Social Networks and Vaccination Decisions*

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Abstract

We combine survey responses, network data, and medical records in order to examine how friends affect the decision to get vaccinated against influenza. The random assignment of undergraduates to residential halls at a large private university generates exogenous variation in exposure to the vaccine, enabling us to credibly identify social effects. We find evidence of positive peer influences on health beliefs and vaccination choices. In addition, we develop a novel procedure to distinguish between different forms of social effects. Most of the impact of friends on immunization behavior is attributable to social learning about the medical benefits of the vaccine.

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1 Introduction

Vaccines are one of the signature achievements of modern medicine. Many vaccines provide both a high level of individual protection and large social benefits by reducing the transmission rates of infectious diseases. Moreover, once vaccination rates for a particular disease exceed a certain critical threshold, *herd immunity* arises such that even unvaccinated members of a community are protected from infection because a small disease cluster can no longer induce a large-scale outbreak. Governments in the United States and many other countries have therefore pursued public health policies that aim to raise vaccination levels sufficiently in order to eliminate large-scale outbreaks or even eradicate certain diseases altogether. For example, school districts in the United States routinely require children in public schools to be immunized. Other countries, such as Australia, make certain government benefits only available to families who have their children immunized.

Despite these public health policies, vaccination rates can vary considerably across communities and over time. First of all, the uptake rates for elective vaccines remain low, even though many health care facilities offer them for free.[1] Second, a growing number of parents claim personal belief exemptions to avoid compulsory immunization for their children.[2] Epidemiologists have detected a high degree of spatial variation in personal belief exemptions from vaccination (May and Silverman, 2003). In the state of Washington, the overall exemption rate was 5.1 percent among children in the 2010-2011 school year, but exemptions varied across counties from a low of 1.0 percent to a high of 25.3 percent (Ernst and Jacobs, 2012). The geographic clustering of inoculation rates is suggestive evidence that social networks affect immunization decisions. Individuals might seek advice about medical treatments from their relatives or feel pressured to take the same preventative actions as their friends. Several other important medical outcomes like obesity, drug use, and health plan choice also exhibit clustering within geographic groups or closely knit social networks (Christakis and Fowler, 2007; Bobashev and Anthony, 1998; Sorensen, 2008).

Clustering induced by positive peer effects does not necessarily have any effect on the *average* vaccination rates in a population: if social effects are linear, then vaccination rates across communities can remain unchanged. However, clustering increases the *variance* in vaccination rates across communities and therefore interacts with the herd immunity effect (May and Silverman, 2003; Salathé and Bonhoeffer, 2008; Eames, 2009). Therefore, even if average vaccination rates in a county are high, peer effects can give rise to geographic clusters with vaccination rates well below the herd immunity thresholds. For instance, a Dutch

[1] For example, only 28.6% of individuals aged between 18 and 49 obtained a flu shot during the 2011-2012 flu season (McIntyre et al., 2013).

[2] For example, 5.4% of children in Vermont received an immunization exemption during the 2010-2011 school year (Ernst and Jacobs, 2012).

religious community opposed to immunization suffered a polio epidemic in 1992 (Oostvogel et al., 1994). Similarly, outbreaks of measles are common among students at Steiner and Waldorf schools, which promote anthroposophical and homeopathic beliefs that discourage vaccination (Muscat, 2011).

This paper uses a unique dataset to examine how peers influence the decision to get vaccinated against the flu. We combine survey data and medical records with detailed information on the social network of students at a large private university. The random assignment of students to residential houses generates exogenous variation in access to the flu vaccine. Some residences host flu clinics that dispense the vaccine for free, but other residences do not have a facility for distributing the vaccine. Individuals assigned to houses with flu clinics are significantly more likely to receive a flu shot.[3] They may find it especially convenient to get vaccinated or be better informed about the location of clinics. This setup enables us to obtain credible estimates for the impact of friends on vaccination decisions.

There is a large literature that exploits random assignment in college settings to estimate peer effects (Sacerdote, 2001; Zimmerman, 2003; Foster, 2006). Unlike most existing research in this area, the students in our study can select their peers, although they cannot choose where their peers live. This is an important distinction because social interactions may be stronger among individuals who actively decide to become friends than among subjects who are involuntarily grouped together. As Carrell et al. (2009) argue, studies of peer effects focusing on randomly assigned dormmates and roommates often find only weak evidence of social effects because students have a broad network of friends outside of their dorm or room. The social groups in our study are based not on randomized housing assignments, but on an online economic experiment that incentivized participants to truthfully reveal their closest friends.

In order to identify peer effects, we test whether the share of a student's friends assigned to houses with flu clinics affects the student's beliefs and actions. Information on health attitudes is elicited using an online survey. Data on vaccination decisions is obtained from medical records. Unlike some previous studies about the adoption of medical technologies, we find evidence of positive social effects on both attitudes and decisions.[4] A 10 percentage point increase in the share of one's friends in treated houses raises one's evaluation of the vaccine's health benefits by about 5 dollars and one's probability of getting immunized by

[3] Assignment to a house with a flu clinic results in a 15 percentage point increase in the probability of being immunized.

[4] Kremer and Miguel (2007) observe that social learning reduces the acceptance of new deworming drugs among Kenyan villagers, perhaps because social contacts provide unfavorable information. Oster and Thornton (2012) note that peers enhance the uptake of menstrual cups among schoolgirls in rural Nepal, not because of social learning about medical benefits, but because of help with the proper usage of the device.

over 1 percentage point.

Beyond demonstrating the existence of social interactions, we distinguish between different forms of peer effects. Many authors have sought to detect social learning in a variety of contexts such as retirement plans, crop choice, movie sales, farming techniques, restaurant dining, and financial decisions (Duflo and Saez, 2003; Bandiera and Rasul, 2006; Cai et al., 2009; Conley and Udry, 2010; Moretti, 2011; Bursztyn et al., 2012). We contribute to this line of research by documenting the role of social learning in health care decisions and by quantifying the magnitude of social learning relative to other peer influences. A knowledge of the specific mechanism responsible for spillover effects can be useful to policymakers when designing health care programs. For example, if social learning about the medical benefits of vaccination is a major factor, then individuals might be highly responsive to interventions like educational mailings or instructional sessions that disseminate credible information about the preventative value of the vaccine.

