Incentives’ Effect In Influenza Vaccination Policy *

Arieh Gavious † Dan Yamin ‡

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Abstract

In the majority of developed countries, the level of influenza vaccination coverage in all age groups is sub-optimal. Hence, the authorities offer different kinds of incentives for people to become inoculated 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 inoculation 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, greater for the non-elderly population rather than the elderly, and should rise as high as $60 per inoculated individual so that all children between the ages of six months and four years will be inoculated. Keywords: influenza; vaccination; game theory, incentive, SIR

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†Department of Industrial Engineering and Management, Faculty of Engineering Sciences, Ben-Gurion University, P.O. Box 653, Beer-Sheva 84105, Israel, ariehg@bgumail.bgu.ac.il

‡Department of Industrial Engineering and Management, Faculty of Engineering Sciences, Ben-Gurion University, P.O. Box 653, Beer-Sheva 84105, Israel, yamind@bgu.ac.il
1 Introduction

Influenza is the most common respiratory illness, leading to an annual infection rate of 5-20% in developed countries. In the U.S. alone, more than 200,000 people are hospitalized every year due to influenza-related complications. Furthermore, about one in every 1,000 patients dies from the flu every year (Fiore et al. 2010). The disease is transferred from person to person through the air, usually by coughing or sneezing. Healthy adults may infect others beginning one day before symptoms develop and up to five to seven days after main symptoms disappear. On average, every eight years, as a result of a massive genetic change in the virus, a more pathogenic and contagious influenza type is reported. In April 2009, a novel influenza 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 A (H1N1) 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 following season. Since influenza is a contagious disease, inoculation is vital in reducing mortality, not only for those who become inoculated, 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 Center 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 per-
sonal 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 taken 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 inoculation (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. 2008). In the context of personal health care 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 sub-optimal (Blank et al. 2008, Fiore et. al. 2010, Mereckiene et al. 2008).

In order to define a national policy, one must first study the individual’s decision making process regarding vaccination. Game theory provides an analytical framework for predicting the outcome of the conflict about becoming vaccinated (Funk et al. 2010). Fine and Clarkson (1986) distinguished between two motivations for becoming vaccinated—self-interests and the interests of society. Self-interests motivate individuals to act in order to maximize their own utility. Vaccination coverage based on the interests of the group maximizes the overall utility of society at large. However, when game theory is applied, 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. 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 prompt the vaccination of the non-elderly, 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 this study, we will examine self-interests versus group interests as a motivation for becoming inoculated. In practice, group interests refer to the interests of the health care 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 inoculation more accessible, reimbursing hospitalization fees only to inoculated individuals or any other action such as those suggested by the Advisory Committee on Immunization Practices (ACIP) (Fiore et al. 2010). Although previous studies pointed out the need for subsidizing vaccinations in order to prevent outbreaks of influenza (e.g., Cook et al. 2009, Galvani et al. 2007, Shim et al. 2010), no model has ever studied the impact of incentives on the decisions that people make and on 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. 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 term to the field of epidemiology that is more informative and more practical to use than the term ‘herd immunity’. Our new parameter describes the marginal contribution generated by a single additional inoculated 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 inoculation 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 that goal, we have built a dynamic, two-stage game theory model with complete information. In the model, we first assume that health care authorities announce the incentive that will be provided to an inoculated individual. Then, every individual decides whether to accept or reject the vaccination. Using the model, we will determine the magnitude of the optimal incentive and the corresponding vaccination coverage obtained in equilibrium. The model is based on epidemic and game theory modeling and is tested using 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.

Contrary to intuition, our findings suggest that the contribution of one additional in-
oculated individual is greater in less contagious types of influenza than in more contagious
types. Therefore, 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, sub-
sidizing 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 inoculated indi-
viduals should be as high as $60.1 Contrary to the CDC’s policy of focusing on incentives
to populations at higher risk (Fiore et al. 2010), our results suggest that bigger incentives
should be offered to those who serve as spreaders of the disease. These groups include the
non-elderly population and 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 sub-group will decline dramatically.

