our model. Then, we present the simulations that cover the following three problems:

1. the marginal contribution of a vaccinated individual (the NIS presented in Equation (8)) for homogeneous and heterogeneous populations;
2. the level of vaccination coverage and the optimal incentive provided in a homogeneous population (p_{eq}, p_{opt}, p_{SGP}, and π^* in Propositions 2 and 4 and Theorem 3);

3. the level of vaccination coverage and the optimal incentives provided in a heterogeneous population; in this section, we investigate the case of two subgroups: the elderly versus others and children versus others.

We conducted the simulation studies and the interviewer's data analysis using Mathematica 7 and SPSS 16, respectively.

4.1. Data Set and Parameters

To evaluate the missing parameters related to individual perceptions about influenza and to verify the findings presented in the preceding section, we conducted a telephone survey in Israel. Questions related to costs were asked in terms of Israeli currency, the shekel, which was equal to \$0.28 at that time. According to the Israeli Central Bureau of Statistics (2010), the median salary for a household in Israel was about 11,000 shekels (about \$3,080) per month at that time.

In March 2011, the B. I. and Lucille Cohen Institute for Public Opinion Research conducted the survey. The date was chosen to mitigate the issue of time bias as much as possible, because it was the end of the flu season.[5] The survey posed short answer and multiple choice questions. In the latter, all of the questions were blended to prevent placement deviation. The sample included 917 individuals over 18 years of age from a representative sample of Israeli households. To obtain a representative sampling, we used data from the Israeli Central Bureau of Statistics to divide the Israeli population into statistical layers based on sociodemographic characteristics such as geographic region of residence, length of time in the country, level of religious observance, and socioeconomic levels (salary and formal education). We then selected a random sample size from each layer proportional to its representation in the population. Double blind interviews were conducted in the sense that the pollsters did not know the layer to which their interviewee belonged. Interviews were conducted in Hebrew, Russian (to make the sample more representative, especially among older immigrants from the former Soviet Union who were not Hebrew speakers), and Arabic. In cases in which there was no answer on the phone, the pollsters called up to five times within a period of three weeks. If the recall procedure was not successful by the fifth time, another individual from the same statistical layer was chosen. Of the 917 interviewers, 83 proved to be unavailable. Of that sample, 364 refused to participate in the poll, leaving us with a final total of 470 interviewees (a response rate of 56.7%). Of them, 192 were older than 50 years of age, and 244 were parents of children under 18 years old. Questions about these children were directed to their parents. If a parent had more than one child, each parent was asked questions about one of the children. With regard to the children, 90 of them were under or equal to four years of age, and 144 were over four. When formulating the survey questions, we consulted Weinstein et al. (2007). They suggested that in the case of influenza vaccination, questions designed to assess perceived risk that were phrased in terms of feelings were better predictors than those phrased as purely cognitive probability judgments. Accordingly, the questions where formulated. The relevant questions from the survey and our method for estimating the parameters from those questions are detailed in Appendix D. All parameter values used in our model are presented in Table 1.

4.1.1. Perceptions About Self-Interests. The basic assumption in game theoretical models is that players are rational. This assumption allowed us to determine the level of vaccination coverage based on self-interests, p_{eq}. Recall from Proposition 2 that p_{eq} in equilibrium was found to be a function of the perceived costs of getting vaccinated, D_v, the perceived costs of getting sick, D_s, the actual efficacy of the vaccination, r, and the probability of infection, $\tilde{\phi}$. To support our assumption regarding rationality, we checked to see if, indeed, those parameters affected people's decisions. We asked our interviewees several questions to assess their perceptions about the above parameters (see Appendix D). We divided the data into four age groups: 0–4 years, 5–18 years, 19–65 years, and over 65. Of these age groups, 26.6% (24), 23.61% (34), 22.2% (86), and 41.17% (28) stated that they intended to take the vaccine (or vaccinate their children) in the upcoming season regardless of any incentives provided by the authorities to encourage vaccination. However, regardless of the age group, the estimators of the perceived values of $\tilde{\phi}$, D_s/D_v, and r calculated by the data from the survey were significantly correlated with the decision of an individual to accept or reject vaccination (P-value < 0.01). We also formulated a binary logistic regression for the question about whether an individual intended to take or refuse the vaccination in the upcoming season. The regression is as follows:

$$p = \frac{\exp(\beta_0 + \beta_1(D_s/D_v) + \beta_1 r + \beta_2\tilde{\phi} + \varepsilon)}{[\exp(\beta_0 + \beta_1(D_s/D_v) + \beta_1 r + \beta_2\tilde{\phi} + \varepsilon) + 1]}, \quad \text{where } \varepsilon \sim N(0, \sigma_\varepsilon^2),$$

where β_i are the coefficient values Ds/D_v, r and $\tilde{\phi}$ represent the independent variables and the probability of getting vaccinated, and p represents the dependent variable. Regression results suggest that these three estimators are strong predictors of who

[5] According to the Israeli Centers for Disease Control and Prevention's "Surveillance of Influenza-Like Illness in Israel," the infection rate was fewer than 5 people per 10,000; see http://www.old.health.gov.il/pages/default.asp?pageid=5312&parentid=507&catid=78&maincat=25 (accessed April 26, 2013).

intends to get the vaccination (P-value < 0.001), providing an 87.74% correct classification.[6] Hence, the logistic regression suggests that individuals tend to make their decisions based on benefits and disadvantages to their self-interests, which they assess in light of the risks they perceive. Those three dependent variables are central to most health-specific behavioral theories including the "health belief modeling," "protection motivation theory," and the "extended parallel process model" (Brewer et al. 2007).

4.1.2. Individuals' Utility Function. The next step is to describe the individual's utility from the incentive π provided by the HCP, $q(\pi)$. We looked for a subsidy function that describes consumption and satisfies the conditions of $q(\pi)$ (namely, $q(0) = 0$, $dq(\pi)/d\pi \geq 0$, $d^2q(\pi)/d^2\pi \leq 0$, and $dq(\pi = 0^+)/d\pi \geq 1$). We chose the isoelastic function, $q(\pi) = \pi^{(1-a)}/(1-a)$, which is used in the context of incentives (Holt and Laury 2002) where a is a parameter that reflects the change in the perceived value of the incentives by the individuals. Note that if $a = 0$, $q(\pi) = \pi$. Given that the value of a is unknown, we conducted simulation analyses of a broad spectrum of parameters. For example, simulations were created in which a \$50 incentive offered by the SP was perceived as \$17 and up to \$50 when a equaled 0.4 and 0, respectively.

4.2. NIS Analysis

In §2.1, we argued that the marginal contribution of one additional vaccinated individual is important in understanding the relevance of incentives. In this section, we calculate the NIS and demonstrate its importance.

Pandemic influenza does not inherently have a higher R_0 than seasonal flu because the population's immunity might be lower than with seasonal flu (Barnea et al. 2011, Katriel and Stone 2010). In the case of influenza, it is possible that part of the population has been exposed in the past to the specific type of flu. Therefore, not all vaccinated individuals are susceptible. In this case, the effective basic reproductive ratio is $R_{eff} = R_0 S_0$, where S_0 represents the initial susceptible proportion of the population.

One may expect that in cases of more contagious influenza strains (i.e., in terms of a higher R_{eff}),[7] an infected individual might easily infect others. Therefore, it seems that a vaccinated individual would protect more individuals the more contagious the influenza strains are. However, the simulations contradict that intuition.

The simulations (Figure 2, panels (A) and (B)) show that as long as the level of vaccination coverage is less than herd immunity, the NIS is higher in the case of less contagious types of influenza ($R_{eff} = 1.2$) than in more contagious ones. In panel (A), in which we assume that the vaccination efficacy is equal to 80% (i.e., $r = 0.8$), the NIS ranges between 0.82 and 1.12 individuals. When vaccination efficacy is assumed to be 60%, the NIS for p below p_{herd} declines and ranges between 0.63 and 0.81 individuals, as shown in panel (B).

The second insight gained from the numeric simulations is that as long as the level of vaccination coverage is less than herd immunity, the higher the level of vaccination coverage, the greater the NIS. For example, at the end of January 2010, H1N1 vaccination rates in the United States ranged from 12.9% in Mississippi to 38.8% in Rhode Island. One might conclude from this data that stronger incentives to become vaccinated should be provided in Mississippi than in Rhode Island. However, in Mississippi, the NIS due to an additional vaccinated individual was less than that for an additional vaccinated individual from Rhode Island (Figure 2, panels (A) and (B)). Given that incentives should be bounded by their benefits, greater incentives should be considered in Rhode Island.