A novel feature of the paper is our strategy for decomposing the mechanisms through which friends affect health care behavior. By analyzing how previous flu experience moderates the impact of friends on students' beliefs and choices, it is possible to differentiate social learning about health benefits from other peer influences on immunization decisions. We argue that previous flu experience affects one's receptiveness to social learning but not one's sensitivity to other peer influences. We thereby obtain separate dollar-valued estimates for the impacts of these two channels. A healthy student's valuation for the flu vaccine rises by \$10.92 to \$12.25 when an extra 10 percent of her friends move to treated houses. Over 75% of this increase can be attributed to social learning about health benefits.

Influenza has a sizeable economic and medical burden. 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). Immunization can have substantial health benefits. The vaccine is 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). Because of positive externalities, developing and evaluating policies for promoting vaccination is an important public 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*.

A number of health care agencies have launched outreach programs to distribute vaccines in public places.[5] This study provides valuable information on the effectiveness of such

[5]For example, Wuorenma et al. (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

interventions. We perform counterfactual experiments to illustrate how the scale of the outreach program affects the immunization rate. The results account for both the direct nonsocial effect of living in a house with a flu clinic and the indirect social effect of having friends in houses with flu clinics. As the fraction of houses with flu clinics grows from one third to two thirds, the vaccination rate among the student body rises by 7.2 to 7.9 percentage points. Over 25% of this increase can be attributed to social effects on vaccination 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.

This paper focuses on the 2003–2004 flu season, an account of which is provided by Meadows (2004). The flu began earlier than normal with the variant in circulation being relatively serious. Media stories of deaths among children due to the flu seem to have raised the number of people seeking flu shots. Nonetheless, the vaccine was not fully effective in preventing the illness because the primary strain of the virus in the environment differed from those covered by the vaccine.[6]

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 January 2013, membership at `facebook.com` has expanded to over one billion users, including 167 million individuals in the United States. 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.

stores were equipped with in-house pharmacies that dispensed vaccines to shoppers.

[6] The available health records from HUHS for the 2003–2004 academic year were used to examine the effect of the vaccine on the incidence of flu-related illness. A significantly positive relationship between vaccination and the probability of illness is seen in the raw data, perhaps because sickly individuals are more likely to get immunized. Using assignment to a residence with a clinic as an instrument for receipt of the vaccine, the estimates are too imprecise to detect a significant impact of vaccination on illness.

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 et al. (2006) design a Trivia Game (TG) among students at Harvard College who are listed on `facebook.com`. The 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 TG provided subjects with incentives to list friends with whom they spend a lot of time and with whose habits they are therefore familiar.[7]

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. The mean number of friends for a student is 7.9, and the standard deviation for the number of friends is 3.4.

Note that the information on social networks was collected during the 2004–2005 school year, although the paper studies vaccination decisions in the 2003-2004 school year. As a result, seniors graduating in 2004 are excluded from the analysis.[8] In addition, there

[7]To test whether participants in the TG tended to identify stronger instead of weaker friends, we examined the relationship of a subject's vaccination decision to both the share of one's friends from `facebook.com` in treated houses and the share of one's friends from the TG in treated houses. Friends from the TG are seen to have a greater estimated impact on a subject's vaccination probability than friends from `facebook.com`, although the estimates are too imprecise to statistically distinguish the two coefficients from each other.

[8]Nonetheless, about 10% of the individuals in the estimation sample are classified as seniors in the 2003–2004 academic year. This group includes seniors who graduated late as well as juniors with advanced standing who decided not to graduate early.

might be a problem of reverse causality in which flu clinics during the 2003–2004 school year affect the social network in the 2004-2005 school year. However, this issue is unlikely to be important in the current setting. A flu clinic is not a major event for socializing with other individuals, and students have several other opportunities to make friends in college. It is unlikely that students form close relationships with individuals whom they see in line at a clinic.

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 regarding the influenza virus and the flu vaccine. Of the 802 residents in Lowell and Kirkland, 569 individuals responded to the survey. Respondents were asked about the following: the importance of getting vaccinated against the flu; the probability of a vaccinated person contracting the flu; the probability of an unvaccinated person contracting the flu; and the disutility of becoming sick with the flu. 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. About 33 percent of subjects got flu shots during the 2002–2003 flu season. During the 2003–2004 flu season, flu clinics were held at several locations on campus including 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. 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 to 30 minutes, 30 minutes to 1 hour, 1 to 2 hours, 2 to 4 hours, 4 to 8 hours, or more than 8 hours). The subject was paid a small amount (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 spent together each week. We made the expected payoff for each probability (25.0 or 37.5 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. 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. HUHS also hosted clinics at other locations on campus. Most clinics took place in late November or early December. 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.

3 Empirical Strategy

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 attributes among members of the same group.[9] Manski argues that endogenous social effects cannot be identified unless suitable data are available on individuals' reference sets.

[9] In the sociology literature, the tendency of people to associate with those who are similar to them is known as homophily.

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.

Individuals assigned to houses with clinics may get vaccinated at a higher rate and be more conscious about flu prevention. In section 3.1, we describe how to estimate the impact of assignment to a house with a clinic on the likelihood of getting a flu shot. 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 provides 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 Kremer and Miguel's (2007) study of social learning about new medical technologies.

Section 3.3 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 3.4 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.

Section 3.5 illustrates how the uptake of the vaccine among the student body changes with the scale of the program to provide flu shots in residential houses. We estimate the impacts of one's own assignment to a treated house and the share of one's friends in treated houses on a person's probability of being immunized. The vaccination rate among students is predicted for different numbers of houses with clinics. We compute separate estimates for students living in treated and untreated houses.

