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Social Networks and Vaccination Decisions

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Abstract:
We combine information on social networks with medical records and survey data in order to examine how friends affect one's decision to get vaccinated against the flu. The random assignment of undergraduates to residential halls at a large private university allows us to estimate how peer effects influence health beliefs and vaccination choices. Our results indicate that social exposure to medical information raises people's perceptions of the benefits of immunization. The average student's belief about the vaccine's health value increases by $5.00 when an additional 10 percent of her friends are assigned to residences that host inoculation clinics. Among students with no recent flu experience, a 10 percent rise in the number of friends living in residences with clinics raises cumulative valuations of the vaccine by $10.92, with 85 percent of this increase attributable to heightened perceptions about the medical benefits of immunization. We also find evidence of positive peer effects on individuals' vaccination decisions. A student becomes up to 8.3 percentage points more likely to get immunized if an additional 10 percent of her friends receive flu shots. Furthermore, the excess clustering of friends at inoculation clinics suggests that students coordinate their vaccination decisions with their friends.

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1 Introduction

Friends influence one's medical beliefs, health care decisions, and use of clinical services. Epidemiologists and public health scholars have long documented the role of social networks on the spread of infectious diseases (Potterat et al. (2002); Morris (1997); Liljeros et al. (2001); Jones and Handcock (2003); Sattenspiel and Simon (1988)). In a recent intriguing study, Christakis and Fowler (2007) present suggestive evidence from the long-running Framingham Heart Study to argue that seemingly non-contagious obesity also "spreads" through social networks. In contrast, public health literature on prevention and education has for the most part focused on individual level interventions such as reminders and education campaigns (Smith et al. (1999); Marron et al. (1998); McDowell, Newell, and Rosser (1996); Siriwardena et al. (2002)). Since peer effects can amplify the efficacy of such interventions through social learning, measuring how one's medical beliefs and healthcare decisions are influenced by social interactions can aid in the design of cost-effective public health interventions. In a recent seminal paper, Miguel and Kremer (2007) examine how social learning among Kenyan villagers affects the spread of new deworming medicines. Deri (2005) presents evidence of neighborhood effects on health service use among immigrants. In several instances, policymakers have begun to design interventions that utilize peer interactions to achieve public health goals. Wiist and Snider (1991), for example, discuss the use of peer educators in youth anti-smoking campaigns. Speizer, Tambashe, and Tegang (2001) evaluate a community-based program in Cameroon, in which teenagers are recruited to promote contraceptive use among their friends. Such peer promotion programs seek to exploit the strong social effects that influence adolescent behavior.

This paper investigates peer influences on an individual's decision to get vaccinated against the flu. In the United States, about 24.7 million cases of influenza are reported annually, resulting in an estimated 3.1 million days in the hospital, 44.0 million missed workdays, and 0.6 million lost years of life (Molinari et al., 2007). Vaccination can be between 50 percent and 90 percent effective in protecting against influenza, depending on which strains of the virus are circulating in a particular year (Bridges et al., 2000). Given the sizeable economic burden of the disease and the potential benefits of immunization, several health care agencies have launched outreach programs to distribute vaccines in public places. For example, Wuorenma, Nichol, and Vonsternberg (1994) study a health maintenance organization that sponsored a series of walk-in inoculation clinics for members. Weitzel and Goode (2000) describe a supermarket chain whose stores were equipped with in-house pharmacies that dispensed vaccines to shoppers. In this paper, we examine whether peer effects can widen the impact of such programs, improving vaccine coverage in communities at large.

Our study of a targeted immunization program at a large private university indicates that social effects increase the likelihood of an untargeted student's becoming vaccinated by 3.3 percentage points. This finding suggests that localized public health interventions may be able to reach a broader population through social networks than can be reached through individual level interventions. In principle, there are several channels through which social contacts can influence an individual's vaccination decision. Friends may exchange medical information among themselves, shaping one another's beliefs about the influenza virus and the flu vaccine. In addition, when many members of a group get flu shots, unvaccinated members may feel social pressure to get one too. Our analysis reveals that social learning about medical benefits accounts for 85 percent of combined social effects on an individual's valuation of the vaccine.

As Manski (1993) observes, measuring peer effects involves significant challenges. Similar behavior among peers can often be attributed to shared environments or associative sorting. Moreover, peers simultaneously influence one another's behavior, complicating the task of identifying how one peer affects another. To address these issues, estimates of social effects often rely on instruments to proxy for peer behavior. For example, Case and Katz (1991) use the behavior of peers' parents as an instrument for criminal activity and drug use among one's peers. Evans, Oates, and Schwab (1992) try to account for endogenous high-school selection, by using economic indicators in one's MSA as an instrument for the economic background of one's peers.

To measure peer influences, we use data on the social networks and vaccination histories of students at Harvard College. Each spring, groups of rising sophomores are randomly assigned to one of Harvard's twelve residential houses. During the fall vaccination clinics are held at four of these houses. Individuals living in houses with clinics may find it especially convenient to get vaccinated. They may also be better informed about when and where flu clinics take place. In this way, the randomization procedure helps to generate exogenous variation in individuals' propensities to get vaccinated. This enables us to distinguish peer influences from selection effects.

Several earlier studies have used randomized experiments to estimate peer influences. Sacerdote (2001) uses data on randomized dorm and room assignments of freshmen at Dartmouth College, in order to estimate peer effects for college GPA and fraternity membership. Zimmerman (2003) studies peer influences on students' academic outcomes, arguing that freshman housing assignments at Williams College are independent of students' academic abilities. Marmaros and Sacerdote (2002) use random assignment to measure social effects on labor-market outcomes. The housing lottery at Harvard permits Ward (2004) to examine the effect of physical distance on the structure of social networks.

These studies use randomization to assign reference groups to individuals. Our setup differs in that individuals can select their peers but not where their peers live. Thus, each individual's allocation of social contacts across houses will be exogenous. Sections 3.2 and 4.1 use this insight to study social learning about the influenza virus and the flu vaccine. We examine how social ties to houses with flu clinics influence students' clinical beliefs. Our framework is closest to Miguel and Kremer's (2007) study of social learning in Kenyan villages, which utilizes the random assignment of villages to treatment categories in order to identify the effect of friends on villagers' beliefs about deworming practices. Unlike those authors, we find evidence of positive peer effects on health care decisions. Moreover, we devise a procedure to obtain separate dollar-valued estimates of social learning and other peer influences. We can thereby show that our positive results are attributable to social learning about medical benefits as opposed to mere imitation effects.

This paper also investigates the interrelationships among the medical choices of friends. Sections 3.3 and 4.2 analyze how students who decide to get flu shots, choose which clinic to attend. We adapt Ellison and Glaeser's (1997) dartboard technique to test whether friends tend to cluster together at flu clinics. Sections 3.4 and 4.3 measure peer effects on an individual's vaccination decision. We use the share of one's friends in houses with clinics as an instrument for friends' decisions to get vaccinated. Sections 3.5 and 4.4 attempt to isolate the mechanisms whereby peers influence one's behavior. By analyzing how influenza infections moderate the impact of friends on students' beliefs and choices, we can distinguish social effects on perceptions about health benefits from other peer influences on immunization decisions.

The balance of the paper is organized as follows. Section 2 presents our data sources. Section 3 describes our empirical strategy, and section 4 presents our results. Section 5 concludes.

2 Data

To study peer effects on vaccination decisions, we combine data from three sources: the Trivia Game (TG), the House Experiment (HE), and Harvard University Health Services

(HUHS). The social network of Harvard College was constructed using data from the TG. The HE asks students about their beliefs on health topics. The data set from HUHS contains a record of students' vaccination histories.

2.1 Social Network Elicitation - Trivia Game

Information on social networks was collected through an online Trivia Game at the website `facebook.com`. This website was launched in February 2004 by Harvard student Mark Zuckerberg, in order to promote social networking among college students. As of November 2007, membership at `facebook.com` has expanded to over 46 million users, including 85 percent of students at four-year colleges nationwide. Members post an online profile of themselves, including a photograph, biographical data, and information about activities and interests. The site `facebook.com` also allows members to create a list of their friends and to view the friends of their friends. In this way, members construct a map of the relationships among students at their campuses.

As Ward (2004) notes, members often compile lists of over 100 friends, containing many people with whom they maintain only weak social ties. To identify students' stronger relationships, Mobius, Niehaus, and Rosenblat (2006) design a Trivia Game (TG) among students at Harvard College who are listed on `facebook.com`. TG is a web-based economic experiment in which participants are incentivized to truthfully reveal their friendship links. Upon login to `facebook.com`, participants were asked to choose 10 friends among their `facebook.com` friends. Over the course of several weeks, a computer program randomly selected some of these participant-friend links and sent an e-mail message to the participant's friend, asking him to select the correct answer to a multiple choice question, such as what time he gets up in the morning. Once a participant's friend had answered the question, the participant received an e-mail directing her to a web page where she had a 15 second time limit to answer the same multiple choice question about her friend. If the participant and her friend submitted identical answers, they both won a prize. The trivia game provided subjects with incentives to list friends with whom they spend a lot of time and with whose habits they are therefore familiar. The participants include 2,939 of the 6,389 undergraduates at Harvard during the 2004–2005 academic year. Upperclassmen had higher participation rates than freshmen, with only 34 percent of freshman responding, but 45 percent, 52 percent, and 53 percent of sophomores, juniors, and seniors participating, respectively. The social network of Harvard College was constructed using the 10 friends named by each participant. Individuals were connected using an or-link definition, where two subjects were related if either one named the other as a friend. The data set comprises 23,600 links among students, with 12,782 links occurring between participants. In total, 5,576 of the 6,389 undergraduates at Harvard College had either participated or been named by a participant. The social network of 5,576 individuals contains a single component having a mean path length of 4.2 between participants.