2 The Model

Like Bauch et al. (2003), we consider a non-atomic population game where the size of
the population is scaled to one unit, where the effect of a single individual (player) on the
others is negligible. In the model, which is expanded upon later on, it is assumed 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 inoculated individual. The sequence of the game starts with the SP
announcing the amount of the incentive \( \pi \) 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 \( \{\text{accept, reject}\} \). We let the individual
players use mixed strategies where a player may accept the vaccine with probability \( p \) or
reject with probability \( 1 - p \). The proportion of the population who choose to get the
vaccine is the level of vaccination coverage. 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 for an individual to become infected if he is not vaccinated
as a function of the level of vaccination coverage \( p \). In Section 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

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1Hereafter, all prices are in U.S. dollars.
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 vaccination is given by:

\[ U(\text{reject}; p) = -D_s \phi(p). \]  

(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 \( \pi \) represent the financial investment of the SP to encourage vaccination, and let \( q(\pi) \) represent the individual’s utility from \( \pi \). We assume that the SP is rational, and therefore will offer incentives from the most cost effective to the least (i.e. in a Pareto efficient order) so that \( q(0) = 0 \), \( \frac{dq(\pi)}{d\pi} \geq 0 \), and \( \frac{d^2q(\pi)}{d\pi^2} \leq 0 \), namely \( q \) is increasing and concave (presenting a diminishing marginal benefit from the incentives). Note that one possible type of incentive is to provide a financial grant to those who choose to be inoculated. Hence, we demand that \( \frac{dq(\pi=0^+)}{d\pi} \geq 1 \). The expected payoff for an individual who chooses the accept vaccination strategy given that the population’s level of vaccination coverage is \( p \) is:

\[ U(\text{accept}; p) = -D_v + q(\pi) - (1 - r)\phi(p)D_s \]  

(2)

where \( r \) is the efficacy of the vaccination (i.e., the probability that the vaccination will be effective). We assume that \( D_v \leq D_s \). In other words, the overall perceived costs due to infection are higher than the perceived costs due to vaccination.

The SP is interested in minimizing the overall financial losses that result from the individuals’ decisions. Alternatively, the SP may be a health care provider 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. Scaling the population size to one unit, the SP’s expected payoff is given by

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

(3)

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

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

(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, well-known SIR epidemic model (e.g., Choisy et al. 2007). Let $S(t), I(t), R(t)$ 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:

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

(5)

where $\beta$ and $\gamma$ represent the infectious and recovery rates, respectively. Note that in the basic SIR model $\frac{\beta}{\gamma}$ is equal to $R_0$, the number of secondary cases caused by a single infected case in a completely susceptible population (Choisy et al. 2007). The initial conditions are given by

$$
\begin{align*}
S(0) &= 1 - i_0 - rp, \\
I(0) &= i_0, \\
R(0) &= rp,
\end{align*}
$$

(6)

where $i_0$ represents the initial number of infected individuals.

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

$$
\phi(p) = \begin{cases}
1 - \frac{\gamma}{\beta(1+i_0+rp)}W\left(-\frac{\beta}{\gamma}(1-rp-i_0)e^{-\frac{\beta}{\gamma}(1-rp)}\right), & 0 \leq p < 1 - p - i_0, \\
0, & \text{otherwise},
\end{cases}
$$

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

**Proof:** See Appendix A.

**Corollary 1** $\phi(p)$ is decreasing monotonously, and for $R_0 > 1$, $\phi(p)$ 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', which represents the critical level of vaccination coverage needed to eradicate the disease (Choisy et al. 2007), and is given by:\(^2\)

\[ p_{\text{herd}} = \frac{R_0 - 1}{rR_0} \]  \( (7) \)

In practice, the level of influenza vaccination coverage worldwide is below the 'herd immunity' level. In addition, reaching the point of 'disease eradication' might not be cost effective or even possible to achieve. Instead, the cost of incentives should be bounded by their benefits. Hence, decision makers should determine the marginal contribution of an inoculated individual given a particular level of vaccination coverage, rather than the level of vaccination coverage above which the marginal contribution of an inoculated individual will be close to zero (i.e. herd immunity). To that end, we introduce a new parameter called the NIS, the marginal 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 inoculated later on, because the NIS depends on the proportion of the population that already took the vaccine. In order 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 is defined by:

\[ NIS(p, R_0) = - \lim_{\Delta p \to 0} \frac{\phi(p + \Delta p)[1 - i_0 - r(p + \Delta p)] - \phi(p)(1 - i_0 - rp)}{\Delta p} = - \frac{d\phi(p)}{dp} (1 - i_0 - rp) + \phi(p)r. \]  \( (8) \)

The NIS is composed of the sum of two components: the self-interest component \( \phi(p)r \), and the altruistic component \( -\frac{d\phi(p)}{dp} (1 - i_0 - rp) \). Both can be written in terms of the Lambert W function. \( \phi(p)r \) in (8) represents the marginal contribution of an inoculated individual in reducing the probability of becoming infected himself, whereas \( -\frac{d\phi(p)}{dp} (1 - i_0 - rp) \) represents the marginal contribution to the entire population. From (8), we see that the self-interest component declines with \( p \) and with \( R_0 \), whereas the altruistic component might increase. This is why the free rider phenomenon is common and incentives for inoculation 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 inoculation. Numeric simulations presented later emphasize that the incentive policy should depend not only on the virulence of the influenza strain, but

\(^2\)If \( p > p_{\text{herd}} \), the disease will be eradicated.
also on the predicted level of vaccination coverage in the region. Counterintuitively, 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 U.S. (Fiore et al. 2010).