3.1 Residential Clinics and Inoculation Rates

The empirical strategy exploits the randomized housing assignments of students to estimate peer effects on medical beliefs and choices. 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. 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 probit model:

$$FLUSHOT_i = \begin{cases} 1 & F_i > 0 \\ 0 & F_i \leq 0 \end{cases}, \; F_i = \alpha + \lambda \cdot CLINICHOUSE_i + \varepsilon_i \;, \tag{1}$$

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 probit specification in equation (1) redefining the latent variable F_i as:

$$F_i = \alpha + \delta_c \cdot CURRIER_i + \delta_e \cdot ELIOT_i + \delta_l \cdot LEVERETT_i + \delta_m \cdot MATHER_i + \varepsilon_i \;, \tag{2}$$

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

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 569 participants in the HE, a total of 167 were also among the 2,360 individuals who took part in the TG. 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 each other, 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." 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:

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

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. We fit a set of models that take the form:

$$BELIEF_i = \alpha + \delta \cdot PERCLINIC_i + \varepsilon_i \ , \tag{4}$$

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 (3) and (4) by adding an indicator for influenza infection and an interaction with friends in treated houses. In our ordered response model for the importance of vaccination, the latent variable Q_i is redefined as:

$$\begin{aligned} Q_i = \alpha \ \cdot FLUVICTIM_i + \beta \ \cdot PERCLINIC_i \times NOTVICTIM_i \\ + \gamma \cdot PERCLINIC_i \times FLUVICTIM_i + \varepsilon_i \ , \end{aligned} \tag{5}$$

where $NOTVICTIM_i$ is an indicator equal to 1 if subject i did not recall having the flu during the last three years, and $FLUVICTIM_i$ is an indicator equal to 1 if subject i did report catching the flu during that period of time. 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 assessments of students without a recent episode of the flu. The coefficient γ reflects how social contacts affect the ratings of students with recent flu experience.

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

$$BELIEF_i = \delta + \theta \cdot FLUVICTIM_i + \kappa \cdot PERCLINIC_i \\ + \lambda \cdot PERCLINIC_i \times FLUVICTIM_i + \varepsilon_i \ , \tag{6}$$

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 (3) through (6), 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 Social Interactions and Vaccination Decisions

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. Merging social network data from the TG with vaccination records from HUHS as in section 3.1, we obtain a sample covering 1173 of the 4299 upperclassmen in the 2003–2004 academic year. Of these 1173 students, 776 were assigned to houses without clinics, but 84 of them were instead placed in overflow dormitories. Students in the latter group are isolated from their own houses and live with individuals who were originally assigned to other houses. Therefore, our analysis will focus on the 692 students who do not reside in overflow dormitories. However, we also report results for all 776 students who were originally assigned to houses without clinics. We estimate the following reduced-form probit model for the vaccination decisions of these students:

$$GOTSHOT_i = \begin{cases} 1 & S_i > 0 \\ 0 & S_i \leq 0 \end{cases}, \ S_i = \alpha + \beta \cdot PERCLINIC_i + \delta \cdot MALE_i + \varepsilon_i \ , \tag{7}$$

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.

We also document how the size of social effects varies with friendship strength. As explained in section 2.1, a random sample of links from the TG were tested by asking one friend to answer a multiple choice question about the other friend. The ability to select the correct answer can be used as an indicator for the closeness of two friends. Each link between two friends is classified as weak, strong, or untested.[10] The probit model in equation (7) is then reestimated with S_i now defined as:

$$\begin{aligned} S_i = \alpha + \beta_s \cdot PERCLINICS_i + \beta_w \cdot PERCLINICW_i \\ + \beta_u \cdot PERCLINICU_i + \delta \cdot MALE_i + \varepsilon_i \end{aligned}, \tag{8}$$

where $PERCLINICS_i$, $PERCLINICW_i$, and $PERCLINICU_i$ respectively denote the shares of student i's strong, weak, and untested friends who live in houses with clinics.[11]

In order to explore factors that might affect the degree of peer influence, we compute separate estimates for various subsamples of the data set, and we analyze several alternative definitions for the social group of each student. First, many authors have found evidence of gender differences in network effects.[12] Therefore, we estimate specifications that distinguish between the impacts of female and male friends on the decisions of students from each gender. Second, the friends of one's friends as well as one's direct friends might affect a person's choices, and students who name a person as a friend might have a different effect than students whom a person names as a friend. Hence, we estimate specifications that discriminate between the impacts of first- and second-order links in treated houses and

[10] A link is said to be weak if one friend provided a wrong answer to the question about the other friend. A link is said to be strong if neither friend gave an incorrect response and either friend gave a correct response. A link is said to be untested if neither friend was asked a question about the other friend.

[11] $PERCLINICS_i$, $PERCLINICW_i$, and $PERCLINICU_i$ are respectively set equal to zero if student i has no strong, weak, and untested friends. In addition, the specification contains indicator variables for students without strong, weak, and untested friends.

[12] For example, see Kling et al. (2007), Stinebrickner and Stinebrickner (2006), and Zimmerman (2003).

that incorporate the shares of in- and out-links in treated houses as distinct regressors. Third, past health care behavior might be an important determinant of current medical choices. Consequently, we calculate separate estimates depending on whether a student was vaccinated during freshman year.

Finally, we investigate whether individuals with high social status exert a bigger or smaller influence on the vaccination decisions of their friends. A bigger effect might be expected if high status individuals are trendy and knowledgeable with their medical decisions widely known. A smaller effect might be expected if high status individuals are busy and unapproachable with their medical decisions kept private. Two measures of social status are used: popularity and centrality. A student's popularity is defined as the number of individuals listing the student as a friend. A student's centrality is computed based on an eigenvector for the adjacency matrix of the social network.[13] The median centrality and popularity of each person's friends are then determined. Each person's friends are classified into two equally sized groups, the first containing friends with a centrality or popularity greater than or equal to the median, and the second containing friends with a centrality or popularity less than or equal to the median. The share of individuals in treated houses is calculated for each of the two groups. The two resulting variables are included as regressors in a probit model of vaccination decisions.

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 estimate an instrumental-variables probit model of friends' vaccination decisions using the method of maximum likelihood.[14] In particular, we jointly estimate the following system of equations for students in houses without clinics:

$$GOTSHOT_i = \begin{cases} 1 & H_i > 0 \\ 0 & H_i \leq 0 \end{cases}, \; H_i = \alpha + \beta \cdot PERSHOT_i + \delta \cdot MALE_i + \epsilon_i \; , \tag{9}$$

where $PERSHOT_i$, which represents the share of student i's friends who get vaccinated for the flu, is specified as:

$$PERSHOT_i = \gamma + \lambda \cdot PERCLINIC_i + \theta \cdot MALE_i + \eta_i. \tag{10}$$

[13]In particular, the eigenvector centrality index from Bonacich (1972) is employed. This measure assigns each student a centrality such that each student's centrality is proportional to the sum of the centralities for the student's friends. Because the adjacency matrix will generally have multiple eigenvectors, the convention of using the eigenvector associated with the largest eigenvalue is followed.