2.2 Health Beliefs and Behavior - House Experiment

The House Experiment (HE) was conducted at Lowell and Kirkland Houses during the 2003–2004 academic year. Between November 25 and December 11, students living in these houses were invited to complete an online survey about their beliefs about the influenza virus and the flu vaccine. Of the 802 residents in Lowell and Kirkland, 509 individuals responded to the survey. Table 1 lists the questions that were asked to elicit respondents' beliefs. Respondents were asked about the following: the importance of getting vaccinated against the flu; the probability of a vaccinated person's contracting the flu; the probability of an unvaccinated person's contracting the flu; and the disutility of becoming sick with the flu. Tables 2 and 3 summarize the responses to these questions. Students feel that the cost of catching the flu is about $102. They believe on average that the flu vaccine reduces the risk of infection from 44 percent to 16 percent. About 27 percent of them reply that it is either important or very important to get vaccinated against the flu.

Subjects also answered questions about their vaccination records and medical histories. Table 4 summarizes subjects' responses to the questions in this component. About 33 percent of subjects got flu shots during the 2002–2003 flu season. During the 2003–2004 flu season, Harvard University Health Services (HUHS) operated vaccination clinics at the dates and locations shown in Table 5. Flu clinics were held at four residential houses: Currier, Eliot, Leverett, and Mather. No flu clinics were held at Lowell or Kirkland, where the survey was conducted. About 21 percent of subjects in Kirkland and 19 percent of those in Lowell reported being vaccinated during the 2003–2004 flu season. Table 5 displays the number of respondents who visited each of the vaccination clinics run by HUHS. Another 27 percent claimed that they were planning to get vaccinated within the next few months. Since only 33 percent got flu shots during the 2002–2003 flu season, many subjects who plan on being vaccinated, may not end up getting a flu shot.

The HE also collected data on the social ties among residents of Lowell and Kirkland Houses using a coordination-game technique. Each participant was told to list her 10 best friends and indicate the average amount of time she spends with each of them per week (0–

30 minutes, 30 minutes to 1 hour, 1–2 hours, 2–4 hours, 4–8 hours, or more than 8 hours). The subject was paid a small amount (in our case, 50 cents) with 50 percent probability for each listed friend who also listed her. The probability increased to 75 percent if subjects also agreed on the amount of time they spend together each week. We made the expected payoff for each probability (25 or 37.50 cents) large enough to give subjects an incentive to report their friends truthfully and small enough to discourage coordinated "gaming." The randomization was included to limit disappointment if a subject was named by few people. We then connected residents using an or-link definition, whereby two residents were related if either one specified the other as a friend. All 802 residents of Lowell and Kirkland Houses either participated or were named by a participant. The social network comprises a single cluster with a mean path length of 3.3 between participants.

A component of the HE asked subjects about peer influences on their vaccination decisions. Table 1 lists the questions that were included in this component. Subjects' responses are summarized in Table 6. About 43 percent of those who got flu shots, reported that their friends influenced their decision to get vaccinated. Of the 114 subjects who got flu shots, 37 percent went to a flu clinic with their friends, and 18 percent were accompanied by their roommates. Only 13 subjects visited a flu clinic with one of the 10 friends whom they specified in the survey.

2.3 Vaccination Records - Harvard University Health Services

Harvard University Health Services (HUHS) provided us with information on the medical histories of 10,091 students in the graduating classes of 2002 to 2006. The data set includes students' vaccination records for the academic years from 2001–2002 to 2003–2004. Each year, HUHS held flu clinics at four residential houses: Currier, Eliot, Leverett, and Mather. The dates and locations of these clinics are listed in Table 7. HUHS also hosted clinics at other locations on campus. Most clinics took place in late November or early December. Table 8 provides the vaccination rates for the residents of each house. About 20 percent of students got flu shots in the 2001–2002 and 2002–2003 academic years. In 2003–2004, almost 27 percent of students were vaccinated.

Houses with clinics tend to have higher vaccination rates. In 2003–2004, for example, about 32 percent of students in houses with clinics got flu shots, but only 24 percent of those in houses without clinics were vaccinated. In houses with clinics, most students who decided to get a flu shot were vaccinated at the clinic in their house. To illustrate, Table 9 displays the number of Leverett residents who got vaccinated on each date during the 2003–

2004 school year. The vaccination rate rose sharply on November 24, when HUHS held a clinic at the Leverett dining hall.

3 Empirical Strategy

3.1 Background

Much of our analysis aims to identify the influence of group choices on individual choices. Manski (1993) discusses the problems in inferring whether the average behavior within a group affects the behavior of each group member. Peers may display similar behavior because of both social and nonsocial effects. In Manski's terminology, social effects can be classified into endogenous effects and contextual effects. The former arise when an individual's behavior depends on the behavior of her peers. The latter reflect the impact of peers' background characteristics on an individual's behavior. Nonsocial effects include common environments or positive sorting, which contributes to similar observable and unobservable environments among members of the same group. Manski argues that endogenous social effects cannot be identified unless suitable data are available on individuals' reference sets.

The quasi-experimental setup at Harvard College enables us to separate social effects from nonsocial effects. Each spring, freshmen at Harvard participate in a housing lottery, forming blocking groups that consist of up to eight individuals. These groups are then randomly assigned to one of Harvard's twelve residential houses. During the fall, HUHS sponsors flu clinics at several locations on campus. In particular, four residential houses host clinics, where students can get vaccinated free of charge. If most friendships are formed during freshman year, then the housing lottery will randomize the allocation of friendships across houses. Specifically, rising sophomores will take as exogenous the share of their friends in houses with clinics.

Even if students make new friends after freshman year, we argue that they would not purposefully seek out contacts in houses with clinics. Since students are randomly assigned to houses, students' personal characteristics will not be correlated with their place of residence. So while students would continue to select peers who are similar to them, they would not target the individuals living in a specific house, because the students in one house will have the same distribution of characteristics as those in other houses. In other words, it is unlikely that health-conscious students will befriend the residents of houses with clinics at a disproportionately high rate.

Students in other houses may learn about flu-related topics from their friends who live in houses with clinics. Specifically, the share of a student's friends who live in houses with clinics will provide an exogenous measure of a student's exposure to medical information through social ties. In section 3.2, we outline a procedure for measuring how friends influence an individual's beliefs about the influenza virus and the flu vaccine. Our methodology is similar to that used in Miguel and Kremer's (2007) study of social learning about new medical technologies.

As listed in Table 5, HUHS sponsors several walk-in clinics where students can get flu shots free of charge. Students who decide to get vaccinated can attend any one of these clinics. We wish to examine whether friends make similar location decisions, congregating at the same clinic. In section 3.3, we adapt Ellison and Glaeser's (1997) dartboard approach to detect excess clustering among friends. This procedure will also prove useful in distinguishing peer influences from shared characteristics among friends.

Section 3.4 describes our strategy for estimating social effects on students' vaccination decisions. Since students are randomly assigned to residential houses, we use the share of a student's friends in houses with clinics as an instrument for friends' decisions to get vaccinated. Section 3.5 develops a framework to analyze the channels through which friends affect one's choices. In particular, we decompose one's valuation of the vaccine into believed health benefits and other unobserved factors. To isolate the effect of peers on each component, we examine how influenza infections alter the responsiveness of students' beliefs and choices to interactions with friends in houses with clinics.

3.2 Social Interactions and Health Beliefs

To study how friends influence one another's beliefs, we combine social network data from the TG with information on health beliefs from the HE. Of the 509 participants in the HE, a total of 167 were also among the 2,360 individuals who took part in the TG. Table 1 lists the questions that were asked of participants in the HE. Each participant in the TG reported the names of 10 students who were her friends. Thus, we have information on friendships and beliefs for the 167 students who participated in both the HE and the TG.

During the fall of 2003, HUHS organized flu clinics at four residential houses: Currier, Leverett, Eliot, and Mather. The first of these clinics occurred on November 19, and the last on December 3. These timings roughly coincide with those of the HE, which lasted from November 25 through December 11. Students' health beliefs are likely to be affected during this period. Eliot residents, for example, will have noticed a flu clinic taking place in the house cafeteria. They may decide to get vaccinated and inform their friends in Lowell about the flu clinic. Students may also notice signs advertising the benefits of vaccination or overhear individuals speaking about their experiences at the clinic.

We would expect these effects to be especially strong in houses with flu clinics. Residents of these houses would find it more convenient to get vaccinated. They may also be more aware of the time and place of flu clinics. It would be unsurprising if these individuals were getting vaccinated at a higher rate or had more optimistic beliefs about vaccination. What would be remarkable, however, is if their vaccination decisions or favorable views were influencing the beliefs of their friends in other houses. To identify these effects, we use data on the social ties and medical beliefs of students who took part in both the HE and the TG.

In our setup, we seek to estimate peer effects by using the proportion of an individual's friends who live in houses with a vaccination clinic. The random assignment of students to residential houses permits us to treat the distribution of friendships across houses as exogenous. Since the HE was open only to the residents of Lowell and Kirkland, the 167 students in our data set live in houses without vaccination clinics. These students have 8.7 friends on average, out of which about 1.6 live in houses with a clinic. If friends exchange medical information with one another, then students' beliefs may be influenced by their social ties to houses with clinics.