3 Equilibrium and Optimal Outcomes for Society

In this section, we show analytically that providing incentives to inoculated individuals will always improve the individual’s utility, the welfare of society in general, and the health care 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:

\[
p_{eq} = \begin{cases} 
\phi^{-1} \left( \frac{D_v}{rD_s} \right) & ; \phi(0) > \frac{D_v}{rD_s}, \\
0 & ; \text{Otherwise},
\end{cases}
\]  

(9)

where \( \phi^{-1} \) is the inverse function of \( \phi \).

**Proof:** In a mixed strategies equilibrium, a player is indifferent about alternatives and thus, \( U(\text{accept}; p_{eq}) = U(\text{reject}; p_{eq}) \). Substituting \( q = 0 \) and solving for \( p_{eq} \) yields the result. Since \( \phi(p) \) is a monotonically decreasing function with \( p \), and the expression \( \frac{D_v}{rD_s} \) is constant, if there exists \( p \) in which \( \phi(p) = \frac{D_v}{rD_s} \), 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 $D_v r D_s$ decreases with $r$ and $D_s$ and increases with $D_v$, the result follows from (9). \(\square\)

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

Figure 1 demonstrates proposition 3. In the figure, the point at which $U^{SW}$ reaches its maximum represents the welfare of society as a whole, namely, 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 $p_{eq} < p_{opt}$. Simulations presented below show that the gap in vaccination coverage between self-interests and group interests can rise from 5% to 30%. The gap is wider when dealing with less contagious and less hazardous types of influenza.

We continue with the more general case in which the SP can offer incentives to inoculated 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 sub game perfect Nash equilibrium $(\pi^*, p_{SGP})$, where $\pi^*$ is the planner’s optimal incentive given $p_{SGP} = p_{SGP}(\pi)$, which is the individual’s best response in mixed strategies given an incentive $\pi$.

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

$$p_{SGP}(\pi) = \begin{cases} \phi^{-1} \left( \frac{D_v - q(\pi)}{r D_s} \right) & ; r \phi(0) D_s > 1 - q(\pi), \\ 0 & ; otherwise. \end{cases}$$
Figure 1: Figure curves depict $U(\text{reject}; p), U(\text{accept}; p)$ and $U^{SW}$ as a function of the level of vaccination coverage $p$.

**Proof:** We solve by backward induction (e.g., Fudenberg and Tirole 1991). Given any incentive $\pi$, 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 $\pi$, $\pi^*$ optimizes the SP’s utility function $U^{SP}$. ⊡

Given that there is no analytic solution for $(\pi^*, p_{SGP}(\pi))$ and $q(\pi)$ is not known, the next step is to find the conditions in which the optimal incentive is a real positive value, (i.e., $\pi^* > 0$) for any set of reasonable 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 $\frac{r p_{eq}}{(1 - r p_{eq})} < \frac{S_s}{D_s}$, then $p_{SGP} > p_{eq}$ and $\pi^* > 0$

**Proof:** See appendix C. ⊡

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 Section 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 welfare of society at large can be overcome by providing the optimal incentives.

4 Data Set and Simulation Analysis

In this section, we will 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 this study (Burch et al. 2009, Fiore et al. 2010, Fraser et al. 2009, Galvani et al. 2007, Pitzer et al. 2007, Ryan et al. 2006). 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 an inoculated individual (the $NIS$ presented in equation 8).

2. The level of vaccination coverage and the optimal incentive provided in a homogenous population ($p_{eq}, p_{opt}, p_{SGP}$ and $π^*$ in propositions 2,4 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 sub-groups: 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

In order 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 U.S. dollars at that time. According to the Israeli Bureau of Statistics, the median salary for a household in Israel was about 11,000 shekels per month at that time$^3$. Note, too, that Israel belongs to the OECD, and the annual level of vaccination coverage for influenza in Israel is more or less the same as in the majority of European countries (Blank et al. 2008). Finally, we should also note that the Ministry of Health in Israel provides

incentives to encourage vaccination, which take the form of a television campaign promoting the vaccination program and the offering of free vaccinations to all age groups. 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. 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. In order to achieve a representative sampling, we used data from the Israeli Central Bureau of Statistics to divide the Israeli population into statistical layers based on socio-demographic characteristics such as geographic region of residence, length of time in the country, level of religious observance and socio-economic 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 interviewees 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. Out of the 917 interviewers, 83 proved to be unavailable. Hence, our representative sample contained 834 individuals. Of that sample, 364 refused to participate in the poll, leaving us with a final total of 470 interviewees (a response rate 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 4 years of age and 144 were above 4. 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.