[14]Evans et al. (1992) use a similar estimation procedure to measure endogenous social effects on a dichotomous outcome variable.

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. The error terms ϵ_i and η_i are assumed to be joint normally distributed independent of $PERCLINIC_i$ and $MALE_i$ with mean zero, respective variances 1 and σ^2, and correlation ρ. If our estimate for ρ is significantly different from zero, then $PERSHOT_i$ is likely to be statistically endogenous in equation (9).

The instrumental-variables procedure relies on the assumption that the share of one's friends in treated houses affects immunization behavior only through the share of one's friends who are vaccinated. Nonetheless, it might be possible for friends in treated houses to have a direct effect on one's vaccination decision. For example, a student with a friend in a house with a clinic might find it convenient to get vaccinated when visiting her friend, or a student in a house with a clinic might not get vaccinated herself but might tell a friend about the vaccination program. The empirical analysis accounts for the former mechanism because the dependent variable excludes any vaccination that occurred in a house with a clinic. However, the instrumental-variables procedure ignores the latter effect. Therefore, the other empirical analyses in the paper use a reduced-form specification in which the explanatory variable is simply the share of one's friends in houses with clinics.

3.4 Decomposition of Peer Effects on Immunization

We next explain our framework for identifying the mechanisms that underlie peer effects on vaccination decisions. Kremer and Miguel (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 et al. (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.

For example, a case of the flu 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. If so, 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.

To document how an episode of the flu changes the impact of friends on choices, we estimate the probit model:

$$\begin{aligned} SEEKSHOT_i &= \begin{cases} 1 & L_i > 0 \\ 0 & L_i \leq 0 \end{cases}, \\ L_i &= \alpha \cdot FLUVICTIM_i + \beta \cdot PERCLINIC_i \times NOTVICTIM_i \\ &\quad + \gamma \cdot PERCLINIC_i \times FLUVICTIM_i + \delta \cdot MDPARENT_i + \varepsilon_i \ , \end{aligned} \tag{11}$$

where $SEEKSHOT_i$ indicates whether the respondent seeks a flu shot, $PERCLINIC_i$ is the share of one's friends in houses with clinics, $NOTVICTIM_i$ is a dummy variable for not having a recent case of the flu, $FLUVICTIM_i$ is a dummy variable for recently being sick with the flu, $MDPARENT_i$ signifies whether the respondent has a parent with a medical degree, and ε_i is an idiosyncratic error term. The coefficient α captures the impact of flu experience on the vaccination decisions of respondents without friends in treated houses. The coefficient β represents the influence of friends on the behavior of individuals without flu experience. The coefficient γ measures the effect of friends on the choices of flu victims. The coefficient δ accounts for the potential role of having a parent who is a physician.

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:

$$WANTSHOT_i = \begin{cases} 1 & V_i > 0 \\ 0 & V_i \leq 0 \end{cases}, \; V_i = HEALTHVALUE_i + OTHERVALUE_i \; , \qquad (12)$$

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:

$$\begin{aligned} HEALTHVALUE_i = {} & \alpha_H + \beta_H \cdot PERCLINIC_i + \gamma_H \cdot FLUVICTIM_i \\ & + \delta_H \cdot PERCLINIC_i \times FLUVICTIM_i \\ & + \theta_H \cdot MDPARENT_i + \varepsilon_{Hi} = \mu_{Hi} + \varepsilon_{Hi} \end{aligned} \qquad (13)$$

and

$$\begin{aligned} OTHERVALUE_i = {} & \alpha_O + \beta_O \cdot PERCLINIC_i + \gamma_O \cdot FLUVICTIM_i \\ & + \theta_O \cdot MDPARENT_i + \varepsilon_{Oi} = \mu_{Oi} + \varepsilon_{Oi} \; , \end{aligned} \qquad (14)$$

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 (14) 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% 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 (13) and (14) 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.[15] 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 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 $MDPARENT_i$.

3.5 Scale of Program and Uptake of Vaccine

In practice, four of the twelve residential houses at Harvard College host flu clinics each fall. This section assesses how the inoculation rate among students would change in response to an expansion or contraction of the outreach program. As in sections 3.1 and 3.3, we merge network data from the TG with medical records from HUHS, assembling a data set on 1173 students during the 2003-2004 school year.

We start by calculating the effects of one's own assignment to a treated house and the share of one's friends in treated houses on a person's decision to get vaccinated. The following probit model is estimated based on students in both treated and untreated houses:

$$FLUSHOT_i = \begin{cases} 1 & F_i > 0 \\ 0 & F_i \leq 0 \end{cases}, \tag{15}$$

$$F_i = \alpha + \lambda \cdot CLINICHOUSE_i + \beta \cdot PERCLINIC_i + \delta \cdot MALE_i + \varepsilon_i \ ,$$

[15] A Newton-Raphson algorithm with numerical derivatives is used to maximize the log-likelihood function 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:

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

where $FLUSHOT_i$ represents whether or not student i gets vaccinated, $CLINICHOUSE_i$ is an indicator for student i being assigned to a treated house, $PERCLINIC_i$ denotes the share of student i's friends living in treated houses, and $MALE_i$ is a dummy variable for student i being male. Once estimates for the model have been obtained, each student's immunization probability can be predicted under different assumptions about the student's assignment to a treated house and the share of the student's friends in treated houses.

The relationship between the number of treated houses and the percentage of students vaccinated is estimated as follows. The housing assignment of each student in the sample is identified, and the share of each student's friends in each of the twelve houses is calculated. All the different ways of allocating flu clinics to the twelve houses are enumerated.[16] For every possible combination of treated houses, we determine whether each student in the sample would live in a treated or untreated house, and we calculate the share of each student's friends that would live in treated houses. Each student's vaccination probability is then predicted using the estimates for the probit model in equation (15). The averages of the predictions are computed for students in all houses, untreated houses, and treated houses. This procedure is repeated for every possible combination of treated houses. Finally, we take the means of the results over all the combinations with a given number of treated houses.[17]

4 Results

4.1 Residential Clinics and Inoculation Rates

Our strategy for identifying peer effects relies on the random assignment of students to residential houses. This section documents how assignment to a treated house affects the probability of getting vaccinated. 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 1 presents estimates for specifications (1) and (2) as well as marginal effects for the explanatory variables.[18] The coefficient λ in equation (1) is positive and significant at the 1 percent level, indicating a higher vaccination rate in houses with clinics. Overall, assignment to these houses makes an individual 15.1 percentage points more likely to get vaccinated. Nonetheless, we find substantial variation in vaccination rates across houses with clinics. Compared to living in a house without a clinic, being assigned to Leverett House raises the probability of vaccination by 32.5 percentage points, whereas being assigned to Mather House raises the probability of vaccination by 4.5 percentage points. The vaccination clinic

[16]Because each of the 12 houses is either treated or untreated, there are 2^{12} ways of distributing clinics among the 12 residences.