Participants in the HE were asked to rate the importance of getting a flu shot on a scale from 0 to 3, where 0 stands for "not very important" and 3 for "very important." Table 10 gives a breakdown of participants' responses for those who also participated in the TG. To test for social effects, we fit an ordered probit model of each subject's rating with respect to her share of friends in houses with a flu clinic. Our specification is as follows:

$$FLUIMP_i = \begin{cases} 3 & Q_i > cut3 \\ 2 & cut3 \geq Q_i > cut2 \\ 1 & cut2 \geq Q_i > cut1 \\ 0 & cut1 \geq Q_i \end{cases}, \; Q_i = \beta \cdot PERCLINIC_i + \varepsilon_i \; , \qquad (1)$$

where $FLUIMP_i$ is subject i's rating of the importance of a flu shot, $PERCLINIC_i$ denotes the share of subject i's friends in houses with a flu clinic, and ε_i is an idiosyncratic error term. We estimate the coefficient β and the thresholds $cut1$, $cut2$, and $cut3$. A significantly positive coefficient β would indicate that social ties to houses with flu clinics enhance one's assessment of the importance of being vaccinated.

We also conduct a closer analysis of how friends influence one another's beliefs. Our goal is to examine whether links to houses with clinics alter subjects' perceptions about the risk of infection, the effectiveness of the vaccine, and the disutility of being ill. Table 11 provides descriptive statistics of these variables. We fit a set of models that take the form:

$$BELIEF_i = \alpha + \delta \cdot PERCLINIC_i + \varepsilon_i \ , \tag{2}$$

where $BELIEF_i$ is one of the following: $FLUCOST_i$, subject i's belief about the cost of catching the flu; $FLUVACCNO_i$, her perception of the infection risk if unvaccinated; $FLUVACCYES_i$, her perception of the infection risk if vaccinated; $FLUVACCDIF_i$, the difference $FLUVACCNO_i - FLUVACCYES_i$ between her beliefs about the risk of infection; and $HEALTHVALUE_i$, the product $FLUCOST_i \times FLUVACCDIF_i$ of her beliefs about the cost of being sick with the flu and the decrease in the infection risk from being immunized. We estimate the effect of social contacts on each of these beliefs. We can thereby determine the channels through which friends affect one another's assessments of the benefits of being vaccinated.

Exposure to illness can impact medical beliefs. When evaluating the benefits of immunization, people may rely on their own experiences with disease. A case of influenza could increase one's awareness of the costs of sickness. Flu victims may also feel more vulnerable to infection in the future. Memories of illness, moreover, can affect one's reaction to medical information from friends. Recent flu victims may base their beliefs on their personal knowledge of disease, privileging their own clinical experiences over communications from friends. Alternately, a bout of flu could make one more receptive to information from others about preventing illness.

We wish to study how previous sickness affects social learning. We extend our analysis in specifications (1) and (2), by adding an indicator for influenza infection and an interaction with friends in treated houses. In our ordered response model (1) for the importance of vaccination, the latent variable Q_i is redefined as:

$$\begin{aligned} Q_i = \alpha \ &\cdot FLUVICTIM_i + \beta \ \cdot PERCLINIC_i \\ &+ \gamma \cdot PERCLINIC_i \times FLUVICTIM_i + \varepsilon_i \ , \end{aligned} \tag{3}$$

where $FLUVICTIM_i$ is a dummy variable equal to 1 if subject i reported catching the flu during the last three years. The coefficient α measures the effect of illness on one's baseline evaluation of the importance of immunization. The coefficient β describes how friends influence the evaluations of students who do not recall having had the flu in recent years. The coefficient γ reflects how recent sickness affects the way one's evaluation responds to medical information from friends.

We next analyze the mechanisms whereby exposure to disease affects the process of social learning. We estimate a set of models having the form:

$$\begin{aligned} BELIEF_i = \delta + \theta \cdot FLUVICTIM_i + \kappa \cdot PERCLINIC_i \\ + \lambda \cdot PERCLINIC_i \times FLUVICTIM_i + \varepsilon_i \ , \end{aligned} \tag{4}$$

where $BELIEF_i$ is any of the five health beliefs defined above. The coefficient θ captures the impact of illness on one's medical beliefs. The coefficient κ shows how healthy people update their beliefs in response to health care information from friends. The coefficient λ measures the effect of illness on how one's beliefs change based on communications from social contacts.

Our procedure may be confounded if students first decided whether to get a flu shot and then chose their beliefs to fit their decision. This phenomenon of cognitive dissonance is well established in the social psychology literature. Akerlof and Dickens (1983) describe situations where individuals have preferences over their own beliefs. In our setting, we can imagine a sequence of events where: a student gets invited to his friend's house for dinner; he notices a flu clinic in the house cafeteria; he decides to get vaccinated out of convenience; and he alters his beliefs to justify his decision. In this event, the student's change of beliefs could not be attributed either to information gained through social contacts or to the vaccination decisions of friends. To address this issue, we also estimate specifications (1) through (4), dropping students who were vaccinated at one of the four residential houses with flu clinics. Of the 167 students who participated in both the HE and TG, only 7 students got flu shots at one of these houses.

3.3 Clustering of Friends at Flu Clinics

Students who have decided to get vaccinated also choose which clinic to attend. We wish to examine the degree of clustering in the location decisions of friends. Friends might congregate at specific clinics because of shared characteristics or because of peer influences. In the former case, friends have similar schedules and so find it convenient to get vaccinated at the same time and place. In the latter, students pressure their friends to accompany them to the flu clinic. We apply Ellison and Glaeser's (1997) dartboard approach to test whether the extent of clustering among friends is greater than what would be predicted by chance alone.

Ellison and Glaeser (1997) devise a test of whether the geographic concentration of an industry exceeds the level that would be predicted when firms choose their locations at random. In our framework, students play the role of firms, and peer groups correspond to industries. We obtain social network data from the HE, in which participants were asked to name 10 of their friends in Lowell and Kirkland. Two subjects are connected if either lists the other as a friend. Our analysis focuses on the 49 subjects from the HE who reported getting a flu shot at an HUHS clinic and also had a friend who was vaccinated at an HUHS clinic. Subjects' location decisions are divided among 14 of the 22 clinics held by HUHS during the 2003–2004 flu season.

A useful feature of Ellison and Glaeser's setup is their index of geographic concentration, which we adapt to examine the clustering among friends' choices of clinic. Utilizing their raw concentration measure, we define the index G_i for subject $\imath$ as:

$$G_i = \frac{\sum_{k=1}^{12} (s_{ik} - x_k)^2}{1 - \sum_{k=1}^{12} x_k^2} \,, \tag{5}$$

where x_k denotes the share of subjects who visit clinic k, and s_{ik} denotes the share of subject i and her friends who visit clinic k. We calculate the index G_i for each subject i and then take the average of the G_i across the 49 subjects. We denote this average index value by G.

Our goal is to test whether friends' choices of clinic show an excess of clustering over what would arise if they visited clinics at random. To this aim, we perform Monte Carlo simulations for a model in which each subject is assumed to visit clinic k with probability x_k, independently of the choices made by other subjects. We simulate the average index value G for 10,000 iterations. We then compute the mean and standard deviation for our simulations of G.

We next attempt to distinguish between the effects of peer influences and shared characteristics on the location decisions of friends. Participants in the HE were asked if any of the 10 friends whom they named had also accompanied them to a flu clinic. Of our sample of 49 subjects, 10 subjects had gone to a clinic with one of their 10 specified friends. To differentiate coordinated location decisions from clustering due to similar attributes, we compute the average index G separately for the 10 subjects who went with their friends and the remaining 39 subjects who went alone. We then run 10,000 simulations of G for each group, randomly assigning subjects to clinics as above. If excess clustering in friends' choices is largely attributable to unobserved similarities among friends, then both groups will have an average index G that is significantly higher than the baseline level predicted when subjects choose clinics at random. If, however, clustered choices are the result of explicit coordination among friends, then the average index G will exceed this baseline only for the 10 subjects who were accompanied to a clinic by a friend.

3.4 Social Interactions and Vaccination Decisions

This section outlines our strategy for measuring how friends influence one another's decision whether to get vaccinated against the flu. We combine social network data from the TG with vaccination records from HUHS. The merged data set contains information on 1173 of the 4299 upperclassmen at Harvard College during the 2003–2004 academic year. The random assignment of students to residential houses will help us identify peer effects on students' vaccination decisions. Our analysis assumes that students assigned to houses with clinics are more likely to get flu shots. To test this assumption, we fit the following model:

$$FLUSHOT_i = \alpha + \lambda \cdot CLINICHOUSE_i + \varepsilon_i \ , \tag{6}$$

where $FLUSHOT_i$ represents whether or not student i gets vaccinated, $CLINICHOUSE_i$ is a dummy variable that equals 1 if student i lives in a house with a clinic, and ε_i is an idiosyncratic error term. If students in houses with clinics get vaccinated at a higher rate, then the coefficient λ will be significantly positive. To check whether vaccination rates vary across houses with clinics, we also estimate the specification:

$$\begin{aligned} FLUSHOT_i = \alpha &+ \delta_c \cdot CURRIER_i + \delta_e \cdot ELIOT_i \\ &+ \delta_l \cdot LEVERETT_i + \delta_m \cdot MATHER_i + \varepsilon_i \ , \end{aligned} \tag{7}$$

where the explanatory variables are dummies that equal 1 if student i lives in the house of the same name. If some in-houses clinics are better located or open for longer, then students in those houses would be immunized at a higher rate.