The basic assumption in game theory 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

\footnote{According to the Israeli Center for Disease Control and Prevention, the infection rate was fewer than 5 people per 10,000, see http://www.health.gov.il/Download/pages/flu050311.pdf}
vaccination $r$, and the probability of infection $\phi$. To verify our model, we checked to see if, indeed, those parameters affected people's decision. 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 they intended to take the vaccine in the upcoming season (or vaccinate their children) regardless of any incentives provided by the authorities to encourage vaccination. However, regardless of the age group, the estimators of the perceived values of $\phi$, $\frac{D_s}{D_v}$ 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 < 0.001). 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:

$$p = \frac{\exp(\beta_0 + \beta_1 \frac{D_s}{D_v} + \beta_1 r + \beta_2 \phi + \varepsilon)}{\left[\exp(\beta_0 + \beta_1 \frac{D_s}{D_v} + \beta_1 r + \beta_2 \phi + \varepsilon) + 1\right]}$$

where $\varepsilon \sim N(0, \sigma^2)$

where $\beta_i$ are the coefficient values $\frac{D_s}{D_v}$, $r$ and $\phi$ 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 intends to get the vaccination (P-value < 0.001), providing an 87.74\% correct classification. Hence, the logistic regression suggests that individuals tend to make their decision according to the reality of the situation, which converges to equilibrium.

The next step is to describe the individual’s utility from the incentive $\pi$ given by HCP, $q(\pi)$. We looked for a subsidy function that describes consumption and satisfies the conditions of $q(\pi)$ (Namely, $q(0) = 0$, $\frac{dq(\pi)}{d\pi} \geq 0$, and $\frac{d^2q(\pi)}{d\pi^2} \leq 0$ and $\frac{dq(\pi=0^+)}{d\pi} \geq 1$). We chose the isoelastic function, $q(\pi) = \frac{\pi^{(1-a)}}{1-a}$, 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, simulation analyses were performed on a vast 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 $a$ equalled $0.4$ and $0$, respectively.
Table 1: Parameters used in the simulation analysis. Values, range of tested values and sources used for revaluation of parameters to the basic model.

### 4.2 NIS analysis

In Section 2.1, we argued that the marginal contribution of one additional inoculated individual is important in understanding the relevance of incentives. In this section, we calculate the NIS and present comparative simulation results demonstrating its importance.

Intuitively, one would expect that in cases of more contagious influenza strains, 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. Simulations performed (Figure 2A and 2B) show that as long as the level of vaccination coverage is less than herd immunity, the NIS is greater in the case of less contagious types of influenza ($R_0 = 1.2$) rather than in more contagious seasonal strains, 1.6 H1N1 pandemic strains.

---

1.2 seasonal strains, 1.6 H1N1 pandemic strains
ones ($R_0 \geq 1.6$ such as the H1N1). In Figure 2A, in which we assume that the vaccination is completely effective (i.e., $r = 1$), the number of NIS ranges between 1.4 and 1.9 individuals. The gap in the NIS between weak influenza strains and strong strains narrows when the efficacy of the vaccination is lower. In Figure 2B, we present the NIS for the case in which the efficacy of the vaccination is 70% (i.e., $r = 0.7$).

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 U.S. ranged from 12.9% in Mississippi to 38.8% in Rhode Island. One might conclude from these data that stronger incentives to become inoculated 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 2A, 2B). Given that incentives should be bounded by their benefits, greater incentives should be considered in Rhode Island.

As suggested in the former section, the NIS is made up of two components: self-interests and altruism. Figures 3C and 3D present the NIS and the corresponding two components for $R_0 = 1.2$ and $R_0 = 1.6$. In all strains of influenza in the range of $1 \leq R_0 < 1.75$, that is, epidemic and pandemic influenza such as H1N1, an inoculated 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 an inoculated individual to himself decreases with $p$, whereas his contribution to society at large increases with $p$ (figure 3C, 3D). 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.

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 the flu season. In this case, the effective basic reproductive ratio is used, $R_{eff} = R_0 S_0$, where $S_0$, represents the initial susceptible proportion of the population. Simulations show that even when only 60% of the population is susceptible, the trends remain the same.