[17]There are $\binom{12}{k}$ combinations of k treated houses from a set of 12 houses.

[18]The marginal effects are calculated by comparing the predicted vaccination probability for students in a given house or group of houses with the predicted vaccination probability for students in houses without clinics.

at Mather House may have been poorly placed or open for only a short time.

4.2 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 upper panel of Table 2 presents average marginal effects for the ordered probit model in equation (3). An increase in the share of friends in houses with clinics significantly raises the probability that a subject rates immunization as being important or very important and significantly lowers the probability that a subject rates immunization as being unimportant. Many social processes could give rise to these effects. 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 lower panel of Table 2 reports marginal effects for the ordinal response model in equation (5). Healthy individuals become significantly more likely to regard immunization as being important or very important and significantly less likely to regard immunization as being unimportant when a greater share of their friends are assigned to houses with clinics. Exposure to illness has no significant impact on perceptions about the importance of being immunized, although the effects of friends in treated houses appears to be somewhat weaker for recent flu victims.

We next attempt to identify the channels through which social contacts affect students' medical beliefs. Table 3 presents estimates for the set of models in equations (4) and (6). We begin by measuring peer influences on people's perceptions about their susceptibility to disease. In the first column of Table 3, 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 3 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 seventh column of Table 3 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 eighth 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 ninth column of Table 3 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 tenth 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, we estimate specifications (3) through (6), dropping students who got flu shots at houses with clinics. Our results change little.[19] 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.

4.3 Social Interactions and Vaccination Decisions

This section estimates social effects on the decision to get a flu shot. We examine how social ties to houses with flu clinics affect immunization behavior. The immunization rate among students in houses without clinics 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. The upper panel of Table 4 presents reduced-form estimates for specification (7). 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 4.2, 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.

We also investigate how peer influences vary with friendship strength, which is measured as the ability of friends to answer personal questions about each other. The lower panel of Table 4 presents estimates for equation (8), which uses the shares of one's strong, weak,

[19]These estimates are available in the supplemental appendix.

and untested friends in treated houses as explanatory variables. The coefficient on the share of strong friends in treated houses is positive as well as significant at the 1 or 5 percent level depending on whether students in overflow dormitories are excluded or included. By contrast, the point estimate for the coefficient on the share of weak friends in houses with clinics is negative.[20]

In addition, we explored several extensions to our baseline specification of social effects on vaccination decisions.[21] First, we computed separate estimates for respondents of each gender. The shares of female and male friends in treated houses were also included as individual regressors. Male friends in treated houses have a significantly positive impact on the immunization probability of men but not of women. Female friends in treated houses do not have a significant influence on the immunization behavior of either gender. Second, we estimated models that differentiate between the shares of first- and second-order links in treated houses or between the shares of in- and out-links in treated houses. Second-order links in treated houses have a much smaller estimated impact than first-order links in treated houses. The estimated impacts of in-links and out-links in treated houses are roughly similar. Third, we performed separate regressions based on whether an individual got a flu shot in freshman year. Only previously immunized students exhibit a statistically significant response to friends in treated houses.

Finally, we examined the role of social status. The shares of one's more and less popular friends in treated houses were used as explanatory variables in a probit model of vaccination decisions. Less popular friends in treated houses are seen to have a positive and significant effect on the probability of immunization, whereas the coefficient on more popular friends is insignificantly negative.[22] Overall, the findings appear to suggest that low status friends exert a stronger influence on a person's vaccination decisions than high status friends. This situation might arise if high status individuals are more occupied and less accessible, leading a person to spend less time with more popular friends.[23]

To measure endogenous effects, we carry out the instrumental-variables probit strategy outlined in section 3.3. The lower half of Table 5 reports estimates for equation (10), which

[20]Moreover, the difference between the coefficients on strong and weak friends in houses with clinics is statistically significant at least at the 5 percent level.

[21]These results are available in the supplemental appendix.

[22]A student's popularity is defined as the number of individuals listing the student as a friend. The regressions were also run using eigenvector centrality instead of popularity. In this case, the estimated coefficient is higher for less than for more central friends, although it is positive in both cases.

[23]To substantiate this explanation, we combined information from the TG on the number of in-links for every person with data from the HE on the amount of time per week a person spends with each of her friends. A significant negative relationship was found between the amount of time a person spends with a friend and the number of in-links her friend has, provided that the person resides in a different house from her friend.

relates the share of one's friends in houses with clinics to the share of one's friends receiving flu shots. 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. The upper half of Table 5 provides estimates for equation (9), which relates the share of one's friends receiving flu shots to one's own decision to get vaccinated. When students in overflow dormitories are excluded, the coefficient on the share of friends in houses with clinics is positive and significant at the 1 percent level after controlling for gender. 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.[24] Specifically, if an extra 10 percent of one's friends receive flu shots, then a typical student becomes 5.5 to 8.8 percentage points more likely to get immunized.[25] The estimate for the parameter ρ, representing the correlation between the error terms in equations (9) and (10), is insignificantly negative.[26] Hence, there is insufficient evidence that the share of friends vaccinated is statistically endogenous in equation (9).

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. About 49 percent of subjects reported catching the flu within the past three years.[27] 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, Tables 6 and 7 reports results for both current and planned vaccination decisions, including and excluding a control for children of physician

[24] The observed peer influences operate in the opposite direction as epidemiological effects, whereby one's risk of being infected and one's incentive to get vaccinated decrease when one's friends receive flu shots.