We next examine how social ties to houses with clinics affect students' decisions to get vaccinated. Students who have friends in houses with clinics may receive more information about the flu vaccine, because their friends are more likely to be immunized. Of the 1173 students in our data set, 776 were assigned to houses without clinics, but 84 of them were instead placed in overflow dormitories. These students are isolated from their own houses and live with individuals who were originally assigned to other houses. Our analysis will focus on the 692 students who do not reside in overflow dormitories. But we also report results for all 776 students who were originally assigned to houses without clinics. We estimate the following reduced-form model for the vaccination decisions of these students:

$$GOTSHOT_i = \alpha + \beta \cdot PERCLINIC_i + \delta \cdot MALE_i + \varepsilon_i \ , \tag{8}$$

where $GOTSHOT_i$ indicates whether or not student i gets vaccinated, $PERCLINIC_i$ denotes the share of student i's friends in houses with a clinic, and $MALE_i$ is a dummy variable equal to 1 if student i is male.

Our specification would overestimate peer effects if students who had friends in houses with clinics, got vaccinated at their friends' houses out of convenience. To illustrate, a student may eat dinner at his friend's house and notice a flu clinic in the dining hall. Because he is near a clinic, this individual may get vaccinated, even without being influenced by his friends. To address this issue, the dummy variable $GOTSHOT_i$ omits vaccinations that occurred at houses with flu clinics. Specifically, we set $GOTSHOT_i$ equal to 0 if student i did not get a flu shot or if student i got vaccinated at one of the four houses with flu clinics. This procedure ensures that our estimates of peer effects will be conservative.

To identify endogenous effects, we use an instrumental-variables approach. Since students are randomly assigned to residential houses, we can treat the distribution of friendships across houses as exogenous. The share of one's friends in houses with clinics will serve as an instrument for the share of one's friends who are vaccinated. We use two-stage least squares to estimate our model of friends' vaccination decisions. In the first stage, we run the following regression for students in houses without clinics:

$$PERSHOT_i = \gamma + \lambda \cdot PERCLINIC_i + \theta \cdot MALE_i + \eta_i \ , \tag{9}$$

where $PERSHOT_i$ represents the share of student i's friends who get vaccinated for the flu. We use the fitted values from this regression to estimate the second-stage model:

$$GOTSHOT_i = \alpha + \beta \cdot PERSHOT_i + \delta \cdot MALE_i + \varepsilon_i \ . \tag{10}$$

The coefficient β measures how the vaccination decisions of friends are interrelated. When

β is positive, students become more likely to get vaccinated if their friends receive flu shots.

3.5 Decomposition of Peer Effects on Immunization

We next explain our framework for identifying the mechanisms that underlie peer effects on vaccination decisions. Miguel and Kremer (2007) discuss several channels through which social networks can affect medical choices. Friends may exchange information about the health effects or proper use of clinical technologies. Individuals may imitate the health care behavior of their peers, so as to conform with the norms of their reference group. When patients undergo preventive medical procedures, they may also decrease others' exposure to disease, lowering their friends' incentives to guard against infection. This section attempts to distinguish empirically between social learning about the health benefits of the flu vaccine and other peer influences on an individual's decision to get immunized. As in section 3.2, we focus on the 166 students participating in both the HE and the TG for whom information on vaccinations, illnesses, friendships, and health beliefs is available.

Decomposing social effects involves estimating two equations. To identify social learning about health effects, we might regress an individual's belief about the medical benefits of immunization on an individual's share of friends in houses with clinics. To detect other channels of social influence, we might specify a probit model of vaccination decisions, where the explanatory variables are the share of the individual's friends living in houses with clinics and the individual's belief about the vaccine's medical benefits. The potential endogeneity of health beliefs, however, complicates the estimation of the latter specification. If individuals alter their beliefs to justify their actions, then a naive estimation procedure would overstate the importance of social learning relative to other peer influences.

To account for feedback between beliefs and choices, we pursue an instrumental variables strategy for estimating a probit model with an endogenous regressor. Evans, Oates, and Schwab (1992) use a similar procedure to resolve the endogeneity between the demographic background of schoolmates and dichotomous outcomes like dropout and pregnancy. In our setup, we instrument for medical beliefs by interacting the share of friends in houses having clinics with an indicator of having caught the flu within the last three years. That is, exposure to disease is assumed to alter social learning about health topics but not other processes whereby friends can affect vaccination decisions.

A case of the flu, for example, constitutes an informative private signal about the risk of infection and the cost of illness; thus, flu victims may be more knowledgeable about the benefits of being immunized and less sensitive to information from friends when forming health beliefs. In this case, the instrumental variables assumption would enable us to identify peer influences besides social learning, by measuring the differential effect of friends on the vaccination decisions of flu victims relative to healthy people. If friends have the same effect on the choices of flu victims and healthy individuals, then social learning is unimportant in determining clinical behavior in comparison with other peer influences. If, however, flu victims are less responsive to friends when making decisions, then social learning has a substantial effect on behavior.

We now furnish the details of our estimation framework. In order to express our estimates of social effects in dollar terms, we restrict the coefficient on beliefs about the vaccine's health benefits to be 1, instead of standardizing the error term as in the usual probit setup. Thus, each subject faces the decision problem:

$$WANTSHOT_i = \begin{cases} 1 & V_i > 0 \\ 0 & V_i \leq 0 \end{cases}, \; V_i = HEALTHVALUE_i + OTHERVALUE_i \;, \qquad (11)$$

where $WANTSHOT_i$ indicates whether or not subject i wishes to obtain a flu shot, and V_i represents her valuation of the vaccine, which is decomposed into the believed health benefits $HEALTHVALUE_i$ of immunization and other factors $OTHERVALUE_i$ affecting her choice. The variable $HEALTHVALUE_i$ is constructed as in section 3.2, using information on medical beliefs from the HE. Because $OTHERVALUE_i$ represents unobserved influences on behavior, it is not included in our data set. The variable $WANTSHOT_i$ is derived from the responses of participants in the HE. Since the HE ended in December, 2003, and flu season lasted until May, 2004, $WANTSHOT_i$ equals 1 if and only if subject i either received the current flu vaccine by the time of participation or planned to get vaccinated later in the season. We also report results using instead the variable $HAVESHOT_i$, which equals 1 if and only if subject i obtained the current flu vaccine before participating in the HE.

We next specify the relationship between subject i's valuation of the vaccine and the exogenous variables in our setup. The two components of her valuation can be expressed as:

$$\begin{aligned}
HEALTHVALUE_i &= \alpha_H + \beta_H \cdot PERCLINIC_i + \gamma_H \cdot FLUVICTIM_i \\
&\quad + \delta_H \cdot PERCLINIC_i \times FLUVICTIM_i \\
&\quad + \theta_H \cdot MDPARENT_i + \varepsilon_{Hi} \\
&= \mu_{Hi} + \varepsilon_{Hi}
\end{aligned} \tag{12}$$

and

$$\begin{aligned}
OTHERVALUE_i &= \alpha_O + \beta_O \cdot PERCLINIC_i + \gamma_O \cdot FLUVICTIM_i \\
&\quad + \theta_O \cdot MDPARENT_i + \varepsilon_{Oi} \\
&= \mu_{Oi} + \varepsilon_{Oi} \ ,
\end{aligned} \tag{13}$$

where $PERCLINIC_i$ denotes the share of her friends in houses with clinics, $FLUVICTIM_i$ is a dummy variable equal to 1 if she caught the flu within the last three years, and $MDPARENT_i$ indicates whether either of her parents completed medical school. The error terms ε_{Hi} and ε_{Oi} are assumed to be bivariate normal with 0 means, correlation ρ, and respective variances σ_H and σ_O. The terms β_H and $\beta_H + \delta_H$ represent peer influences on the clinical beliefs of uninfected individuals and flu victims, respectively. The parameter β_O captures other social effects on the decision to get vaccinated. Equation (13) omits the interaction term between friends in houses with clinics and subjects with recent cases of the flu, thereby imposing the instrumental variables assumption that influenza infections do not affect peer interactions other than social learning. In our sample, about 25 percent of subjects have at least one parent who graduated from medical school. Since these subjects could enjoy easier access to clinical services and exhibit health care behavior different from other individuals, equations (12) and (13) control for students whose parents are physicians, although we also report results excluding this variable.

The model is estimated by the method of maximum likelihood.[1] To assess whether health beliefs are endogenous, we perform a Wald test of the hypothesis that the correlation parameter ρ is equal to 0. If our estimate of ρ does not differ significantly from 0, then there is insufficient evidence that subjects endogenously select their beliefs to conform with their

[1] A Newton-Raphson algorithm with numerical derivatives is used to maximize the log-likelihood func-

choices. In this case, adequate estimates of peer effects other than social learning could also be obtained from a simple probit regression of $WANTSHOT_i$ on $PERCLINIC_i$, $FLUVICTIM_i$, and $MDPARENT_i$.

4 Results

4.1 Social Interactions and Health Beliefs

This section details how social ties to houses with flu clinics influence an individual's beliefs about the influenza virus and the flu vaccine. We first test whether friends affect students' perceptions about the importance of getting a flu shot. The first column of Table 12 presents our estimate for the coefficient β in the ordered probit model given by equation (1). We obtain a positive and significant coefficient on the share of friends in houses with clinics. This indicates that stronger social ties to treated houses increase the perceived importance of being vaccinated. Many social processes could give rise to this positive effect. Students in houses with clinics may get vaccinated at a higher rate and discuss their medical experiences with their friends. Vaccinated students may inflate their own beliefs and convince their friends of the benefits of vaccination.