### 4.3 Optimal incentive – The homogenous population

In the preceding section, we focused our discussion on three cases involving different levels of vaccination coverage: $p_{eq}$, $p_{opt}$ and $p_{SGP}$. The five panels in Figure 3 summarize the
Figure 2: NIS as a function of level of vaccination coverage for different values of $R_0$. In Figure A, the efficacy of the vaccination is complete. In Figure B, the efficacy of the vaccination is 70%. In Figures C and D, the efficacy of the vaccination is complete, and $R_0$ equals 1.2 and 1.6, respectively.

Simulation results based on Table 1. In each panel, two vertical axes are shown; the left axis represents the level of vaccination coverage and the right axis represents incentives in U.S. dollars. The dashed curves represent the three levels of vaccination coverage $p_{eq}$, $p_{opt}$ and $p_{SGF}$. The solid curve represents the optimal incentive that supports the corresponding $p_{SGF}$. Figure 3A shows the level of vaccination coverage and the optimal incentive as a function of the basic reproductive ratio, $R_{eff}$. Figures 3B and 3C represent selected one-way sensitivity analyses as follows: B1 and B2 summarize the results as a function of perceptions about the costs of the disease $D_s$ when $R_{eff} = 1.2$ and 1.6. C1 and C2 summarize the results as a function of the efficacy of the vaccination when $R_{eff} = 1.2$ and 1.6.

Simulations show that when no incentive is provided, the level of vaccination coverage attained through self-interests ranges between 0 and 37.7%. The optimal level of vaccination coverage, however, ranges between 25.2% and 59.1%. The gap between the two ranges between 21.4 and 27% (Figure 3A). Simulations suggests that the larger the ratio between
those getting vaccinated and those refusing to do so \( \frac{D_s}{D_a} \), the smaller the gap between \( p_{eq} \) and \( p_{opt} \). If an optimal incentive is provided to the inoculated, the gap between the optimal level of vaccination coverage, \( p_{opt} \) and the predicted one, \( p_{SGP} \) ranges between 3.5% in seasonal influenza strains and up to 9.5% in pandemic ones (Figure 3A).

The optimal incentives for the SP, \( \pi^* \), range between $36 and $65 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. 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, particularly when dealing with seasonal influenza strains. 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 60% efficacy and 100% efficacy was less than $5 per person (Figure 3, graphs C1 and C2). 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 the inoculated of up to $15 (Figure 3, graphs B1 and B2). Trends remain more or less the same as shown in Figure 3A when running the simulations with different values of \( S_a \) or \( a \) in the range shown in Table 1.
4.3.1 Optimal incentive – The heterogeneous population

In this section, we will examine the heterogeneous model for the case of the two sub-groups considered. The formulation of the model for the heterogeneous population is detailed in Appendix E. 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, $p_{eq}^{i}$, the optimal incentives $\pi^{\ast i}$ and the corresponding vaccination coverage $p_{SGP}^{i}$. 

The elderly versus 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 the rest of the population (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 theelderly and the non-elderly (see Appendix E for details).

The simulation results are summarized in Figure 4. In the figure we present the level of vaccination coverage achieved by the self-interests of the elderly and the non-elderly when incentives are not provided (Figure 4A1) and when optimal incentives are provided (Figure 4A2). In Figure 4A2, the left axis represents the level of vaccination coverage, whereas the right axis represents the costs in U.S. dollars. The dashed curves 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 contiguous influenza strains are reported (i.e. $R_{eff}=1.2-1.35$), the self-interests of the non-elderly 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 ($R_{eff}=1.35-1.8$), the self-interests of the non-elderly 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 non-elderly inoculated individual reduces the probability of infection for the entire population, including the elderly. Hence, for the elderly, the motivation to get vaccinated declines. In that sense, the elderly choose to free ride, and 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 inoculated person in reducing the probability of infection for both age groups is less than the contribution of a non-elderly inoculated person. As a result, when considering incentives, authorities should realize that greater incentives offered to the non-elderly are more effective for the elderly as well (Figure 4A2). As in the homogenous model, we found that the more infectious the influenza strain, the lower the optimal incentive should be. In seasonal influenza strains ($R_{eff} = 1.2 - 1.5$), no incentive is offered to the elderly because the probability of their reducing the chance of infection among the rest of the population is relatively low. However, an incentive for the non-elderly 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. $R_{eff} > 1.5$), the elderly’s self-interests in getting inoculated increase rapidly. Even if no
incentive or a very small incentive is offered to the elderly, they will take the vaccine anyway because it is in their personal interests to do so.