[25] These figures are obtained as follows using the estimates in Table 5. First, the predicted vaccination probability is calculated for a person with the average values of the explanatory variables in each specification. Second, the predicted vaccination probability for this person is calculated after raising the share of friends immunized by 10 percentage points. Third, the former probability is subtracted from the latter probability.

[26] In addition, the share of friends receiving flu shots has a lower estimated marginal effect in a simple probit analysis of equation (9) than in the instrumental-variables probit analysis from Table 5.

[27] Three years was chosen as a cutoff when dividing the sample between flu victims and healthy individuals because approximately half of the participants recalled having the flu within the past three years. The number of years since the last flu episode was specified as a binary instead of a continuous variable since the survey responses were top coded at five years.

parents.

As explained in section 3.4, the identification strategy involves comparing the effects of friends on the medical beliefs and choices of recent flu victims. The results in section 4.2 indicate that friends in treated houses do not impact the beliefs of flu victims regarding the health value of the vaccine. Hence, if friends in treated houses affect the vaccination decisions of flu victims, then peer influences other than social learning about the health value of the vaccine are likely to be important. By contrast, if the choices of flu victims are unaffected, then other social effects may be negligible. Table 6 presents estimates for specification (11), which describes how experience with influenza alters immunization behavior. Although the estimates are imprecise due to the small sample size, friends in treated houses appear to have a much smaller effect on flu victims than on healthy people. If an additional 10 percent of one's friends are assigned to houses with clinics, then a typical flu victim's probability of being immunized rises by less than 1.1 percentage points as compared to more than 5.0 percentage points for a healthy person.[28] Overall, the beliefs and choices of flu victims do not show a large response to friends in treated houses, which suggests that peer effects other than social learning may be limited.

Table 7 contains estimates for the model in equations (12) to (14), which differentiate social learning about health benefits from other mechanisms of peer influence. The upper panel shows the effect of friends on beliefs about the medical value of the vaccine. As in section 4.2, social ties to treated houses reliably increase the believed health benefits of immunization, 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 (13) 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

[28] These figures are derived from the estimates in Table 6 by applying the following procedure separately to flu victims and healthy people. First, the predicted vaccination probability is calculated for a person with the average values of the explanatory variables in each specification. Second, the predicted vaccination probability for such a person is calculated after raising the share of friends immunized by 10 percentage points. Third, the former probability is subtracted from the latter probability.

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 7 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 at least some evidence against the hypothesis that subjects alter their beliefs to suit their actions.[29]

4.5 Scale of Program and Uptake of Vaccine

A change in the number of houses with clinics would affect the immunization rate by altering a student's probability of living in a treated house as well as the share of a student's friends living in treated houses. This section evaluates the effect of the scale of the immunization program on the percentage of students getting vaccinated. Table 8 presents

[29] The values in Tables 6 and 7 were also computed after dropping students vaccinated in houses with clinics. Although the estimates are somewhat imprecise, friends in treated houses still have a smaller estimated impact on flu victims than on healthy people, and most of the observed effect of friends on the total valuation for the vaccine is still attributable to social learning about medical benefits. These results are available in the supplemental appendix.

estimates for equation (15), which relates a person's vaccination decision to one's own assignment to a treated house and the share of one's friends assigned to treated houses. We report results both including and excluding a dummy variable for gender and both dropping and keeping students in overflow dormitories. The coefficient on one's own treatment status is in each case significant at the 5 percent level. The coefficient on the share of one's friends in the treatment is significant at the 5 or 10 percent level depending on the specification. Assignment to a treated house makes a student 8.7 to 10.0 percentage points more likely to get vaccinated on average. If an additional 10 percent of one's friends are placed in treated houses, then one's probability of getting a flu shot increases by 1.0 to 1.3 percentage points for a student in an untreated house and by 1.2 to 1.6 percentage points for a student in a treated house.[30]

As described in section 3.5, it is now possible to predict the relationship between the number of treated houses and the percentage of students vaccinated. Table 9 displays the results of this procedure. A separate set of estimates is generated for each specification from Table 8. As the number of houses with flu clinics rises from four to eight, the vaccination rate among all students increases from between 29.3 and 30.6 percent to between 36.7 and 38.2 percent. This change is attributable to students having both a greater probability of living in a treated house and a higher share of their friends living in treated houses. The former mechanism can be regarded as a direct nonsocial effect. The latter mechanism can be regarded as an indirect social effect. The table also contains separate estimates for students in treated and untreated houses. An increase in the number of treated houses from four to eight raises the vaccination rate by 2.0 to 2.5 percentage points among students in untreated houses and by 2.3 to 3.0 percentage points among students in treated houses. These changes are due primarily to students having a larger share of their friends living in treated houses.

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 inoculation clinics held at some residence halls increase the probability that students living elsewhere get vaccinated. In particular, a typical student in a residence without a clinic becomes 1.1 to 1.8 percentage points more likely to receive a flu shot if an additional 10 percent of one's friends are assigned

[30] These figures are derived from the estimates in Table 6 by applying the following procedure separately to students in untreated and treated houses. First, the vaccination probability is predicted for a person with the average values of the covariates. Second, the vaccination probability for such a person is predicted after raising the share of friends in treated houses by 10 percentage points. Third, the former probability is subtracted from the latter probability.

to residences with clinics.[31]

In addition, we decompose the mechanisms responsible for social effects on vaccination decisions, obtaining dollar value estimates of social learning and other peer interactions. Using data on a student's health beliefs, we directly measure social learning about the medical benefits of immunization. The average student's belief about the vaccine's health value increases by \$5.00 when an additional 10 percent of one's friends are assigned to residences with clinics. We identify other peer interactions by examining how influenza infections alter the effects of friends on an individual's beliefs and choices. A 10 percentage point increase in the proportion of friends in residences with clinics raises overall valuations of the vaccine by \$10.92 to \$12.25 among students with no recent flu experience, with more than 75 percent of this effect being attributable to social learning about medical benefits.

Expanding vaccine coverage is a national health goal. As a result, many health care organizations have implemented mass inoculation programs that dispense vaccines at public sites. Our analysis of the immunization program at a large private university suggests that social effects can contribute to the success of such interventions by raising the demand for vaccines in the community at large. Using our estimates for the impacts of one's own and one's friends' housing assignments on the probability of vaccination, we perform counterfactual experiments to assess the relationship between the scale of the outreach program and the uptake of the flu vaccine. If the proportion of residences with clinics is increased from one third to two thirds, then the vaccination rate among the student body rises by 7.2 to 7.9 percentage points, with more than 25% of this effect being attributable to social influences on immunization behavior.