As noted in the former section, the NIS is made up of two components: self-interests and altruism. Panels (C) and (D) of Figure 2 present the NIS and the corresponding two components for $R_{eff} = 1.2$ and $R_{eff} = 1.6$. In all strains of influenza in the range of $1 \leq R_{eff} \leq 1.8$ and $0.3 \leq S_0 \leq 1$, that is, epidemic and pandemic influenza such as H1N1, a vaccinated individual contributes to the well-being of the group more than he contributes to himself. Moreover, as long as the level of vaccination coverage is less than herd immunity, the contribution of a vaccinated individual to himself decreases with p, whereas his contribution to society at large increases with p. The self-interest of the individual to get vaccinated is lower in regions where a high level of vaccination coverage is expected. However, the group interests increase with p. That insight explains why, economically, the HCP should provide greater incentives in Rhode Island than in Mississippi. When we simulated the NIS in the heterogeneous model, we found that the NIS of children ranged between one and up to four individuals with the same three trends discussed above for the homogeneous population. In contrast, the effect of a single vaccinated elderly person on others is relatively low. As a result, the NIS of the elderly declines when there is a higher level of vaccination coverage and rises with R_{eff} (see Appendix E).

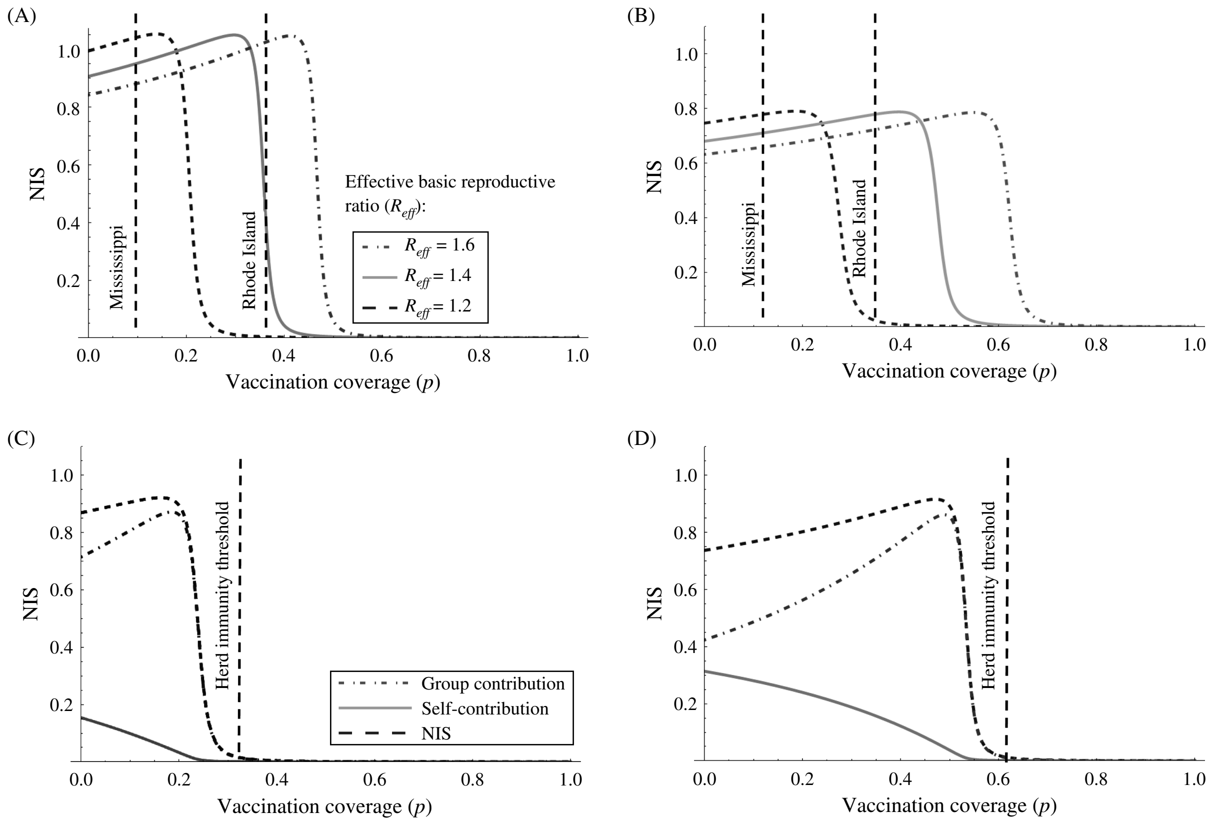
4.3. Optimal Incentives—The Homogeneous Population

In the preceding section, we focused our discussion on three cases involving different levels of vaccination

[6] About 30% declared that they would take vaccination in the upcoming influenza season.

[7] Here we assume higher basic reproductive ratio for any given fraction of susceptible individuals, S_0 in the range $[0.3, 1]$.

Figure 2 Number of Individuals Saved (NIS) Due to an Additional Vaccinated Individual as a Function of Vaccination Coverage for Different Values of R_{eff}



Notes. In panels (A) and (B), the vaccination's efficacy is 0.8 and 0.6 respectively for different values of R_{eff}. In panels (C) and (D), the efficacy of the vaccination is 0.7, and R_{eff} equals 1.2 and 1.6, respectively. The vertical dashed lines in panels (A) and (B) represent an example of the reported vaccination coverage in Mississippi and Rhode Island for the 2009 H1N1 pandemic influenza season. The vertical dashed lines in panels (C) and (D) represent the vaccination coverage that would lead to eradication of the disease, namely, the herd immunity threshold.

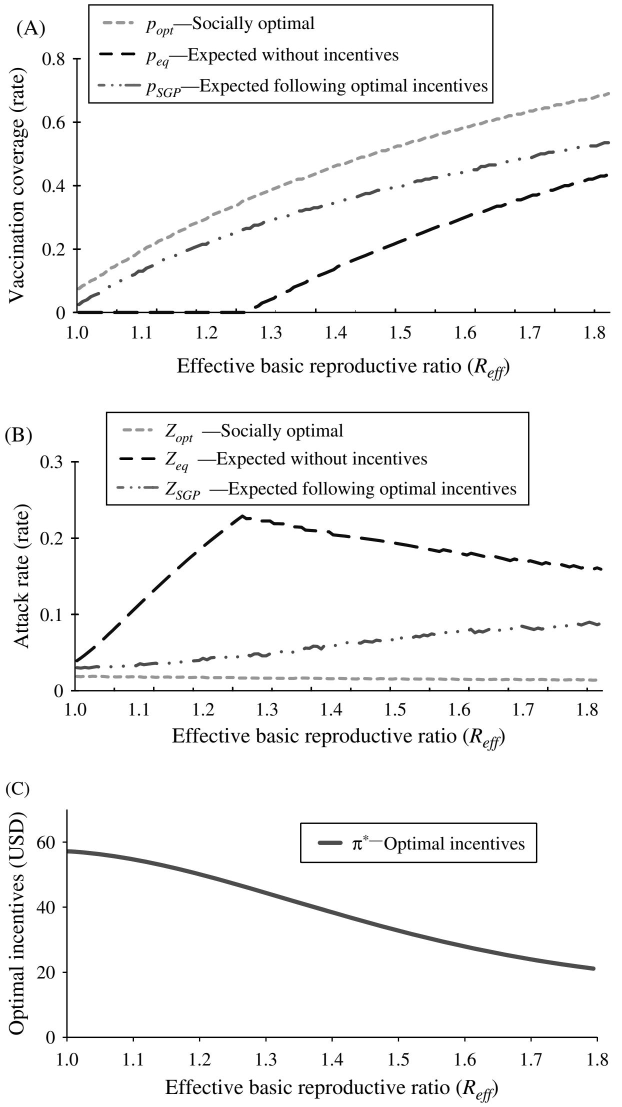
coverage: p_{eq}, p_{opt}, and p_{SGP} for all range of parameters suggested in Table 1. The three panels in Figure 3 summarize the simulation results based on Table 1.

Panel (A) of Figure 3 represents the three levels of vaccination coverage p_{eq}, p_{opt}, and p_{SGP} as a function of the effective basic reproductive ratio, R_{eff}. Panel (B) represents the corresponding expected attack rate (i.e., the expected rate of infection among the entire population), given those three levels of vaccination coverage. Panel (C) represents the optimal incentives that lead to the corresponding level of vaccination coverage, p_{SGP}.