**Children versus others**  As with the elderly, the costs to the SP and the perceived costs to parents are greater when children are considered (See appendix E). 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).

Figures 4B1 and 4B2 present the results when children versus others are considered. Results suggest that when no incentive is given to become inoculated, the level of vaccination coverage in children should be higher than 30% and should increase as $R_{eff}$ increases. When incentives are offered, all children should be inoculated in all simulations performed. In seasonal types of influenza, vaccinating children in this age group can be achieved by offering the proper incentives. In pandemic situations, there is no need to offer incentives, because their parents are motivated to give them the vaccination anyway.

### 5 Conclusions and 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 theoretical model to evaluate the optimal magnitude of incentives for inoculation and proved analytically that because the level of vaccination coverage is sub-optimal for the general welfare of society and the HCP, it is important to offer incentives that will motivate people to become inoculated. Based on the survey data we have found that indeed people make their vaccination decision based on their self interest what supports our analytical finding that providing incentives is crucial.

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 $35 in cases of more contagious influenza up to $60 in cases of less contagious strains.

The heterogeneous model showed that the SP should favor giving greater incentives to the non-elderly 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 inoculated. 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 maintain that it expands the use of herd immunity to create more realistic levels of vaccination coverage which takes into consideration cost effectiveness. The NIS is comprised of the contribution of a vaccinated individual to 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 10% is the contribution made by the individual’s self-interests and the rest is attributable to the 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 10 times higher than the overall costs of the vaccination. Simulations suggests 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.

A Proof of Proposition 1

From standard arguments (see, for example, Diekmann et al. 2000 ) we get from (5,6):

\[ S_\infty = (1 - rp - i_0)e^{\frac{\beta}{\gamma}(S_\infty + rp - 1)} \]

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

\[ S_\infty = -\frac{\gamma}{\beta}W\left(\frac{\beta}{\gamma}(1 - rp - i_0)e^{\frac{\beta}{\gamma}(1-rp)}\right), \tag{10} \]

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

\[ \phi(p) = \frac{1 - rp - i_0 - S_\infty}{1 - rp - i_0}. \tag{11} \]

Substituting (10) in (11) gives (1). \( \square \)
Consider the non-trivial 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 $\frac{dU^{SW}}{dp}|_{p=p_{eq}} > 0$. The social welfare utility is composed of a linear combination of two monotonically increasing functions $U(\text{accept}; p)$ and $U(\text{reject}; p)$. In other words,

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

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

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

All that remains is to show that $\frac{dU^{SW}}{dp}|_{p=p_{eq}} > 0$.

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

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

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

\[\square\]

C Proof of Corollary 3

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

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

\[
= \frac{dp_{SGP}}{d\pi} \bigg|_{\pi=0} \left( S_v - p_{eq} + \frac{S_sD_v}{D_s} \frac{dp_{SGP}}{d\pi} \bigg|_{\pi=0} \right) - \frac{S_s}{rD_s} (1 - rp_{eq}) q'(0)
\]

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

Given that \( \frac{rp_{eq}}{(1-rp_{eq})} < \frac{S_v}{D_v} \) and \( q'(0) \geq 1 \) the result follows. □

**D Questionnaire and Data Analysis**

Presented below the relevant questions from the telephone survey discussed in the data set and simulations section above.\(^6\)

\(^6\)All costs are presented in new Israeli shekels.
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."

<table>
<thead>
<tr>
<th></th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Generally speaking, in your opinion, what are the chances that you will get seasonal influenza if you don’t get vaccinated in that season?</td>
</tr>
<tr>
<td>2</td>
<td>Generally speaking, in your opinion, what is the chances that you will get seasonal influenza if you do get vaccinated in the same season?</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>Is it dangerous for you to contract seasonal influenza?</td>
</tr>
<tr>
<td>4</td>
<td>Is it dangerous for you to get the influenza vaccination?</td>
</tr>
</tbody>
</table>

Please answer the following multiple choice questions

<table>
<thead>
<tr>
<th></th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>In the past six months, did you take the influenza vaccination? A. yes B. no C. don’t remember or refuse to answer.</td>
</tr>
<tr>
<td>6</td>
<td>Before next fall, will you take the influenza vaccination? A. yes B. no C. don’t know or refuse to answer.</td>
</tr>
</tbody>
</table>

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.