We also examine how experience with influenza affects students' evaluations of the flu vaccine. The second column of Table 12 reports our estimates for the ordinal response model described by equation (3). Marginal effects for this model are provided in Table 13. Since the coefficient on social ties to treated houses is significantly positive, medical information from friends makes healthy people regard vaccination as more important. Exposure to illness, however, has no significant effect on perceptions about the importance of being immunized.

We next attempt to identify the channels through which social contacts affect students'

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tion given by:

$$L = \sum_{i=0}^{166} WANTSHOT_i \cdot \ln \Phi(U_i) + (1 - WANTSHOT_i) \cdot \ln[1 - \Phi(U_i)] + \ln \phi \left(\frac{HEALTHVALUE_i - \mu_{Hi}}{\sigma_H} \right) - \ln \sigma_H \ ,$$

where Φ and ϕ respectively denote the cdf and pdf of the standard normal distribution, and U_i is defined as:

$$U_i = \frac{HEALTHVALUE_i + \mu_{Oi} + \rho \cdot (\sigma_O / \sigma_H) \cdot (HEALTHVALUE_i - \mu_{Hi})}{\sigma_O \cdot (1 - \rho^2)^{1/2}} \ .$$

medical beliefs. Tables 14 and 15 present estimates for the set of models given by equations (2) and (4). We begin by measuring peer influences on people's perceptions about their susceptibility to disease. In the first column of Table 14, we regress students' beliefs about the infection risk if unvaccinated on their share of friends in houses with clinics. We observe a positive effect, but it is only marginally significant at the 10 percent level. The second column adds an indicator for illness and an interaction with links to treated houses. The coefficient on friends in houses with clinics now becomes positive and significant at the 5 percent level. When healthy individuals learn about a medical treatment, they may feel more susceptible to illness if left untreated. We also find a negative interaction effect between recent sickness and ties to treated houses. Although this result is only marginally significant, it may suggest that experience with influenza lowers one's receptiveness to medical information from friends.

The third column of Table 14 regresses beliefs about the infection risk if vaccinated on the share of friends in houses with clinics. We observe a negative but insignificant effect. In the fourth column, we examine how exposure to illness affects students' beliefs about their susceptibility after vaccination. The coefficient on the indicator for illness is positive and significant at the 1 percent level. This finding suggests that recent flu victims feel more vulnerable to disease, even after being immunized. Nonetheless, we find no evidence of social learning about the infection risk of vaccinated individuals.

In the fifth column, we regress the perceived cost of catching the flu on the share of friends in treated houses. Although we obtain a positive effect, it is again insignificant. The sixth column also includes an indicator for illness and an interaction with friends in treated houses. The coefficient on friends in houses with clinics is positive and marginally significant. Medical information from friends may make healthy people more aware of the costs of sickness. Moreover, the illness indicator is positive and marginally significant at the 10 percent level, and the interaction effect with links to treated houses is significantly negative at the 5 percent level. Although experience with influenza may raise people's beliefs about the costs of sickness, flu victims do not adjust these beliefs upward by as much as healthy people in response to medical information from friends.

We next construct a more inclusive measure of the perceived health effects of immunization. We subtract each subject's belief about the infection risk if vaccinated from her belief about the infection risk if unvaccinated. The first column of Table 15 regresses the perceived difference in susceptibilities on the share of friends in houses with clinics. The effect of friends in treated houses is positive and significant at the 5 percent level. Students with stronger social ties to houses with clinics appear more optimistic about the benefits of getting vaccinated. In the second column, we add an indicator for illness and an interaction with friends in treated houses. The coefficient on social ties to houses with clinics now becomes significantly positive at the 1 percent level. This finding indicates that friends exert a strong influence on how effective the flu vaccine appears to be to healthy people.

To calculate each subject's belief about the vaccine's health value, we multiply her perceived reduction in the infection risk by her belief about the cost of catching the flu. The third column of Table 15 regresses this product on the share of friends in houses with clinics. The coefficient on links to treated houses is positive and significant at the 5 percent level. When an additional 10 percent of one's friends move to houses with clinics, one's valuation of the vaccine's health effects increases by \$5.00. The fourth column also includes an indicator for illness and an interaction with links to treated houses. The coefficient on friends in houses with clinics is significantly positive at the 1 percent level. A 10 percent rise in the number of friends in treated houses raises a healthy student's valuation of the vaccine's medical benefits by \$9.33. The interaction effect, moreover, is negative and significant at the 1 percent level. This result may indicate that exposure to influenza makes individuals less receptive to health care information from friends. Flu victims seem to base their medical beliefs on their own understanding of disease, disfavoring information from friends who may have less experience with influenza.

Our results would overstate the influence of friends if students first decided whether to get vaccinated and then chose their beliefs to match their decision. To illustrate, imagine a student who has friends in a house with a clinic and who eats dinner at her friends' house. Being near a clinic, she may get vaccinated because of the clinic's proximity, not because of her friends' influence. She may then choose to believe that being vaccinated is more beneficial.

To eliminate this effect, Tables 16, 17, and 18 provide estimates for equations (1) through (4), dropping students who got flu shots at houses with clinics. Our results change little. One's share of friends in treated houses has a significantly positive effect on one's beliefs about the importance of being immunized, the effectiveness of vaccination, and the value of the flu vaccine. Moreover, exposure to influenza significantly changes the way people use medical information from friends when forming beliefs about the cost of sickness and the value of vaccination. Healthy individuals are especially receptive to communications from social contacts.

4.2 Clustering of Friends at Flu Clinics

This section describes how vaccinated students choose which flu clinic to attend. Specifically, we examine whether friends tend to make similar location decisions, congregating at the same flu clinic. The results of the HE, for example, reveal that many students visit flu clinics as part of a group. Of the 114 respondents who got flu shots, about 36 percent report going to a flu clinic with their friends. We wish to explain why friends would get flu shots at the same clinic. To test for excess clustering among friends, we implement the procedure outlined in section 3.3. Our results are presented in Table 19.

The first column characterizes the location decisions of 49 subjects from the HE. We obtain an average index value G of 0.4288 for these individuals. Monte Carlo simulations show that if subjects visited clinics at random, then the average index value G would be distributed with a mean of 0.3442 and a standard deviation of 0.0271. Since the G of 0.4288 for the 49 subjects in our sample is significantly higher than 0.3442, we find strong evidence for excess clustering in subjects' location choices.

We now examine whether this finding can be attributed to peer influences or to shared characteristics among friends. The second column analyzes the clinic choices of the 39 subjects who did not visit a flu clinic with a friend. If the clustering in clinic choices reflects unobservable similarities among friends, then the average index value G for subjects visiting a flu clinic alone would be significantly higher than the value predicted by random assignment to clinics. These 39 subjects have a G of 0.3820. Monte Carlo simulations show that when they are randomly assigned to clinics, the average index value G is distributed with mean 0.3610 and standard deviation 0.0301. Since the G of 0.3820 for these 39 subjects is not significantly different from 0.3610, their location decisions are consistent with random assignment to clinics. This suggests that the excess clustering noted above is not due simply to shared attributes among friends.

In fact, the third column reveals that the 10 subjects who visited a clinic with a friend, have a G of 0.6113, which significantly exceeds the mean G of 0.2785 under random assignment. It thus seems likely that the observed clustering among friends reflects peer influences. Students may prefer going to the clinic when joined by their friends. Peers may also put pressure on one another to accompany them to the clinic.

4.3 Social Interactions and Vaccination Decisions

We now examine how friends affect an individual's decision to get vaccinated. Our identification strategy relies on the random assignment of students to residential houses. Table 20 provides descriptive statistics for the immunization rate and the distribution of students across houses. During the 2003–2004 school year, 29.6 percent of students received flu shots, and about 33.8 percent of students were living in houses with a flu clinic. Table 21 presents our estimates for specifications (6) and (7). The coefficient λ in equation (6) is positive and significant at the 1 percent level, indicating a higher vaccination rate in houses with clinics. On average, students assigned to these houses are 15 percentage points more likely to get vaccinated than their counterparts in other houses. Nonetheless, we find substantial variation in vaccination rates across houses with clinics. About 57.0 percent of Leverett residents were vaccinated, but only 29.0 percent of students in Mather received flu shots. The vaccination clinic at Mather House may have been poorly placed or open for only a short time.

We next describe how social ties to houses with flu clinics affect students' vaccination decisions. Table 22 summarizes the vaccination records and social networks of students in houses without flu clinics. The immunization rate for these students was 24.5 percent during the 2003–2004 school year. About 18.6 percent of their friends were living in houses with clinics, and the vaccination rate was 26.4 percent among their friends. Table 23 presents reduced-form estimates for specification (8). After controlling for students' gender, the coefficient on friends in houses with clinics is positive and significant, indicating that individuals with social ties to these houses are more likely to get vaccinated. In particular, when all students who were originally assigned to houses without clinics are included, the social effects are marginally significant at the 10 percent level. However, students placed in overflow dormitories do not physically reside in any of the twelve residential houses and may have a weaker affiliation with their assigned houses. When these students are excluded, the effect of friends becomes significant at the 5 percent level. These findings coincide with our results in section 4.1, where friends in houses with clinics raised students' beliefs about the importance of getting vaccinated. Friends influence one's decision to get vaccinated, as well as one's beliefs about health topics.