The optimal level of vaccination coverage ranges between 7.5% and 68.5%, whereas the gap between the two ranges between 7.5% and 38%. Panel (B) of Figure 3 reveals that when incentives are not provided and only pure self-interest is concerned, a higher R_{eff} does not necessarily lead to a higher attack rate, because as R_{eff} increases, the motivation to become vaccinated based on self-interests increases. Observe that the attack rate increases with R_{eff} for values where $p_{eq} = 0$. When R_{eff} is higher, the attack rate declines because people start to take the vaccine. Moreover, applying optimal incentives to increase vaccination can dramatically reduce the rate of infection, especially in cases where self-interest without incentives is on the threshold between accepting and rejecting the vaccination (Figure 3, panel (B)). If optimal incentives are provided to become vaccinated, the gap between the optimal level of vaccination coverage, p_{opt}, and the predicted one, p_{SGP}, ranges between 5% in seasonal influenza strains and up to 16% in pandemic ones (Figure 3, panel (A)). The optimal incentives for the SP, π^*, range between 21 and 57 and are affected mainly by the extent of the disease's contagion (i.e., R_{eff}). As with the trends we found for the NIS, the larger R_{eff} is, the smaller the magnitude of the incentive should be (Figure 3, panel (C)). These results may explain why just covering the cost of the vaccination, which is about \$18 per shot, is not enough to encourage people to get vaccinated in particularly, when dealing with seasonal influenza strains.

Sensitivity analysis performed on all of the parameters in the range shown in Table 1 demonstrate that the results are robust, since the trends remain the same (see Appendix E).

Figure 3 **Strategies and Corresponding Attack Rates Arise from Self-Interest, Social Interest, and Heathcare Provider's Interest**



Notes. Panel (A) shows the level of vaccination coverage in the homogeneous model that creates the optimal vaccination coverage for society (p_{opt}), the expected vaccination coverage in equilibrium when no incentives are offered (p_{eq}), and the expected vaccination coverage if the HCP offers the optimal incentives (p_{SGP}). Panel (B) shows the corresponding attack rate that results from the three levels of vaccination coverage. Panel (C) shows the optimal magnitude of incentives provided by the HCP.

4.4. Optimal Incentives—The Heterogeneous Population

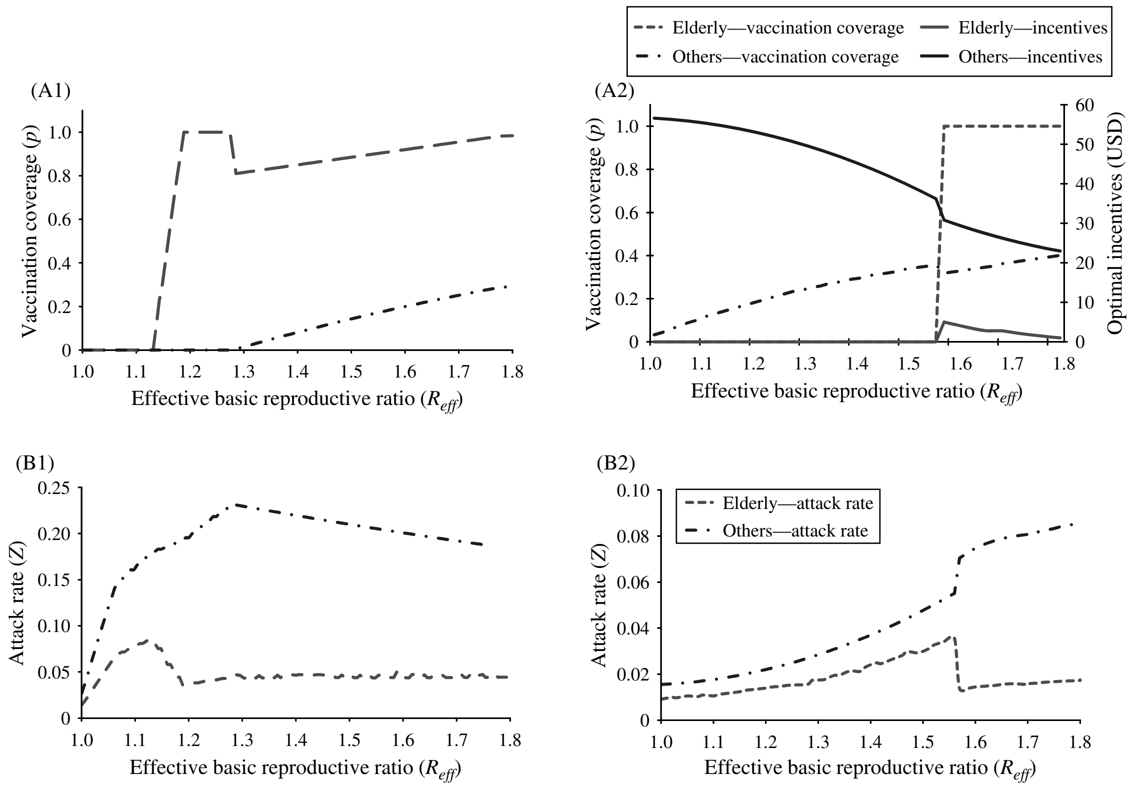
In this section, we will examine the heterogeneous model for the case of the two subgroups considered. The formulation of the model for the heterogeneous population is detailed in Appendix F. We ran two types of simulations with the goal of examining the commonly suggested policy of focusing on vaccinating high risk groups (Fiore et al. 2010). In the first case, we looked at a simulation involving those over 65 years of age as opposed to the rest of the population. In the second simulation, the population was divided into children between six months and four years of age versus the rest of the population. For each age group i, we calculated the expected level of vaccination coverage when no incentive is given, p^i_{eq}, the optimal incentives π^{*i}, and the corresponding vaccination coverage p^i_{SGP}.

4.4.1. Elderly vs. Others. When considering the impact of elderly individuals' behavior on the dynamic of disease, three points are worth mentioning. First, elderly individuals interact less with others. As a result, they are less likely to become infected or to infect others (Fiore et al. 2010, Mossong et al. 2008). Second, for the SP, the average costs associated with an elderly infected person, such as hospitalization and the treatment of complications, are higher than those associated with the treatment of the rest of the population (Ryan et al. 2006, Fiore et al. 2010). Third, the perceived loss of getting infected is greater for elderly individuals. Our survey supports this finding with data demonstrating that, more than others, the elderly interviewees felt that the loss due to getting the flu was significantly higher. Accordingly, we estimated the relevant parameters for the elderly and the nonelderly (see Appendix F for details).

Figure 4 summarizes the results of the simulation. In the figure we present the level of vaccination coverage achieved by the self-interests of the elderly and the nonelderly, and their corresponding attack rates when incentives are not provided (panels (A1) and (B1)) and when optimal incentives are provided (panels (A2) and (B2)). In panel (A2), the left axis represents the level of vaccination coverage, whereas the right axis represents the costs in U.S. dollars. The dashed curved lines represent the level of vaccination coverage, p_{eq}, and p_{SGP} for each age group. The flat curve represents the optimal incentive for each age group.

The simulation results for the case in which no incentive is offered demonstrate that when less contagious influenza strains are reported (i.e., $R_{eff} < 1.14$), the self-interests of the nonelderly motivate them to refuse the vaccination. In contrast, the level of vaccination coverage for elderly individuals increases with R_{eff}. When a more contagious strain of flu is expected ($R_{eff} > 1.14$), the self-interests of the nonelderly motivate them to take the vaccination. Thus, there is an increase in the level of vaccination coverage in this age group when R_{eff} increases. A nonelderly vaccinated individual reduces the probability of infection for the entire population, including the elderly. Hence, for the elderly, the motivation to get vaccinated declines if the nonelderly choose to take the vaccination ($R_{eff} > 1.29$). In that sense, the

Figure 4 Levels of Vaccination Coverage and Attack Rates Without Incentives ((A1), (B1)) and with Optimal Incentives ((A2), (B2)) for the Elderly vs. Others



elderly choose to free ride. Thus, the level of vaccination coverage among the elderly drops sharply and then increases with R_{eff}.

The simulations also show that the contribution of an elderly vaccinated person in reducing the probability of infection for both age groups is less than the contribution of a nonelderly vaccinated person (see Appendix F). As a result, when considering incentives, the HCP offers greater incentives to the nonelderly since they are more effective for the elderly as well (Figure 4, panel (B2)). As in the homogeneous model, we found that the more infectious the influenza strain, the lower the optimal incentive should be. In less contagious influenza strains ($R_{eff} < 1.57$), no incentives are offered to the elderly, because their NIS is relatively low (see Appendix F). However, an incentive for the nonelderly group leads to an increase in the level of the vaccination coverage among this group. As a result, the probability of infection is reduced, so the elderly are better off rejecting the vaccination. When more contagious strains of flu are expected (i.e., $R_{eff} > 1.57$), the elderly's self-interests in getting vaccinated increase rapidly. Even if no incentives or very small incentives are offered to the elderly, they will take the vaccine anyway because it is in their personal interests to do so.