<table>
<thead>
<tr>
<th></th>
<th>Question</th>
</tr>
</thead>
<tbody>
<tr>
<td>7</td>
<td>Hypothetically, what is the maximum amount you would be willing to pay to buy that drug? A. I would not agree to pay for the drug B. 0-50 C. 50-100 D. 100-300 E. 300-500. F. 500-1000. G. more than 1000</td>
</tr>
<tr>
<td>8</td>
<td>In the past six months, did you have influenza? A. yes (or think so) B. no C. don’t remember or don’t know</td>
</tr>
<tr>
<td>9</td>
<td>If you said yes (or think so) in question 8, did you see a doctor when you were sick? A. yes B. no C. don’t remember</td>
</tr>
<tr>
<td>10</td>
<td>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 didn’t go to the doctor</td>
</tr>
</tbody>
</table>

Table 2: The relevant questions from the survey.

For each interviewee, the estimation of the perceived cost of being sick was calculated by using the 'willingness to pay' method (Prosser et al. 2005), and the answers to question 7. 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.

E Heterogenous Population: Modeling and Estimation of Parameters

E.1 Modeling

In this section, we generalize our model for a heterogenous population with two age groups.\footnote{Generally, the population may be divided into sub-groups not just by age, but also with respect to any social or geographical parameters.}

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 benefit $\pi^i$ that will be granted to a vaccinated individual from group $i$.\footnote{Observe that if for political reasons the SP must offer the same incentive for all populations, then $\pi = \pi^i$ for all $i$. In such a case, the model becomes similar to the one we have in the homogenous case, but with different levels of vaccination coverage for different age groups.}

We assume that the magnitude of the incentive for vaccinated individuals according to the age groups is non-negative and identical for all of the vaccinated individuals in the same age group. The individual’s strategies remain \{accept, reject\}. Let $\alpha^i$ and $\rho^i$ be the proportion of individuals and the level of vaccination coverage in sub-group $i$, $i = 1, 2$ among the entire population respectively. As in the homogenous model, the expected utility for an individual in age group $i$ who chooses to accept or reject vaccination is given by:

$$U^i(\text{reject}; \rho^1, \rho^2) = -D_v^i \phi_i(\rho^1, \rho^2), \ i = 1, 2,$$

$$U^i(\text{accept}; \rho^1, \rho^2) = -D_v^i + q^i(\pi^i) - (1 - r)D_s^i \phi_i(\rho^1, \rho^2), \ i = 1, 2.$$

The SP’s utility is given by:

$$U^{SP}(\pi^1, \pi^2, \rho^1, \rho^2) = \sum_{i=1}^{2} \alpha^i [p^i(-S_v^i - \pi^i - (1 - r)S_s^i \phi_i(\rho^1, \rho^2)) - (1 - p^i)S_s^i \phi_i(\rho^1, \rho^2)].$$
As in the argument in Proposition 4, the sub game perfect Nash equilibrium \(((\pi^1, \pi^2), p^1, p^2)\) should satisfy the system

\[
\max_{\pi^1, \pi^2 > 0} \{ U^{SP}(p^1, p^2) \}
\]

s.t. \(\phi^i(p^1, p^2) \leq \frac{D_i^i - q^i(\pi^i)}{rD_i^i}, \quad i = 1, 2. \) (13)

Note that if \(\phi^i(p^1, p^2) < \frac{D_i^i - q^i(\pi^i)}{rD_i^i}\) in equilibrium, it follows that \(p^i_{SGP} = 0\). 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:

\[
\begin{align*}
\frac{dS^1(t)}{dt} &= -\beta^{11} S^1(t) I^1(t) - \beta^{12} S^1(t) I^2(t), \\
\frac{dI^1(t)}{dt} &= \beta^{11} S^1(t) I^1(t) + \beta^{12} S^1(t) I^2(t) - \gamma^1 I^1(t), \\
\frac{dR^1(t)}{dt} &= \gamma^1 I^1(t), \\
\frac{dS^2(t)}{dt} &= -\beta^{22} S^2(t) I^2(t) - \beta^{21} S^2(t) I^1(t), \\
\frac{dI^2(t)}{dt} &= \beta^{22} S^2(t) I^2(t) + \beta^{21} S^2(t) I^1(t) - \gamma^2 I^2(t), \\
\frac{dR^2(t)}{dt} &= \gamma^2 I^2(t),
\end{align*}
\]

where \(S^i(t), I^i(t), R^i(t)\) are the proportions of susceptible, infectious and recovered individuals respectively for age group \(i\) at time \(t\). \(\beta^{ij}\) is the infectious rate of individuals from age group \(i\) when they encounter individuals from age group \(j\). \(\gamma^i\) 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

\[
\begin{align*}
S^i(0) &= \alpha^i - i_0^i - r^i p^i, \quad i = 1, 2, \\
I^i(0) &= i_0^i, \quad i = 1, 2, \\
R^i(0) &= r^i p^i, \quad i = 1, 2.
\end{align*}
\]