To measure endogenous effects, we carry out the IV-2SLS procedure outlined in section 3.4. Table 24 reports our results for the first-stage model (9). The coefficient on the share of friends in houses with clinics is positive and significant at the 1 percent level. Students who have friends in houses with clinics, are also more likely to have friends who are vaccinated. Table 25 provides IV-2SLS estimates for equation (10). When students in overflow dormitories are excluded, the coefficient on the share of friends in houses with clinics is positive and significant at the 5 percent level. This result indicates that an individual's vaccination decision is influenced by the choices of her friends. Students become more likely to get vaccinated when their friends do so too. Specifically, if an extra 10 percent of one's friends receive flu shots, then one becomes 8.3 percentage points more likely to get immunized.

4.4 Decomposition of Peer Effects on Immunization

This section attempts to decompose social effects on immunization into two components: information from friends about the vaccine and other peer influences on clinical behavior. To discriminate between these mechanisms, we present results from an instrumental variables procedure that measures how exposure to influenza moderates social effects on medical beliefs and vaccination decisions. Our analysis uses data on the clinical histories, health care beliefs, and social networks of students participating in both the TG and the HE. Table 11 provides summary statistics for these individuals. About 49 percent of subjects reported catching the flu within the past three years. Only 20 percent had obtained a flu shot before participating in the HE, but an additional 31 percent planned to be immunized later in the season. Moreover, a sizeable 25 percent had at least one parent who had completed medical school. Because so many students anticipated getting vaccinated later or were children of a medical doctor, Table 26 reports results for both current and planned vaccination decisions, including and excluding a control for children of physician parents.

The upper panel shows the effect of friends on beliefs about the vaccine's medical value. As in section 4.1, social ties to treated houses reliably increase the believed health benefits of vaccination, especially among students without a recent case of the flu. In particular, a healthy student's perception of the vaccine's health benefits rises by \$9.33 when an extra 10 percent of her friends are assigned to houses with clinics. This substantial positive effect, moreover, is statistically significant at the 1 percent level. By contrast, social contacts do not significantly influence the medical beliefs of students who have caught the flu within the past three years. Our estimate of the interaction coefficient δ_H in equation (12) is negative and significant at the 1 percent level, indicating that experience with influenza makes students less sensitive to social contacts when forming beliefs about the medical benefits of the vaccine. Flu victims may have more precise beliefs about the consequences of disease and their susceptibility to infection; thus, they would be less receptive to health care information from friends. This finding allows us to identify peer influences besides social learning, by determining whether influenza infections also make students' vaccination decisions less responsive to friends in houses with clinics.

The lower panel displays estimates of social influences on determinants of medical choices other than perceptions about health effects. These alternate channels include peer pressure to adhere to group norms, preferences for coordinating decisions with friends, and positive health externalities from immunization. Although the size of our sample limits the statistical significance of the results, our estimates might be helpful in gauging the importance of social learning relative to other peer influences on subjects in our sample. Depending on the specification chosen, a 10 percent rise in the number of friends in treated houses raises one's valuation of the vaccine by \$1.59 to \$2.92 through peer interactions besides social learning. None of these estimates, however, differs significantly from zero.

Table 26 also calculates the cumulative effect of friends on a subject's valuation of the vaccine. We find that a healthy student's valuation rises by \$10.92 to \$12.25 when an extra 10 percent of her friends move to treated houses. Controlling for individuals with a physician parent, these effects are significant at the 10 percent and 5 percent levels for current and planned vaccination decisions, respectively. Of this \$10.92 to \$12.25 increase in the total value of immunization, a substantial \$9.33 can be credited to social learning about health effects, with the remainder being attributable to other peer influences. Since exposure to influenza seems to inhibit the process of social learning, having friends in treated houses does not have a significant effect on valuations among flu victims.

To check for the endogeneity of medical beliefs, we examine the correlation ρ between unobserved influences on believed health benefits and other determinants of behavior. Our estimates of the parameter ρ range from -0.1923 to -0.2473 and do not differ significantly from zero. In other words, unknown factors that make subjects more likely to get vaccinated are associated with insignificantly lower beliefs about the health value of immunization. This finding indicates that health care beliefs may not be endogenous with vaccination decisions and provides weak evidence against the hypothesis that subjects alter their beliefs to suit their actions.

5 Conclusion

Using the random assignment of college students to residence halls, we identify peer influences on immunization decisions. Our results indicate that social networks can amplify the impact of policies designed to promote vaccination. We find that the inoculation clinics held at four residences make students living elsewhere more likely to get vaccinated. In particular, a student becomes 1.8 percentage points more likely to receive a flu shot when an additional 10 percent of her friends are assigned to residences with clinics.

By exploiting social effects on health care decisions, targeted interventions can alter behavior among the broader population. In our study, 18.6 percent of the average student's friends live in houses with clinics; thus, social ties to treated houses directly raise the immunization rate by 3.3 percentage points among residents of other houses. This finding shows that social networks can improve the coverage of vaccine delivery systems. Individuals who receive flu shots at outreach clinics, encourage their friends to get vaccinated as well.

Expanding vaccine coverage is a national health objective. The U.S. Department of Health and Human Services (2000) lists influenza immunization as a leading health indicator, establishing a target vaccination rate of 90 percent among high-risk adults in its bulletin *Healthy People 2010*. To achieve governmental health goals, many health care organizations have implemented mass inoculation programs that dispense vaccines at public sites, including schools, pharmacies, and supermarkets. Our analysis of the immunization program at Harvard College suggests that social effects can contribute to the success of such interventions by raising the demand for vaccines in the community at large.

Our results contrast with Miguel and Kremer's (2007) finding that social learning discourages Kenyan villagers from adopting new deworming drugs. Those authors examine a setting in which individuals are reluctant to bear the substantial private costs of adopting a treatment that has high social benefits. They argue that a social planner may need to subsidize medical technologies with significant positive externalities. In our study, individuals are not deterred by the unpleasant side effects that may inhibit the adoption of deworming drugs in Miguel and Kremer's study. Instead, treated students appear to provide favorable evaluations to their friends, enhancing perceptions about the medical benefits of immunization. Beliefs about the vaccine's health effects increase by an average of $5.00 in response to a 10 percent rise in the number of friends assigned to residences with clinics. In addition, we find evidence of endogenous peer effects, indicating that inoculation programs can have multiplier effects on vaccine uptake.

A notable feature of our analysis is that we decompose social effects on vaccination decisions, obtaining dollar value estimates of social learning and other peer interactions. Using data on each student's health beliefs, we directly measure social learning about the medical benefits of immunization. Other peer interactions are identified by examining how influenza infections alter the effects of friends on an individual's beliefs and choices. We find that a 10 percent rise in the share of friends in residences with clinics raises overall valuations of the vaccine by $10.92 among students with no recent flu experience, where 85 percent of this increase can be attributed to social learning about medical benefits. Our investigation of clustering at flu clinics, moreover, suggests that friends coordinate their choices of clinic with one another. Thus, while learning from peers may be the main social determinant of vaccination decisions, other social interactions like peer pressure and companionship appear to influence locational choices.

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Table 1: Description of variables from the House Experiment (HE).

Category	Variable	Description
Background	HOUSE	Upperclass House
	YEAR	College Class
	MALE	Gender
Beliefs	FLUIMP	How important is it to get a flu shot?
	FLUCOST	Imagine you were about to get the flu. How many dollars would you pay for a medicine that would prevent the flu for sure and had no side effects?
	FLUVACCNO	What do you think is the probability that you will catch a flu if you come in contact with the flu virus if you did not get a flu shot?
	FLUVACCYES	What do you think is the probability that you will catch a flu if you come in contact with the flu virus if you have gotten a flu shot?
Vaccination	OLDSHOT	Did you get a flu shot last year?
	HAVESHOT	Have you gotten a flu shot this year?
	SHOTPLANNED	Do you plan to get a flu shot this year?
	SHOTWHERE	Where did you get vaccinated for the flu?
Friends	FRIENDS	Please select 10 friends.
	FRIENDSINFL	Did your friends influence your decision to get a flu shot?
	WENTRMATES	Did you visit a flu clinic with any of your roommates?
	WENTFRIENDS	Did you visit a flu clinic with any of your friends?
	WENTSPECFRIENDS	Which of your 10 selected friends accompanied you to the flu clinic?

Note: The HE was conducted between November 25 and December 11 of 2003. See Table 7 for the dates and locations of flu clinics sponsored by HUHS.

Table 2: Beliefs about the importance of getting vaccinated against the flu. 569 respondents.

Variable	Question	Answer	Frequency	Percentage
FLUIMP	How important is it to get a flu shot?	0-Not Very Important	216	37.96%
		1-Somewhat Important	199	34.97%
		2-Important	106	18.63%
		3-Very Important	46	8.08%

Table 3: Descriptive statistics for the beliefs component of the HE. 569 respondents

Variable	Description	Mean	Std Dev
FLUCOST	Cost of being sick with the flu	\$102.00	\$61.23
FLUVACCNO	Infection risk if unvaccinated	43.71%	25.13%
FLUVACCYES	Infection risk if vaccinated	15.81%	15.70%

Table 4: Summary of the vaccination component of the HE. 569 respondents.

Variable	Question	Yes	Percent Yes
OLDSHOT	Did you get a flu shot last year?	189	33.2%
HAVESHOT	Have you gotten a flu shot this year?	114	20.0%
SHOTPLANNED	If you did not do so yet, do you plan to get a flu shot this year?	153	26.9%

Table 5: Dates and locations of flu clinics during the 2003–2004 school year.