Our homogeneous model assumes that before the outbreaks, susceptibility rates in both age groups are the same for a specific influenza, when in fact, this assumption is not necessarily correct. Some populations may be partly immune to the disease due to previous exposure. However, if older individuals are considered more likely to be protected, as Laurie et al. (2010) suggested, it may even strengthen our findings that greater incentives should be provided to the nonelderly rather than the elderly.

4.4.2. Children vs. Others. As with the elderly, the costs to the SP and the perceived costs to parents are greater when children are considered (see Appendix F). However, in contrast to the elderly, children are infected more easily and can remain infected for a longer period of time than others (Fiore et al. 2010).

The four panels in Figure 5 present the results when children versus others are considered. Results suggest that without incentives vaccination coverage in children ranges from 0%–100%, and increases with R_{eff}. When optimal incentives are offered, our simulations determined that for nearly all strains, all children should be vaccinated (Figure 5, panel (A2)). In seasonal types of influenza, vaccinating children in this age group can be achieved by offering incentives as high as \$50–\$60. In pandemic situations, the magnitude of the incentives provided by the HCP declines, because their parents are more motivated to give them the vaccination.

As with the homogeneous model (see Figure 3), we saw the same trends when we performed sensitivity analyses of r, D_s, and S_s in the heterogeneous model for both the elderly versus others and children versus others. In other words, increasing D_s^i or r^i for each age group i reduces the optimal magnitude of the incentive provided for that group, whereas increasing S_s increases the optimal magnitude of the incentive for age group i.

Moreover, when no incentive is provided, increasing D_s^i or r^i in age group i leads to the increase of vaccination coverage in the same age group while reducing the motivation to become vaccinated in the other group, leading to a lower level of vaccination coverage. Correspondingly, the optimal incentive for group i decreases, whereas for the other age group, it increases. When S_s^i increases, age group i receives a greater incentive, leading to a higher level of vaccination coverage in this group. In turn, this increase in coverage reduces the motivation to get vaccinated in the other group, leading to greater incentives being provided to the other age group.

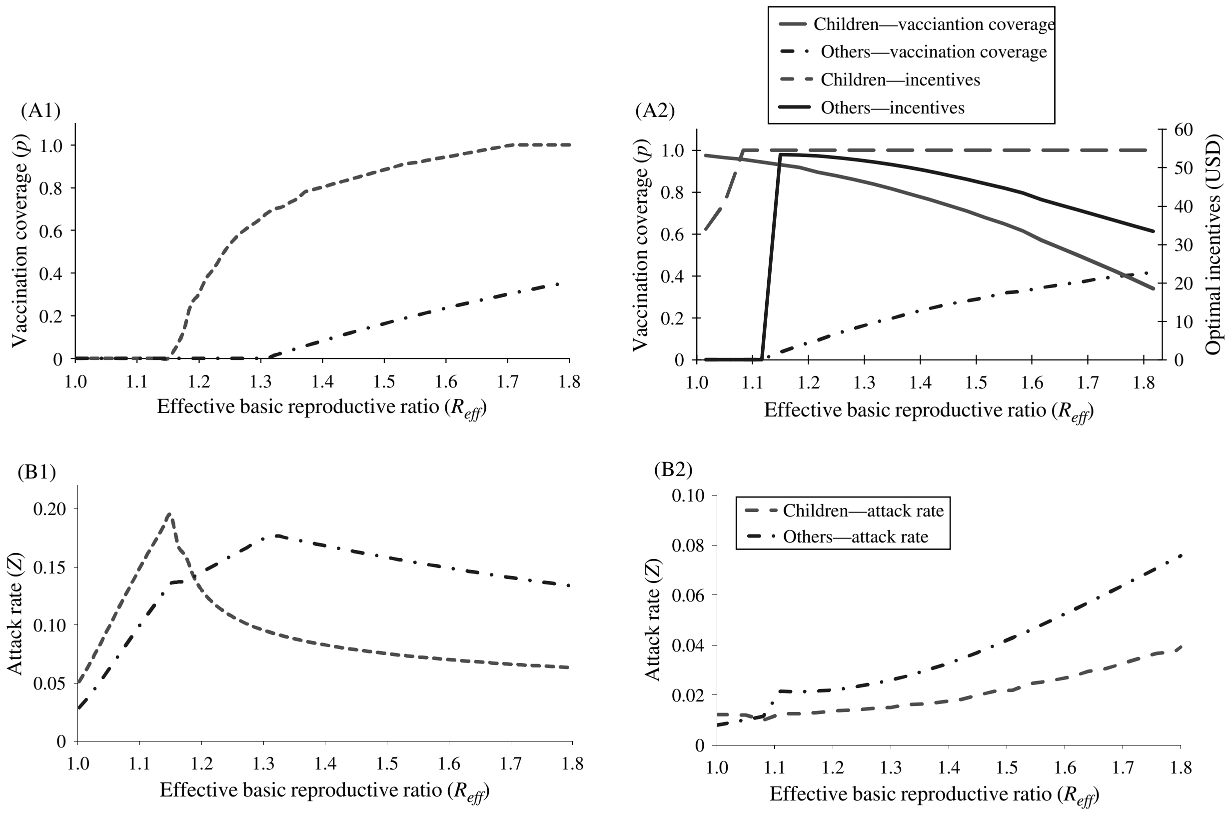
5. Discussion and Managerial Implications

The current study includes several issues that should be addressed. The first issue is that our telephone survey was conducted in Israel. Accordingly, the estimations performed to assess individuals' perceptions might be different than in other countries and affect the results obtained. However, it should be noted that the annual influenza vaccination coverage as well as the reported rate of infection in Israel are, on average, the same as in the majority of European countries (Blank et al. 2009, Organisation for Economic Co-operation and Development 2011, Huppert et al. 2012). Healthcare policy in Israel regarding influenza is similar to the policy suggested by the U.S. CDC, and the parameter values estimated were consistent with estimations performed in the United States (Prosser et al. 2005). In addition, the trends that emerged in the game theoretical model were consistent across the whole spectrum of parameters checked in the sensitvity analysis we conducted. Moreover, the simulation results of the game theoretical model were consistent with the trends evident in the NIS, which does not include the parameters estimated in the telephone survey.

Second, the current study raises several ethical questions. Our heterogeneous model suggests that to benefit the elderly and the HCP, incentives should be offered to the nonelderly population to encourage them to get vaccinated. In the case where no incentives are provided, the self-interests of the nonelderly might prompt them to choose the "reject vaccination" strategy. Indeed, a recent study by Velan et al. (2011) in the Israeli population suggests that about 50% of the population who refused the H1N1 influenza vaccination offered "reasoned or implicit" assessments of their self-interests as reasons why they refused vaccination. This raises the question of whether the authorities have the moral right to encourage vaccination by offering incentives that may tempt people to make a decision that is against their interests, particularly when the ultimate goal of the authorities may be to minimize the impact on another person. Furthermore, in the current paper, we defined an incentive as any legitimate action taken by the authorities whose goal was increasing the level of vaccination coverage. Another ethical question that arises here is, what is a legitimate form of incentive and what is not? Several studies suggest that passiveness and lack of awareness are reasons for refusing to get vaccinated. In such cases, incentives that make vaccination more accessible together with telephone reminders and pamphlets might be both legitimate and efficient actions (Briss et al. 2000; Velan et al. 2011, 2012). However, in the mid-1980s, Japan made influenza immunization for school-age children mandatory (Reichert et al. 2001). Similarly, in several states in the United States, there are fines for noncompliance in childhood vaccinations. Both the effectiveness and ethical aspects of these sanctions have been disputed (Isaacs et al. 2004, Omer et al. 2009). Another ethical question asks whether the utility function should be formulated only in terms of costs. Our theoretical model is general, but we tested our simulation studies for values that represent financial costs. Even though our model considers the costs related to complications from the disease such as hospitalization or even death (Ryan et al. 2006), the HCP might consider other outcomes such as years of life lost, quality adjusted years of life, reputation, and mortality cases (e.g., Medlock and Galvani 2010).