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.
E.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 $\beta_{ij}$ depends mainly on the number of interactions between individuals from age group $i$ with individuals from age group $j$. In order to estimate $\beta_{ij}$, 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+. This data reveal that elderly individuals tend to interact less with others than with themselves and vice versa. We created a $2 \times 2$ matrix, $M^{ob}$ representing the observed average number of contacts between age group $i$ and $j$. Then, we created a $2 \times 2$ 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 had to estimate the proportion of each age group in the population, $\alpha^i$. In our simulations we covered the range $0.08 \leq \alpha^i \leq 0.2$ for the elderly and for children $0.02 \leq \alpha^i \leq 0.06$ so it would match with the majority of developed countries.\footnote{See http://www.un.org/esa/population/publications/worldageing19502050/}

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 $C^{ej}$. We estimated the $\beta_{ij}$ as the multiplication of those coefficients with an infectious rate from the homogeneous model $\beta$ ranged to create $1.2 < R_0 < 1.8$. The recovery time for the elderly and children under 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 4-5 days (Galvani et al. 2007). Accordingly, we assumed $\frac{\alpha^1}{\gamma^1} + \frac{\alpha^2}{\gamma^2} = 4.5$ 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.

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

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.

\[
M^o_b = \begin{pmatrix} 2.38 & 8.34 \\ 0.4 & 13.5 \end{pmatrix}; M^{ex} = \begin{pmatrix} 0.55 & 13.33 \\ 0.55 & 13.33 \end{pmatrix}; C^{ef} = \begin{pmatrix} 4.32 & 0.63 \\ 0.73 & 1.01 \end{pmatrix}; \beta^{ij} = \begin{pmatrix} 4.32\beta & 0.63\beta \\ 0.73\beta & 1.01\beta \end{pmatrix}
\]

Table 2 summarizes the perceived costs estimated by our survey and the ranged check (Confidence interval >95%). Here the currency has been converted to U.S. dollars\(^{10}\):

<table>
<thead>
<tr>
<th>Symbols</th>
<th>Perceived cost due to:</th>
<th>Range checked</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(D_{s}^{elderly} ), (D_{s}^{Non-elderly} )</td>
<td>Cost of illness for elderly (Non-elderly)</td>
<td>250-350, (95,119)</td>
<td>300, (107)</td>
</tr>
<tr>
<td>(D_{s}^{children} ), (D_{s}^{Non-children} )</td>
<td>Cost of illness for children (Non-children)</td>
<td>175-225 (112,132)</td>
<td>200, (122)</td>
</tr>
<tr>
<td>(D_{v}^{elderly} ), (D_{v}^{Non-elderly} )</td>
<td>Vaccination cost for elderly (Non-elderly)</td>
<td>30-60 (30,38)</td>
<td>45, (34)</td>
</tr>
<tr>
<td>(D_{v}^{children} ), (D_{v}^{Non-children} )</td>
<td>Vaccination cost for children (Non-children)</td>
<td>70-90 (28,38)</td>
<td>80, (33)</td>
</tr>
</tbody>
</table>

Table 3: The relevant questions from the survey.

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. 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 3 presents the estimation of the parameters in U.S. dollars and their range checks:

<table>
<thead>
<tr>
<th>Symbols</th>
<th>HCP’s cost due to:</th>
<th>Range checked</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>(S_{s}^{elderly} ), (S_{s}^{Non-elderly} )</td>
<td>Cost of illness for elderly (Non-elderly)</td>
<td>490-510 (188,196)</td>
<td>500 (192)</td>
</tr>
<tr>
<td>(S_{s}^{children} ), (S_{s}^{Non-children} )</td>
<td>Cost of illness for children (Non-children)</td>
<td>330-370 (210,220)</td>
<td>350 (215)</td>
</tr>
<tr>
<td>(S_{v}^{elderly} ), (S_{v}^{Non-elderly} )</td>
<td>Vaccination cost for elderly (Non-elderly)</td>
<td>15-25</td>
<td>20 (20)</td>
</tr>
<tr>
<td>(S_{v}^{children} ), (S_{v}^{Non-children} )</td>
<td>Vaccination cost for children (Non-children)</td>
<td>15-25</td>
<td>20 (20)</td>
</tr>
</tbody>
</table>

Table 4: The relevant questions from the survey.

\(^{10}\)Costs estimations were taken from three different currencies—the Israeli Shekel, the U.S. Dollar and the European Euro. From 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 article presents only the trends that were consistent in all of the ranges.
References