Date	**Location**	**Number of Respondents Vaccinated**
Nov 3	School of Public Health	1
Nov 4	Holyoke Center	7
Nov 6	Holyoke Center	3
Nov 10	School of Public Health	0
Nov 12	Annenburg	0
Nov 13	Holyoke Center	5
Nov 17	Annenburg	0
Nov 18	Holyoke Center	14
Nov 19	Currier	0
Nov 20	Holyoke Center	6
Nov 24	Leverett	10
Nov 25	Holyoke Center	5
Dec 1	Eliot	12
Dec 2	Holyoke Center	3
Dec 3	Mather	1
Dec 4	Holyoke Center	1
Dec 9	Holyoke Center	1
Dec 11	Holyoke Center	2
Dec 16	Holyoke Center	0
Dec 18	Holyoke Center	0
Jan 8	Holyoke Center	0
Jan 15	Holyoke Center	0

Table 6: Summary for the friendship component of the HE. Responses of the 114 participants who got flu shots.

Variable	Question	Yes	Percent Yes
FRIENDSINFL	Did your friends influence your decision to get a flu shot?	49	43.0%
WENTRMATES	Did you visit a flu clinic with any of your roommates?	21	18.4%
WENTFRIENDS	Did you visit a flu clinic with any of your friends?	42	36.8%
WENTSPECFRIENDS	Did you go to a clinic with a friend named in the survey?	13	11.4%

Table 7: Dates and locations of in-house clinics from 2001 to 2003.

Year	Date	Location
2001	Nov 14	Currier
	Nov 19	Eliot
	Nov 27	Leverett
	Nov 28	Mather
2002	Nov 20	Currier
	Nov 25	Leverett
	Dec 3	Mather
	Dec 4	Eliot
2003	Nov 19	Currier
	Nov 24	Leverett
	Dec 1	Eliot
	Dec 3	Mather

Table 8: Share of students vaccinated in each residential house for academic years from 2001–2002 to 2003–2004.

House	**Vaccination Rate by Year**		
	2001–2002	2002–2003	2003–2004
Adams	0.1514	0.2246	0.2407
Cabot	0.2113	0.2000	0.2130
*Currier	0.2006	0.1818	0.3053
Dunster	0.1666	0.1862	0.2283
*Eliot	0.2204	0.2222	0.3154
Kirkland	0.1351	0.1397	0.3505
*Leverett	0.2738	0.2988	0.4032
Lowell	0.1160	0.1594	0.2369
*Mather	0.2128	0.2436	0.2687
Pforzheimer	0.1275	0.1631	0.2145
Quincy	0.1275	0.1659	0.2109
Winthrop	0.3256	0.1526	0.2784
Houses with Clinics	0.2320	0.2409	0.3240
Houses without Clinics	0.1687	0.1730	0.2356
All Houses	0.1892	0.1957	0.2653
Observations	4899	4334	4252

Note: HUHS hosted flu clinics at the houses marked with an asterisk.

Table 9: Number of Leverett residents who were vaccinated on each date during the 2003–2004 academic year.

Date	**Number**	**Percentage**
Oct 15	1	0.57%
Oct 27	1	0.57%
Oct 31	1	0.57%
Nov 4	3	1.71%
Nov 6	1	0.57%
Nov 13	7	4.00%
Nov 17	3	1.71%
Nov 18	11	6.29%
Nov 20	3	1.71%
*Nov 24	109	62.29%
Nov 25	5	2.86%
Dec 1	2	1.14%
Dec 2	5	2.86%
Dec 3	2	1.14%
Dec 4	3	1.71%
Dec 5	1	0.57%
Dec 9	4	2.29%
Dec 11	2	1.14%
Dec 15	2	1.14%
Dec 16	5	2.86%
Dec 17	1	0.57%
Jan 6	1	0.57%
Jan 22	2	1.14%

Note: HUHS held a flu clinic at Leverett House on November 24.

Table 10: Beliefs about the importance of getting vaccinated against the flu. Responses of the 167 participants in both the TG and HE.

Variable	**Question**	**Answer**	**Frequency**	**Percentage**
FLUIMP	How important is it to get a flu shot?	0-Not Very Important	63	37.72%
		1-Somewhat Important	56	33.53%
		2-Important	32	19.16%
		3-Very Important	16	9.58%

Table 11: Descriptive statistics for the 167 participants in HE and TG.

Variable	Description	Mean	Std Dev
PERCLINIC	Percentage of friends in houses with clinics	17.24%	15.03%
FLUCOST	Cost of being sick with the flu	$52.57	$97.73
FLUVACCNO	Infection risk if unvaccinated	42.86%	25.28%
FLUVACCYES	Infection risk if vaccinated	15.26%	13.59%
FLUVACCDIF	FLUVACCNO - FLUVACCYES	27.59%	22.49%
HEALTHVALUE	FLUCOST ×FLUVACCDIF	$16.13	$38.56
HAVESHOT	Already received flu shot for current season	20.36%	40.39%
WANTSHOT	Currently have or planning to get vaccine	50.90%	50.14%
FLUVICTIM	Sick with the flu in the last three years	48.50%	50.13%
MDPARENT	Parent completed medical school	24.55%	43.17%

Note: One subject did not report her cost of being sick with the flu.

Table 12: Ordered probit estimates of social effects on importance of getting vaccinated. Responses of the 167 participants in the HE and TG.

	FLUIMP	
PERCLINIC	1.259*	1.639*
	(0.5607)	(0.7533)
PERCLINIC ×FLUVICTIM		-0.9562
		(1.135)
FLUVICTIM		0.0761
		(0.2597)
thresholds		
cut1	-0.1054	-0.0762
	(0.1358)	(0.1930)
cut2	0.7875	0.8201
	(0.1451)	(0.2007)
cut3	1.552	1.592
	(0.1749)	(0.2224)
Observations	167	167
Log-likelihood	-210.5	-210.0
Pseudo-R^2	0.0118	0.0141

Note: Standard errors in parentheses. * Significant at 5 percent level.

Table 13: Marginal effects for ordered probit models of the importance of vaccination. Responses of the 167 participants in the HE and TG.

	Not Very Important	Somewhat Important	Important	Very Important
		No Flu Effects		
PERCLINIC	-0.4767*	0.0500	0.2208*	0.2059*
	(0.2123)	(0.0420)	(0.1063)	(0.0955)
		Flu Effects		
PERCLINIC	-0.6201*	0.0646	0.2899*	0.2655*
	(0.2849)	(0.0552)	(0.1433)	(0.1268)
PERCLINIC	0.3618	-0.0377	-0.1692	-0.1549
×FLUVICTIM	(0.4295)	(0.0523)	(0.2033)	(0.1850)
FLUVICTIM	-0.0288	0.0030	0.0135	0.0124
	(0.0981)	(0.0103)	(0.0459)	(0.0423)

Note: When an extra 1 percent of a student's friends move to houses with clinics, the percent probability of her selecting a given rating changes by the corresponding marginal effect. Standard errors in parentheses. * Significant at 5 percent level.

Table 14: OLS estimates of social effects on beliefs about the influenza virus and the flu vaccine. Responses of the 167 participants in the HE and TG.

	FLUVACCNO		FLUVACCYES		FLUCOST	
PERCLINIC	0.2159#	0.4083*	-0.0718	0.0128	13.34	114.6#
	(0.1299)	(0.1740)	(0.0702)	(0.0915)	(50.64)	(67.48)
PERCLINIC		-0.4442#		-0.1224		-266.7*
$\times$FLUVICTIM		(0.2637)		(0.1386)		(102.2)
FLUVICTIM		0.0727		0.0904**		43.58#
		(0.0594)		(0.0139)		(23.07)
constant	0.3913**	0.3556**	0.1650**	0.1156**	50.27**	28.28#
	(0.0297)	(0.0430)	(0.0160)	(0.0226)	(11.59)	(16.75)
Observations	167	167	167	167	166	166
R^2	0.0165	0.0333	0.0063	0.0757	0.0004	0.0306

Note: Standard errors in parentheses. # Significant at 10 percent level. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 15: OLS estimates of social effects on perceptions about the benefits of vaccination. Responses of the 167 participants in the HE and TG.

	FLUVACCDIF		HEALTHVALUE	
PERCLINIC	0.2877*	0.3954**	50.03*	93.30**
	(0.1144)	(0.1516)	19.60	25.87
PERCLINIC		-0.3219		-105.3**
×FLUVICTIM		(0.2297)		(39.17)
FLUVICTIM		-0.0177		12.01
		(0.0517)		(8.844)
constant	0.2263**	0.2400**	7.490#	1.944
	(0.0261)	(0.0374)	(4.488)	(6.421)
Observations	167	167	166	166
R^2	0.0369	0.0735	0.0382	0.0847

Note: Standard errors in parentheses. # Significant at 10 percent level. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 16: Ordered probit models of social effects on the importance of vaccination. Responses of the 160 subjects not vaccinated at houses with flu clinics.

	FLUIMP	
PERCLINIC	1.445*	2.067**
	(0.5740)	(0.7782)
PERCLINIC $\times$FLUVICTIM		-1.415
		(1.159)
FLUVICTIM		0.2192
		(0.2673)
thresholds		
cut1	-0.0315	0.0739
	(0.1386)	(0.1992)
cut2	0.8790	0.9899
	(0.1502)	(0.2095)
cut3	1.733	1.855
	(0.1907)	(0.2418)
Observations	160	160
Log-likelihood	-196.2	-195.4
Pseudo-R^2	0.0159	0.0197

Note: Standard errors in parentheses. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 17: OLS estimates of social effects on health beliefs. Responses of the 160 subjects not vaccinated at houses with flu clinics.