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[31]These figures are obtained as follows using the estimates in the upper panel of Table 4. First, the predicted vaccination probability is calculated for a person with the average values of the covariates in each specification. Second, the predicted vaccination probability for this person is calculated after raising the share of friends in houses with clinics by 10 percentage points. Third, the former probability is subtracted from the latter probability.

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Table 1: Probit estimates for the effect of in-house clinics on vaccination decisions.

	Vaccinated	
Resident of a Treated House	0.4257**	
	(0.0804)	
	[0.1506]	
Resident of Currier		0.5054**
		(0.1606)
		[0.1816]
Resident of Eliot		0.2801#
		(0.1441)
		[0.0958]
Resident of Leverett		0.8672**
		(0.1353)
		[0.3252]
Resident of Mather		0.1370
		(0.1231)
		[0.0450]
Constant	-0.6908**	-0.6908**
	(0.0491)	(0.0491)
Observations	1173	1173
Log-likelihood	-698.4	-688.1
Pseudo-R^2	0.0196	0.0340

Note: HUHS operated flu clinics at four residential houses: Currier, Eliot, Leverett, and Mather. The marginal effects are computed as the difference between the predicted vaccination probability for students in a given house or group of houses and the predicted vaccination probability for students in houses without clinics. Standard errors in parentheses. Marginal effects in brackets. # Significant at 10 percent level. ** Significant at 1 percent level.

Table 2: Marginal effects for ordered probit models of the importance of vaccination.

	Not Very Important	Somewhat Important	Important	Very Important
		Without Effect of Flu		
Share of Friends in Treated Houses	-0.4697*	0.0487	0.2128*	0.2083*
	(0.2034)	(0.0399)	(0.0960)	(0.0978)
Observations		167		
Log Likelihood		-210.5		
Pseudo-R^2		0.0118		
		With Effect of Flu		
Share of Friends in Treated Houses	-0.5916*	0.0315	0.2670*	0.2931*
× Not Recent Flu Victim	(0.2611)	(0.0615)	(0.1176)	(0.1426)
Share of Friends in Treated Houses	-0.2625	0.0413	0.1202	0.1010
× Recent Flu Victim	(0.3253)	(0.0571)	(0.1489)	(0.1286)
Recent Flu Victim	-0.0302	0.0078	0.0133	0.0091
	(0.1029)	(0.0269)	(0.0452)	(0.0310)
Observations		167		
Log Likelihood		-210.0		
Pseudo-R^2		0.0141		

Note: In the upper panel, the marginal effects represent the changes in the percent probabilities of an individual selecting the given ratings when an extra 1 percent of her friends move to houses with clinics. In the lower panel, the marginal effects are calculated so as to have the following interpretations. When an additional 1 percent of one's friends move to treated houses, the percent probabilities of a healthy person and a flu victim choosing the given ratings change by the marginal effects in the first and second pairs of rows. If a healthy person with no friends in treated houses becomes a flu victim, then the percent probabilities of her selecting the given ratings change by the marginal effects in the third pair of rows. Standard errors in parentheses. * Significant at 5 percent level.

Table 3: OLS estimates of social effects on beliefs about the influenza virus and the flu vaccine.

	Probability of Flu if Unvaccinated		Probability of Flu if Vaccinated		Cost of Having Flu		Effect of Vaccine in Preventing Flu		Valuation for Health Benefits of Vaccine	
Share of Friends in Treated Houses	0.2159#	0.4083*	-0.0718	0.0128	13.34	114.6#	0.2877*	0.3954**	50.03*	93.30**
	(0.1299)	(0.1740)	(0.0702)	(0.0915)	(50.64)	(67.48)	(0.1144)	(0.1516)	(19.60)	(25.87)
Share of Friends in Treated Houses		-0.4442#		-0.1224		-266.7*		-0.3219		-105.3**
× Recent Flu Victim		(0.2637)		(0.1386)		(102.2)		(0.2297)		(39.17)
Recent Flu Victim		0.0727		0.0904**		43.58#		-0.0177		12.01
		(0.0594)		(0.0139)		(23.07)		(0.0517)		(8.844)
Constant	0.3913**	0.3556**	0.1650**	0.1156**	50.27**	28.28#	0.2263**	0.2400**	7.490#	1.944
	(0.0297)	(0.0430)	(0.0160)	(0.0226)	(11.59)	(16.75)	(0.0261)	(0.0374)	(4.488)	(6.421)
Observations	167	167	167	167	166	166	167	167	166	166
R^2	0.0165	0.0333	0.0063	0.0757	0.0004	0.0306	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 4: Probit estimates of social effects on vaccination decisions.

	Vaccinated at Non-Residential Clinic			
	With Overflow Dormitories		*Without Overflow Dormitories*	
	Same Social Strength			
Share of Friends in Treated Houses	0.3934 (0.2699) [0.1062]	0.5113# (0.2776) [0.1409]	0.5153# (0.2893) [0.1388]	0.6497* (0.2975) [0.1779]
Male Gender		-0.1013 (0.1078) [-0.0277]		-0.1380 (0.1152) [-0.0374]
Constant	-0.9558** (0.0741)	-0.9086** (0.0860)	-0.9803** (0.0794)	-0.9254** (0.0916)
Observations	776	737	692	658
Log-likelihood	-375.6	-363.4	-334.2	-322.7
Pseudo-R^2	0.0028	0.0055	0.0047	0.0091
	Different Social Strengths			
Share of Strong Friends in Treated Houses	0.4215* (0.1793) [0.1143]	0.4403* (0.1817) [0.1209]	0.5619** (0.1885) [0.1541]	0.5915** (0.1912) [0.1632]
Share of Weak Friends in Treated Houses	-0.3760 (0.2594) [-0.0995]	-0.2972 (0.2665) [-0.0793]	-0.4645# (0.2773) [-0.1240]	-0.4127 (0.2837) [-0.1105]
Share of Untested Friends in Treated Houses	0.3512 (0.2485) [0.0942]	0.4051 (0.2516) [0.1109]	0.3614 (0.2696) [0.0959]	0.4169 (0.2732) [0.1125]
Male Gender		-0.1199 (0.1090) [-0.0326]		-0.1626 (0.1170) [-0.0434]
Constant	-0.9650** (0.1072)	-0.9438** (0.1156)	-0.9367** (0.1114)	-0.9033** (0.1210)
Observations	776	737	692	658
Log-likelihood	-371.0	-359.5	-327.8	-317.1
Pseudo-R^2	0.0129	0.0146	0.0219	0.0248