Third, the game model assumes that players are rational and, therefore, want and know how to act to maximize their self-interests. However, this assumption about rationality has long been disputed. Although assuming rationality to predict vaccination decisions is common (see, e.g., Bauch et al. 2003, Fine and Clarckson 1986, Galvani et al. 2007), other studies point out that for various populations the decision about whether to get vaccinated is motivated by reasons other than pure self-interest such as altruism, prosociality, or even cultural conceptions (Hershey et al. 1994, Hoffman et al. 2006, Leask et al. 2006). By estimating sentiments about vaccinations using Twitter messages, Salathe and Khandelwal (2011) suggested that vaccination decisions are affected by the perceptions of the people we interact with, which are

Figure 5 **Levels of Vaccination Coverage and Attack Rates Without Incentives ((A1), (B1)) and with Optimal Incentives ((A2), (B2)) for Children vs. Others**



not necessarily motivated by individuals' pure self-interests. Moreover, rationality assumes that players not only want to maximize their self-interests, but also know how to act to do so. Adding to these gaps in information and different interpretations of the risk from vaccinations and the flu, especially when it comes to probability assessments (Gazmararian et al. 2010, Poland 2010), also undercuts the assumption about rationality.

Nevertheless, influenza is the most common respiratory illness leading to an annual infection rate of 5%–20% each year. Given that influenza is a repeated annual event, most people can make a reasonable assessment about the risk of the disease for them and their likelihood of becoming infected. However, we speculate that pandemic influenza is a disease about which individuals are less aware. As a result, their uncertainty about the risks involved and the probability of becoming infected may hamper their rational assessments. Our survey data demonstrate that, regardless of the age group, people make their considerations based on their self-interests. The estimators of the perceived values of the cost of the disease, the cost of the vaccination, and the vaccination's efficacy were significantly correlated with the individual's decision to accept or reject the vaccination. Along the same lines, the logistic regression (with an 87.74% correct classification, whereas the naive is about 70%) suggests that individuals tend to make their decision in accordance with their self-interests. If people did indeed operate out of altruistic considerations, we should have seen an increase in the vaccination coverage. However, in practice, vaccination coverage in all age groups is still suboptimal (Fiore et al. 2010). Thus, if there is any altruistic behavior, it is relatively weak. Fourth, whereas our research uses a game theoretic model to test the CDC's policy of focusing on vaccinating the elderly and children, the model considers only two age groups. In reality, sociodemographic factors, the environment, age, occupations, and personal habits all affect perceptions about influenza, as do economic and epidemic parameters. Nevertheless, even by using only two groups, our results show that when no incentive is considered, one group may exploit the other by choosing to free ride and refuse the vaccination (e.g., the elderly versus others). We also demonstrate that a social planner can overcome this distortion by offer an incentive scheme that takes into account individuals' self-interests and the economic needs of the social planner.

5.1. Managerial Implications

As we found in this study, incentives can increase the level of vaccination coverage as well as improve social welfare and the HCP's allocation of resources. However, incentives should be applied carefully and when their benefit is worthwhile.

We formulated a two-stage game theoretic model to evaluate the optimal magnitude of incentives for vaccination and proved analytically that because the level of vaccination coverage is suboptimal for the general welfare of society and the HCP, it is important to offer incentives that will motivate people to become vaccinated. Based on the survey data, we found that people do indeed make their vaccination decision based on their self-interests, a determination that supports our analytical finding that providing incentives is crucial.

The simulations suggest that in most cases subsidizing the cost of the vaccine is not enough to motivate individuals to get vaccinated. Moreover, the optimal magnitude of the incentive per vaccinated individual should be from \$20 in cases of more contagious influenza up to \$57 in cases of less contagious strains.

The heterogeneous model showed that the SP should favor giving greater incentives to the nonelderly population over the elderly. The elderly themselves will benefit from this policy, because the probability of infection will decline dramatically. We suggest that all children between six months and four years of age should be vaccinated. In seasonal types of influenza, vaccination of these age groups can be achieved by offering proper incentives. In pandemics, there is no need to give incentives, because people will be motivated by their own self-interests to get the vaccine anyway. These findings are at odds with the CDC's policy of giving incentives to populations at risk rather than to those who are the major spreaders of the disease.

Furthermore, we introduced a simple new term to the epidemiological field called NIS. The NIS counts the overall number of individuals saved due to a single vaccinated individual. We claim that this measure improves upon the use of the concept of herd immunity to create more realistic levels of vaccination coverage that take cost-effectiveness into account. Whereas an individual may think in terms of self-interest and may be satisfied with considering the reduction of his probability to get infected (i.e., vaccination efficacy), authorities should consider the overall contribution of vaccination, which is the value of NIS. The NIS is comprised of the contribution of a vaccinated individual of protecting himself and the contribution of protecting the rest of the population. The simulation studies revealed that the NIS is estimated to be between 0.5 and 1.4 persons, of which less than 50% is the contribution made by the individual's self-interests and the rest is attributable to the interests of others. Hence, these results underscore that from the individual's point of view, vaccination might not be worthwhile. From the HCP's point of view, however, the overall cost of sick individuals is more than 10 times higher than the overall costs of the vaccination. The simulations also suggest that in terms of cost-effectiveness, greater incentives should be provided in regions where higher levels of vaccination coverage are expected and when less contagious types of flu are expected.

Acknowledgments
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Appendix A. Proof of Proposition 1

From standard arguments (see, e.g., Diekmann and Heesterbeek 2000) we get, from (5) and (6),

$$S_\infty = (1 - rp - i_0)e^{(\beta/\gamma)(S_\infty + rp - 1)},$$

where $S_\infty = S(\infty)$ is the proportion of the population that remains susceptible when the disease has been eradicated. Rearranging yields

$$S_\infty = -\frac{\gamma}{\beta} W\left(-(\beta/\gamma)(1 - rp - i_0)e^{(\beta/\gamma)(1-rp)}\right), \qquad (10)$$

where $W(Z)$ is the Lambert W function. The probability of a susceptible individual becoming infected given vaccination coverage p is

$$\phi(p) = \frac{1 - rp - i_0 - S_\infty}{1 - rp - i_0}. \qquad (11)$$

Substituting (10) in (11) gives (1). $\square$

Appendix B. Proof of Proposition 2

Consider the nontrivial case where $p_{eq} > 0$. It is sufficient to show that for $p < p_{eq}$ we have $U^{SW}(p) < U^{SW}(p_{eq})$ and that $(dU^{SW}/dp)|_{p=p_{eq}} > 0$. The social welfare utility is composed of a linear combination of two monotonically increasing functions, $U(accept; p)$ and $U(reject; p)$. In other words,

$$\begin{aligned} U^{SW} &= -p[D_v + (1-r)\phi(p)D_s] - (1-p)[\phi(p)D_s] \\ &= pU(accept; p) + (1-p)U(reject; p). \end{aligned}$$

By Corollary 1, $\phi(p)$ decreases with p. Hence, $U(accept; p)$ and $U(reject; p)$ increase with p where $U(accept; p_{eq}) = U(reject; p_{eq}) = U^{SW}(p_{eq})$. Thus, for $p < p_{eq}$,

$$\begin{aligned} U^{SW}(p) &= pU(accept; p) + (1-p)U(reject; p) \\ &< pU(accept; p_{eq}) + (1-p)U(reject; p_{eq}) = U^{SW}(p_{eq}). \end{aligned}$$

All that remains is to show that $(dU^{SW}/dp)|_{p=p_{eq}} > 0$:

$$\frac{dU^{SW}}{dp} = -D_v + rD_s\phi(p) + (1 - rp)\frac{d\phi(p)}{p}. \qquad (12)$$

From (2), $\phi(p_{eq}) = D_v/rD_s$. Substituting $\phi(p_{eq})$ in (12) gives

$$\left.\frac{dU^{SW}}{dp}\right|_{p=p_{eq}} = -D_v + rD_s\frac{D_v}{rD_s} + (1-rp_{eq})\left.\frac{d\phi(p)}{dp}\right|_{p=p_{eq}}$$
$$= (1-rp_{eq})\left.\frac{d\phi(p)}{dp}\right|_{p=p_{eq}} > 0. \quad \square$$

Appendix C. Proof of Corollary 3

It is sufficient to show that $(dU^{SP}/d\pi)|_{\pi=0} > 0$. The SP's utility is given by (3). In the nontrivial case (i.e., $p_{SGP} > 0$), we find from Proposition 4 that $\phi(p_{SGP}) = (D_v - q(\pi))/rD_s$. Substituting $\phi(p_{SGP})$ in (3) gives

$$U^{SP} = -p_{SGP}(\pi + S_v) - (1-rp_{SGP})\frac{D_v - q(\pi)}{rD_s}S_s.$$

Thus,

$$\frac{dU^{SP}}{d\pi} = -\frac{dp_{SGP}}{d\pi}(\pi + S_v) - p_{SGP} + \frac{(1-rp_{SGP})S_s}{rD_s}q'(\pi) + \frac{S_s(D_v - q(\pi))}{D_s}\frac{dp_{SGP}}{d\pi}.$$