	FLUVACCNO		FLUVACCYES		FLUCOST	
PERCLINIC	0.2150	0.4238*	-0.0735	0.0097	14.41	118.2#
	(0.1310)	(0.1763)	(0.0714)	(0.0934)	(52.37)	(70.19)
PERCLINIC		-0.4680#		-0.1157		-231.5*
×FLUVICTIM		(0.2653)		(0.1406)		(105.5)
FLUVICTIM		0.0842		0.0920**		42.41#
		(0.0602)		(0.0139)		(24.00)
constant	0.3820**	0.3396**	0.1638**	0.1127**	49.55**	28.04**
	(0.0301)	(0.0438)	(0.0164)	(0.0232)	(12.05)	(17.54)
Observations	160	160	160	160	159	159
R^2	0.0168	0.0361	0.0067	0.0802	0.0005	0.0308

Note: Standard errors in parentheses. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 18: OLS estimates of social effects on the perceived benefits of vaccination. Responses of the 160 subjects not vaccinated at houses with flu clinics.

	FLUVACCDIF		HEALTHVALUE	
PERCLINIC	0.2885*	0.4141**	50.52*	96.08**
	(0.1153)	(0.1537)	(20.10)	(26.60)
PERCLINIC ×FLUVICTIM		-0.3524		-110.1**
		(0.2312)		(39.97)
FLUVICTIM		-0.0078		11.77
		(0.0524)		(9.095)
constant	0.2182**	0.2269**	6.764	1.368
	(0.0265)	(0.0382)	(4.624)	(6.647)
Observations	160	160	159	159
R^2	0.0381	0.0748	0.0387	0.0913

Note: Standard errors in parentheses. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 19: Dartboard test for excess clustering of friends at flu clinics. Actual value and simulations of the average index G for participants in the HE.

	All Subjects in Sample	Subjects Going Alone	Subjects Going with Friends
Actual G	0.4288	0.3820	0.6113
		10,000 Simulations of G	
Mean	0.3442	0.3610	0.2785
Std Dev	0.0271	0.0301	0.0453
Number	49	39	10

Note: Higher values of G reflect greater clustering among friends' choices of clinic. The actual G for participants in the HE appears in the top row. The bottom rows report the mean and standard deviation of 10,000 simulations of G under the assumption that subjects choose clinics independently of each other. The 49 subjects in the first column received flu shots at HUHS clinics and each had a friend who was vaccinated at an HUHS clinic. The second column excludes the 10 subjects who visited a flu clinic with their friends. The third column provides results for these 10 individuals.

Table 20: Descriptive statistics for 1173 upperclassmen during the 2003–2004 academic year.

Variable	**Description**	**Mean**	**Std Dev**
FLUSHOT	Vaccinated for the flu	0.2958	0.4566
CLINICHOUSE	Resident of house with vaccination clinic	0.3384	0.4734
CURRIER	Resident of Currier House	0.0580	0.2338
ELIOT	Resident of Eliot House	0.0776	0.2676
LEVERETT	Resident of Leverett House	0.0853	0.2794
MATHER	Resident of Mather House	0.1176	0.3223

Table 21: OLS estimates for the effect of in-house clinics on the vaccination decisions of 1173 upperclassmen during the 2003–2004 school year.

	FLUSHOT	
CLINICHOUSE	0.1506**	
	(0.0278)	
CURRIER		0.1816**
		(0.0565)
ELIOT		0.0958#
		(0.0495)
LEVERETT		0.3252**
		(0.0475)
MATHER		0.0450
		(0.0413)
constant	0.2448**	0.2448**
	(0.0162)	(0.0160)
Observations	1173	1173
R^2	0.0244	0.0445

Note: HUHS operated flu clinics at four residential houses during the 2003–2004 school year. See Table 7 for the dates and locations of clinics sponsored by HUHS. Standard errors in parentheses. # Significant at 10 percent level. ** Significant at 1 percent level.

Table 22: Descriptive statistics for 776 upperclassmen in houses without clinics during the 2003–2004 academic year.

Variable	**Description**	**Mean**	**Std Dev**
FLUSHOT	Vaccinated for the flu	0.2448	0.4303
GOTSHOT	Vaccinated for the flu at an out-house clinic	0.1894	0.3921
PERCLINIC	Share of friends in houses with clinics	0.1864	0.1893
PERSHOT	Share of friends who got vaccinated for the flu	0.2637	0.1897
MALE	Male gender	0.4301	0.4954
OVERFLOW	Residing in an overflow dormitory	0.1082	0.3109

Note: GOTSHOT excludes vaccinations that occurred in houses with clinics. MALE is available for 737 out of 776 students. Students in overflow dormitories live apart from their assigned houses.

Table 23: OLS estimates of social effects on vaccination decisions. Reduced-form results for students in houses without flu clinics.

	GOTSHOT			
	With Overflow Dormitories		*Without Overflow Dormitories*	
PERCLINIC	0.1086	0.1441#	0.1428#	0.1827*
	(0.0743)	(0.0784)	(0.0797)	(0.0838)
MALE		-0.0270		-0.0362
		(0.0296)		(0.0314)
constant	0.1692**	0.1819**	0.1628**	0.1776**
	(0.0197)	(0.0238)	(0.0210)	(0.0252)
Observations	776	737	692	658
R^2	0.0028	0.0055	0.0046	0.0900

Note: GOTSHOT excludes vaccinations that occurred in houses with clinics. Standard errors in parentheses. # Significant at 10 percent level. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 24: Effect of the share of friends in houses with clinics on the share of friends vaccinated. First-stage estimates from IV-2SLS regressions.

	PERSHOT	
	With Overflow Dormitories	*Without Overflow Dormitories*
PERCLINIC	0.2243**	0.2204**
	(0.0364)	(0.0384)
MALE	-0.0167	-0.0254#
	(0.0137)	(0.0144)
constant	0.2285**	0.2327**
	(0.0110)	(0.0115)
Observations	737	658
R^2	0.0502	0.0515

Note: Standard errors in parentheses. # Significant at 10 percent level. ** Significant at 1 percent level.

Table 25: Effect of friends' vaccination decisions on own vaccination decision. Second-stage estimates from IV-2SLS regressions.

	GOTSHOT	
	With Overflow Dormitories	*Without Overflow Dormitories*
PERSHOT	0.6424#	0.8292*
	(0.3559)	(0.3951)
MALE	-0.0163	-0.0152
	(0.0304)	(0.0339)
constant	0.0351	-0.0153
	(0.0974)	(0.1095)
Observations	737	658
R^2	0.0055	0.0090

Note: GOTSHOT excludes vaccinations that occurred in houses with clinics. Standard errors in parentheses. # Significant at 10 percent level. * Significant at 5 percent level.

Table 26: Effect of friends in houses with clinics on the believed medical benefits of immunization and other determinants of vaccination decisions. IV probit estimates of specifications (12) and (13) for 166 participants in HE and TG.

		HAVESHOT		WANTSHOT	
			HEALTHVALUE		
β_H	PERCLINIC	93.30**	93.30**	93.30**	93.30**
		(25.56)	(25.56)	(25.56)	(25.56)
δ_H	PERCLINIC	-105.33**	-105.34**	-105.33**	-105.34**
	×FLUVICTIM	(38.69)	(38.74)	(38.69)	(38.74)
γ_H	FLUVICTIM	12.01	12.01	12.01	12.01
		(8.74)	(8.74)	(8.74)	(8.74)
θ_H	MDPARENT		0.02		0.02
			(6.64)		(6.64)
α_H	constant	1.94	1.94	1.94	1.94
		(6.34)	(6.53)	(6.34)	(6.53)
σ_H		36.78**	36.78**	36.78**	36.78**
		(2.02)	(2.02)	(2.02)	(2.02)
			OTHERVALUE		
β_O	PERCLINIC	29.20	18.20	20.47	15.92
		(78.28)	(61.78)	(54.25)	(48.76)
γ_O	FLUVICTIM	0.55	-0.50	3.98	3.45
		(13.96)	(12.56)	(10.05)	(9.52)
θ_O	MDPARENT		31.76		12.98
			(21.50)		(13.35)
α_O	constant	-68.42	-68.52	-17.73#	-19.95#
		(50.01)	(43.48)	(10.52)	(10.77)
σ_O		56.53	49.05	50.28	47.41#
		(42.24)	(29.92)	(30.71)	(26.63)
ρ		-0.1923	-0.2473	-0.2133	-0.2395
		(0.5266)	(0.5133)	(0.4545)	(0.4480)
$\beta_H + \beta_O$		122.50	111.51#	113.79#	109.22*
		(82.74)	(67.05)	(60.25)	(55.19)

Note: The third through sixth columns provide estimates for the parameters in the first column. The upper and lower panels show the respective effects of the variables in the second column on the perceived health effects of the vaccine and other factors affecting immunization behavior. In the third and fourth columns, vaccinated individuals are those who obtained a flu shot before participating in the HE. In the fifth and sixth columns, this group also includes subjects planning to get immunized later in the season. Standard errors in parentheses. # Significant at 10 percent level. * Significant at 5 percent level. ** Significant at 1 percent level.