Rearranging and substituting $\pi = 0$ gives

$$\left.\frac{dU^{SP}}{d\pi}\right|_{\pi=0} = -\left.\frac{dp_{SGP}}{d\pi}\right|_{\pi=0} S_v - p_{eq} + \frac{(1-rp_{eq})S_s}{rD_s}q'(0) + \frac{S_sD_v}{D_s}\left.\frac{dp_{SGP}}{d\pi}\right|_{\pi=0} = \left.\frac{dp_{SGP}}{d\pi}\right|_{\pi=0} S_s\left(\frac{D_v}{D_s} - \frac{S_v}{S_s}\right) - p_{eq} + \frac{S_s}{rD_s}(1-rp_{eq})q'(0),$$

where $p_{SGP}(0) = p_{eq}$. Given the assumptions $D_v/D_s - S_v/S_s > 0$ and the fact that $\phi(p)$ is a monotonically decreasing function, it appears from (3) that $dp_{SGP}/d\pi > 0$. Hence, $(dp_{SGP}/d\pi)S_s(D_v/D_s - S_v/S_s) > 0$.

Given that $rp_{eq}/(1-rp_{eq}) < S_s/D_s$ and $q'(0) \geq 1$, the result follows. $\square$

Appendix D. Questionnaire and Data Analysis

Presented below are the relevant questions from the telephone survey discussed in the data set and simulations section above.[8]

Estimatation of perceived infection rate without vaccination, $\tilde{\phi}$. The parameter was evaluated as the mean of the results of the answers to question 1 (#1; Table D.1) as suggested by Galvani et al. (2007). In other words, assuming n subjects in the survey, we simply evaluated $\hat{\phi} = (1/n)\sum_{j=1}^{n}(\#1)$.

Estimation of perceived efficacy of the vaccination, r. As Galvani et al. (2007) suggested, we evaluated the parameter as the risk reduction when taking the vaccination as opposed to not taking the vaccination. Accordingly, we used the answers to both questions[9] 1 and 2 for each subject j in the survey; $\hat{r}$ was achieved by $\hat{r} = (1/n)\sum_{j=1}^{n}(1 - \#2/\#1)$.

Table D.1 Relevant Questions from the Survey

Answer the following questions on a scale from 0 to 10, where 0 means "I will definitely not become infected" and 10 means "I definitely will become infected."

1. Generally speaking, what are the chances that you will get seasonal influenza if you do not get vaccinated in that season?
2. Generally speaking, what are the chances that you will get seasonal influenza if you do get vaccinated in the same season?

Answer the following questions on a scale from 0 to 10, where 0 means "not dangerous at all" and 10 means "very dangerous."

3. Do you feel that it is dangerous for you to get seasonal influenza?
4. Do you feel that it is dangerous for you to get the influenza vaccination?

Please answer the following multiple choice questions.

5. In the past six months, did you take the influenza vaccination? A: Yes. B: No. C: Do not remember or refuse to answer.
6. Before next fall, will you take the influenza vaccination? A: Yes. B: No. C: Do not know or refuse to answer.

Consider the following imaginary scenario: Imagine that today you definitely became infected by someone who had influenza. Assume that there was a wonder drug that could prevent the disease with no harmful side effects.

7. Hypothetically, what is the maximum amount you would you be willing to pay to take that drug? (In case did not reply) 300 shekels? (If yes) Would you be willing to pay 500 shekels? (If yes) Would you be willing to pay 1,000 shekels? (If no) Would you be willing to pay 100 shekels? (If no) Would you be willing to pay 50 shekels? (If no) Would you be willing to pay anything?
8. In the past six months, did you have influenza? A: Yes (or think so). B: No. C: Do not remember or do not know.
9. If you said yes (or think so) in question 8, did you see a doctor when you were sick? A: Yes. B: No. C: Do not remember.
10. Generally speaking, how long did it take between the time you started feeling sick and the time you went to the doctor: A: 0–3 days. B: 4–7 days. C: More than 7 days. D: I did not go to the doctor.

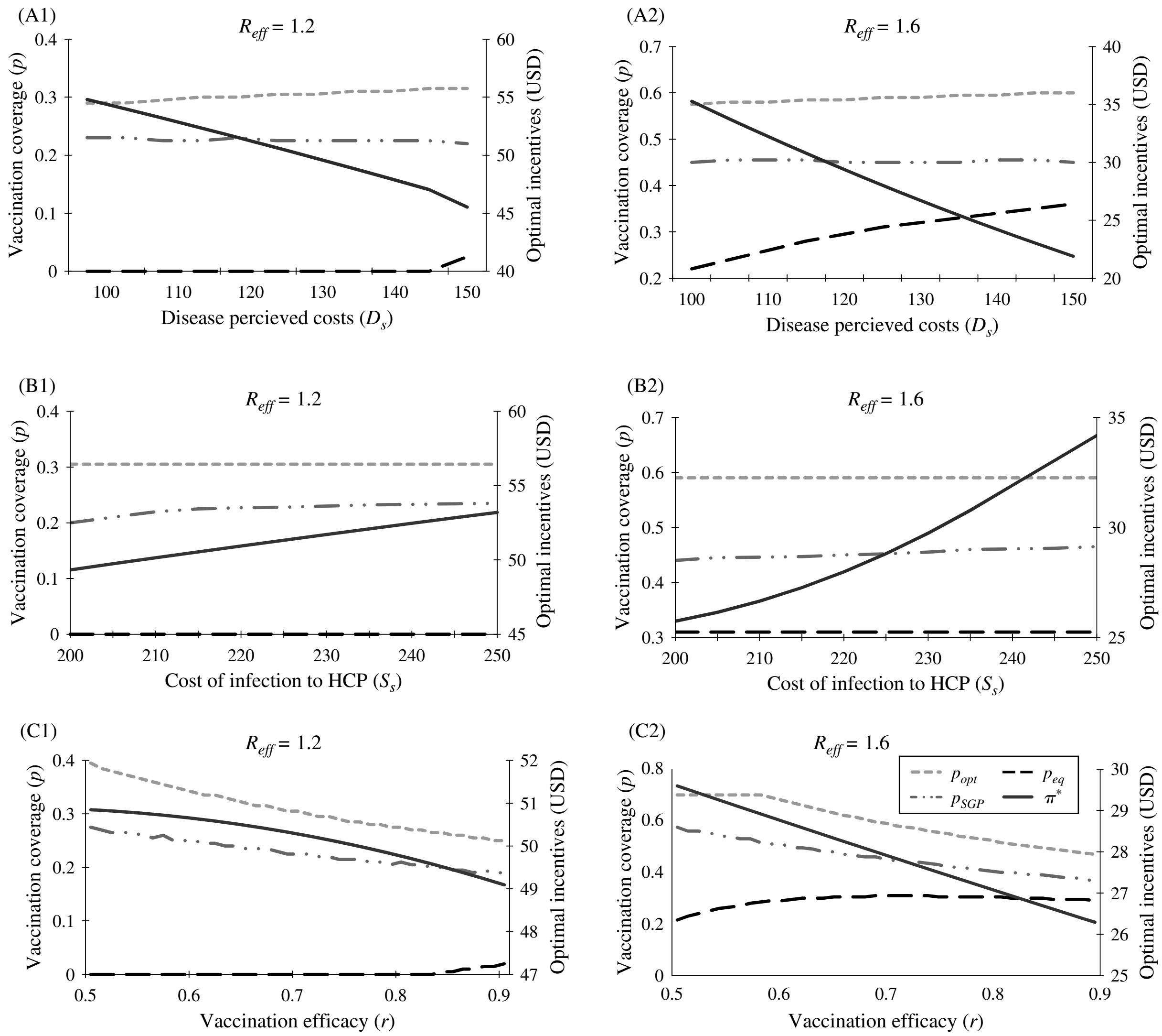
Estimation of perceived costs, D_s and D_v. The parameter reflecting the perceived costs of becoming infected, D_s, was evaluated using the "willingness to pay" method as suggested by Prosser et al. (2005). Accordingly, we evaluated the parameter as the mean of the results received for question 7. For each interviewee j, the perceived cost of the vaccination was evaluated relative to the perceived cost of getting sick. In other words, using answers to questions 7, 3, and 4, the estimations $\hat{D}_s$ and $\hat{D}_v$ were evaluated by $\hat{D}_s = (1/n)\sum_{j=1}^{n}(\#7)$, $\hat{D}_v = (1/n)\sum_{j=1}^{n}(\#7(\#4/\#3))$.

Note that for all estimations performed, to avoid biases of externalities, we removed the upper and lower 5% of the observations. To estimate the cost of taking the vaccine, we multiplied the ratio between questions 3 and 4 by the estimated value of the cost of being sick. Then, we calculated the average cost of the vaccination and being sick for each age group i to estimate D_v^i and D_s^i, respectively.

[8] All costs are presented in new Israeli shekels.

[9] To increase the validity of the answers, pollsters were directed to say, after receiving the two answers and before asking the next question, "So, you think that the vaccination increases your chances of becoming infected" in cases where question 2 < question 1, "reduces your chances" in cases where question 2 < question 1, and "has no effect on your chances of becoming infected" in cases where question 2 = question 1. By doing so, we determined that when question 2 < question 1, the vaccination's efficacy was a negative value.

Figure E.1 **One-Way Sensitivity Analyses for Two Levels of R_{eff}: D_s ((A1), (A2)), S_s ((B1), (B2)), r ((C1), (C2))**



Appendix E. Sensitivity Analysis in the Homogeneous Model

In this subsection we discuss the results we obtained from several one-way sensitivity analyses of the parameters in Table 1. The six panels in Figure E.1 summarize a one-way sensitivity analysis when $R_{eff} = 1.2$ and 1.6 for different values of the perceived cost of infection to the individual, the cost of infection to the HCP, and the vaccination's efficacy, that is, D_s, S_s, and r respectively. Sensitivity analysis shows that changing the perceived cost of the illness, D_s, does not affect the predicted level of vaccination coverage, but does affect the optimal incentive that should be provided to become vaccinated of up to \$15 (panels (A1) and (A2)). The same is true when changing the cost of the illness for the HCP, S_s (panels (B1) and (B2)). Results demonstrate that the greater the efficacy of the vaccine, the smaller the magnitude of the incentive should be. However, we found that the gap in the magnitude of the incentive between 50% efficacy and 100% efficacy was less than \$5 per person (panels (C1) and (C2)). In general, simulations suggest that the larger the ratio rD_s/D_v, the smaller the gap between p_{eq} and p_{opt}. In addition, when running the simulations with different values of in the range shown in Table 1, the trends remain more or less the same as in Figure 3.

Appendix F. Heterogeneous Population: Modeling and Estimation of Parameters

F.1. Modeling

In this section, we generalize our model for a heterogeneous population with two age groups.[10] To formulate a realistic model, we assume that the different groups are not necessarily distributed randomly in the population (e.g., the elderly tend to spend more time with other elderly people). Thus, for each age group, we define different epidemic parameters as well as different perceived losses due to illness. The sequence of the game starts with the planner announcing the size of the benefit π^i that will be granted

[10] Generally, the population may be divided into subgroups not just by age, but also with respect to any social or geographical parameters.

to a vaccinated individual from group i.[11] We assume that the magnitude of the incentive for vaccinated individuals according to the age groups is nonnegative and identical for all of the vaccinated individuals in the same age group. The individual's strategies remain $\{accept, reject\}$. Let α^i and p^i be the proportion of individuals and the level of vaccination coverage in subgroup i, $i = 1, 2$, among the entire population, respectively. As in the homogeneous model, the expected utility for an individual in age group i who chooses to accept or reject vaccination is given by

$$U^i(reject; p^1, p^2) = -D_s^i \phi^i(p^1, p^2), \quad i = 1, 2;$$
$$U^i(accept; p^1, p^2) = -D_v^i + q^i(\pi^i) - (1-r)D_s^i \phi^i(p^1, p^2), \quad i = 1, 2.$$

The SP's utility is given by

$$U^{SP}(\pi^1, \pi^2, p^1, p^2) = \sum_{i=1}^{2} \alpha^i [p^i(-S_v^i - \pi^i - (1-r)S_s^i \phi^i(p^1, p^2)) - (1-p^i)S_s^i \phi^i(p^1, p^2)].$$

As in the argument in Proposition 4, the subgame perfect Nash equilibrium $((\pi^{1*}, \pi^{2*}), p^1, p^2)$ should satisfy the system

$$\max_{\pi^1, \pi^2 > 0} \{U^{SP}(p^1, p^2)\}$$
$$\text{s.t.} \quad \phi^i(p^1, p^2) \le \frac{D_v^i - q^i(\pi^i)}{rD_s^i}, \quad i = 1, 2. \tag{13}$$

Note that if $\phi^i(p^1, p^2) < (D_v^i - q^i(\pi^{*i}))/(rD_s^i)$ in equilibrium, it follows that $p_{SGP}^i = 0$. For a heterogeneous population, there is no explicit solution for $\phi^i(p^1, p^2)$, even in terms of the Lambert W function. The solution obtained by solving the SIR model formulated in the heterogeneous case is as follows:

$$\frac{dS^1(t)}{dt} = -\beta^{11}S^1(t)I^1(t) - \beta^{12}S^1(t)I^2(t),$$
$$\frac{dI^1(t)}{dt} = \beta^{11}S^1(t)I^1(t) + \beta^{12}S^1(t)I^2(t)\beta^{11} - \gamma^1 I^1(t),$$
$$\frac{dR^1(t)}{dt} = \gamma^1 I^1(t),$$
$$\frac{dS^2(t)}{dt} = -\beta^{22}S^2(t)I^2(t) - \beta^{21}S^2(t)I^1(t),$$
$$\frac{dI^2(t)}{dt} = \beta^{22}S^2(t)I^2(t) + \beta^{21}S^2(t)I^1(t) - \gamma^2 I^2(t),$$
$$\frac{dR^2(t)}{dt} = \gamma^2 I^2(t),$$

where $S^i(t)$, $I^i(t)$, and $R^i(t)$ are the proportions of susceptible, infectious, and recovered individuals, respectively, for age group i at time t; β^{ij} is the infectious rate of individuals from age group i when they encounter individuals from age group j; and γ^i represents the recovery rate of an individual from age group i. Notice that $S^1(t) + I^1(t) + R^1(t) = \alpha^1$, $S^2(t) + I^2(t) + R^2(t) = \alpha^2$, where $\alpha^1 + \alpha^2 = 1$. The initial conditions are

$$S^i(0) = \alpha^i - i_0^i - r^i p^i, \quad i = 1, 2,$$
$$I^i(0) = i_0^i, \quad i = 1, 2,$$
$$R^i(0) = r^i p^i, \quad i = 1, 2,$$

where for each age group i, i_0^i and r^i represent the initial number of infected individuals and the efficacy of the vaccination, respectively.

F.2. Estimation of Parameters

In our model, we conducted simulations for two age groups: the elderly over the age of 65 versus others, and children from six months up to four years versus others. The simulations contain epidemic and economic parameters. As for the epidemic parameters, we assumed that the infectious rate β^{ij} depends mainly on the number of interactions between individuals from age group i with individuals from age group j. To estimate β^{ij}, we used the results of Mossong et al. (2008), who asked respondents in eight European countries to keep a diary of their contacts. Using a contact matrix, they then estimated the number of contacts per respondent by the age of the respondent and the age of the contact. The age groups were divided into five-year blocks, such as ages 0–4, 5–9, …, 65–69, and 70+. These data reveal that elderly individuals tend to interact less with others than with themselves and vice versa. We created a 2×2 matrix, M^{ob}, representing the observed average number of contacts between age group i and j. Then, we created a 2×2 matrix, M^{ex}, representing the expected average number of contacts independent of age, based only on the proportion of the age group in the population. To calculate M^{ex}, we

Table F.1 Perceived Cost in the Heterogeneous Model

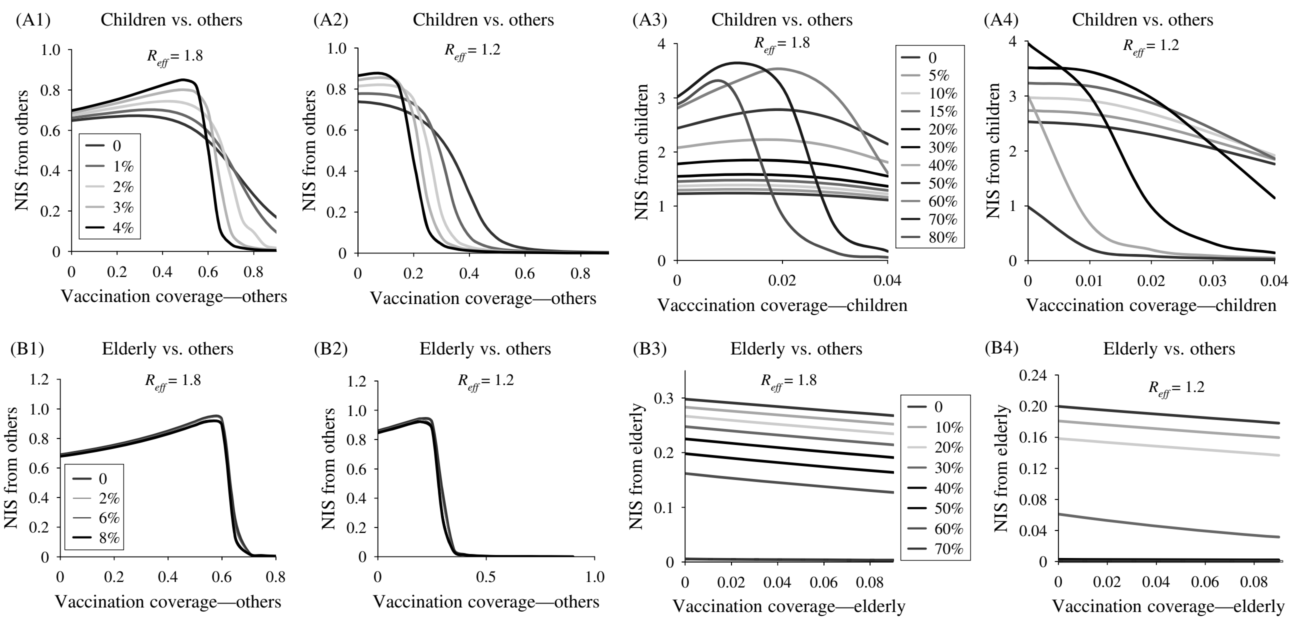
Symbols	Perceived cost due to:	Range checked
D_s^{elderly}, $(D_s^{\text{nonelderly}})$	Cost of illness for elderly (nonelderly)	250–350 (95, 119)
D_s^{children}, $(D_s^{\text{nonchildren}})$	Cost of illness for children (nonchildren)	175–225 (112, 132)
D_v^{elderly}, $(D_v^{\text{nonelderly}})$	Vaccination cost for elderly (nonelderly)	30–60 (30, 38)
D_v^{children}, $(D_v^{\text{nonchildren}})$	Vaccination cost for children (nonchildren)	70–90 (28, 38)

Table F.2 Evaluated Costs to HCP in the Heterogeneous Model

Symbols	HCP's cost due to:	Range checked
S_s^{elderly}, $(S_s^{\text{nonelderly}})$	Cost of illness for elderly (nonelderly)	490–510 (188, 196)
S_s^{children}, $(S_s^{\text{nonchildren}})$	Cost of illness for children (nonchildren)	330–370 (210, 220)
S_v^{elderly}, $(S_v^{\text{nonelderly}})$	Vaccination cost for elderly (nonelderly)	15–25
S_v^{children}, $(S_v^{\text{nonchildren}})$	Vaccination cost for children (nonchildren)	15–25

[11] Observe that if for political reasons the SP must offer the same incentive to all populations, then $\pi = \pi^i$ for all i. In such a case, the model becomes similar to the one we have in the homogeneous case, but with different levels of vaccination coverage for different age groups.

Figure F.1 Levels of NIS in the Heterogeneous Model for Children vs. Others ((A1)–(A4)) and the Elderly vs. Others ((B1)–(B4))



had to estimate the proportion of each age group in the population, α^i. In our simulations, we covered the ranges $0.08 \le \alpha^i \le 0.2$ for the elderly and $0.02 \le \alpha^i \le 0.06$ for children so they would match with the majority of developed countries (see United Nations Populations Division 2001). Then, we scalarly divided the two matrices $(M^{ob})_{ij}/(M^{ex})_{ij}$ to determine the effect of the number of contacts on the rate of infection C^{ef}. We estimated β^{ij} as the multiplication of those coefficients with an infection rate from the homogeneous model β ranged to create $1 < R_{eff} < 1.8$. The recovery time for the elderly and children less than four years of age can be twice as long as the recovery time of others (Fiore et al. 2010). Accordingly, in the simulations in which children versus others were considered, we assumed $\gamma^2 = 2\gamma^1$. In addition, the average period of infection is four to five days (Galvani et al. 2007). Accordingly, we assumed $\alpha^1/\gamma^1 + \alpha^2/\gamma^2 = 4.5$ in all of the simulations. For example, in (14), the estimated matrices for the simulations that looked at elderly people (age group 1) versus others (age group 2), the proportion of the elderly was 0.09:

$$M^{ob} = \begin{pmatrix} 1.96 & 6.24 \\ 0.73 & 13.72 \end{pmatrix}; \quad M^{ex} = \begin{pmatrix} 1.25 & 12.6 \\ 1.25 & 12.6 \end{pmatrix};$$
$$C^{ef} = \begin{pmatrix} 1.57 & 0.5 \\ 0.58 & 1.09 \end{pmatrix}; \quad \beta^{ij} = \begin{pmatrix} 1.57\beta & 0.5\beta \\ 0.58\beta & 1.09\beta \end{pmatrix}. \tag{14}$$

Note that since the elderly interact more with the elderly, the rate of infection of the elderly by the elderly is $\beta^{11} = 1.57\beta$. Similarly, in (15), the estimated matrices for the simulations that looked at children (age group 1) versus others (age group 2), the proportion of children was 0.04:

$$M^{ob} = \begin{pmatrix} 2.38 & 8.34 \\ 0.4 & 13.5 \end{pmatrix}; \quad M^{ex} = \begin{pmatrix} 0.55 & 13.33 \\ 0.55 & 13.33 \end{pmatrix};$$
$$C^{ef} = \begin{pmatrix} 4.32 & 0.63 \\ 0.73 & 1.01 \end{pmatrix}; \quad \beta^{ij} = \begin{pmatrix} 4.32\beta & 0.63\beta \\ 0.73\beta & 1.01\beta \end{pmatrix}. \tag{15}$$

Table F.1 summarizes the perceived costs estimated by our survey (confidence interval > 95%). Here the currency has been converted to U.S. dollars.[12]

Similarly, we estimated the costs to the healthcare provider. The costs were calculated using data from Ryan et al. (2006) and the answers to questions 8–10 from the survey data in the current study. Ryan et al. (2006) detail the costs related to influenza, such as doctor's visits, cost of the vaccine, treatment of side effects of the vaccine, treatment of the flu, and costs of hospitalization, and the probability of their occurrence. Table F.2 presents the estimation of the parameters in U.S. dollars and their range checks.

F.3. NIS in the Heterogeneous Model

In this subsection we show the results obtained from the simulation analysis of the NIS for the heterogeneous model. The eight panels in Figure F.1 describe the NIS (i.e., number of indivduals saved out of the entire population) for of one particular age group given the vaccination coverage of both age groups among the entire population. The four upper panels represent children versus others, whereas the lower panels represent the elderly versus others. The panels represent $R_{eff} = 1.2$ and 1.8. Because of the monotonicity of the results, we have a good picture of what happens in between that range. In panels (A1)–(A4), 4% of the population are children, and 96% are others. In panels (B1)–(B4), 9% of the population are elderly, whereas 91% are the nonelderly.

Similar to the trends we saw in the homogeneous model, when children versus others are concerned, as long as vaccination coverage does not reach herd immunity, the higher

[12] Costs estimations were taken from three different currencies—the Israeli shekel, the U.S. dollar, and the European euro. For obvious reasons, the costs for the same treatment in these three places are not necessarily the same. However, our results were tested using a vast spectrum of parameters and values. This paper presents only the trends that were consistent in all of the ranges.

the vaccination coverage, the greater the NIS, and the higher R_{eff}, the lower the NIS. Note that the NIS of children can reach up to four individuals when $R_{eff} = 1.2$ and vaccination coverage is 30%. In contrast, the NIS among the elderly does not exceed 0.3 individuals. Moreover, the trends in the NIS among the elderly are opposite those in all other age groups. That is because the self component (i.e., the contribution of the elderly to reducing infection to themselves) ranges between 78% and 95%, suggesting that the effect of a vaccinated elderly individual on others is relatively low.

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