Note: The shares of strong, weak, and untested friends in treated houses are respectively set equal to zero for respondents without strong, weak, and untested friends. The specifications in the lower panel contain indicator variables for respondents without strong, weak, and untested friends. Individuals without strong, weak, and untested friends are respectively excluded when calculating average marginal effects for the shares of strong, weak, and untested friends in treated houses. Standard errors in parentheses. Marginal effects in brackets. # Significant at 10 percent level. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 5: IV probit estimates for the effects of friends' assignments to houses with clinics on friends' vaccination decisions and of friends' vaccination decisions on own vaccination decision.

	With Overflow Dormitories		*Without Overflow Dormitories*	
	Vaccinated at Non-Residential Clinic			
Share of Friends Vaccinated	1.8692	2.2023*	2.4869*	2.7528**
	(1.1842)	(1.0713)	(1.1965)	(1.0474)
	[0.4991]	[0.5976]	[0.6622]	[0.7423]
Male Gender		-0.0598		-0.0577
		(0.1068)		(0.1155)
		[-0.0162]		[-0.0155]
Constant	-1.3579**	-1.3793**	-1.4937**	-1.5000**
	(0.2730)	(0.2485)	(0.2526)	(0.2323)
	Share of Friends Vaccinated			
Share of Friends in Treated Houses	0.2076**	0.2243**	0.1986**	0.2204**
	(0.0352)	(0.0363)	(0.0373)	(0.0383)
Male Gender		-0.0167		-0.0254#
		(0.0137)		(0.0143)
Constant	0.2251**	0.2285**	0.2266**	0.2327**
	(0.0093)	(0.0110)	(0.0098)	(0.0115)
ρ	-0.2301	-0.2913	-0.3398	-0.3892#
	(0.2305)	(0.2093)	(0.2327)	(0.2036)
σ	0.1855**	0.1841**	0.1830**	0.1811**
	(0.0047)	(0.0048)	(0.0049)	(0.0050)
Observations	776	737	692	658
Log-likelihood	-166.4	-159.1	-138.3	-129.7

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

Table 6: Probit estimates of social effects on the vaccination decisions of students with and without recent flu experience.

	Have Vaccine		Want Vaccine	
Share of Friends in Treated Houses	1.6539#	1.6673#	1.4862	1.4857
× Not Recent Flu Victim	(0.9418)	(0.9391)	(0.9095)	(0.9105)
	[0.4738]	[0.4595]	[0.5777]	[0.5745]
Share of Friends in Treated Houses	0.1904	0.0058	0.2684	0.1908
× Recent Flu Victim	(1.1785)	(1.1904)	(0.9868)	(0.9855)
	[0.0508]	[0.0015]	[0.1070]	[0.0756]
Recent Flu Victim	0.1847	0.1905	0.2277	0.2320
	(0.3497)	(0.3532)	(0.2993)	(0.2998)
	[0.0439]	[0.0443]	[0.0898]	[0.0910]
Parent Has MD		0.6066*		0.2536
		(0.2452)		(0.2285)
		[0.1834]		[0.0992]
Constant	-1.1097**	-1.2773**	-0.2529	-0.3112
	(0.2511)	(0.2635)	(0.2184)	(0.2251)
Observations	167	167	167	167
Log-likelihood	-82.66	-79.63	-114.3	-113.7
Pseudo-R^2	0.0205	0.0564	0.0123	0.0176

Note: The marginal effects are calculated so as to have the following interpretations. When an additional 1 percent of one's friends move to treated houses, the percent probabilities of a healthy person and a flu victim getting vaccinated change by the marginal effects in the first and second groups of rows. If a healthy person with no friends in treated houses becomes a flu victim, then the percent probability of being immunized changes by the marginal effects in the third group of rows. The marginal effects in the fourth group of rows represent the effect of having a parent with a medical degree on the probability of receiving a flu shot. Standard errors in parentheses. Marginal effects in brackets. # Significant at 10 percent level. * Significant at 5 percent level. ** Significant at 1 percent level.

Table 7: IV probit estimates for the effects of friends in houses with clinics on the believed health benefits of vaccination and on other costs and benefits of immunization.

		Have Vaccine		Want Vaccine	
			Value of Health Benefits		
β_H	Share of Friends in Treated Houses	93.30** (25.56)	93.30** (25.56)	93.30** (25.56)	93.30** (25.56)
δ_H	Share of Friends in Treated Houses × Recent Flu Victim	-105.33** (38.69)	-105.34** (38.74)	-105.33** (38.69)	-105.34** (38.74)
γ_H	Recent Flu Victim	12.01 (8.74)	12.01 (8.74)	12.01 (8.74)	12.01 (8.74)
θ_H	Parent Has MD		0.02 (6.64)		0.02 (6.64)
α_H	Constant	1.94 (6.34)	1.94 (6.53)	1.94 (6.34)	1.94 (6.53)
σ_H		36.78** (2.02)	36.78** (2.02)	36.78** (2.02)	36.78** (2.02)
			Other Benefits and Costs		
β_O	Share of Friends in Treated Houses	29.20 (78.28)	18.20 (61.78)	20.47 (54.25)	15.92 (48.76)
γ_O	Recent Flu Victim	0.55 (13.96)	-0.50 (12.56)	3.98 (10.05)	3.45 (9.52)
θ_O	Parent Has MD		31.76 (21.50)		12.98 (13.35)
α_O	Constant	-68.42 (50.01)	-68.52 (43.48)	-17.73# (10.52)	-19.95# (10.77)
σ_O		56.53 (42.24)	49.05 (29.92)	50.28 (30.71)	47.41# (26.63)
ρ		-0.1923 (0.5266)	-0.2473 (0.5133)	-0.2133 (0.4545)	-0.2395 (0.4480)
$\beta_H + \beta_O$		122.50 (82.74)	111.51# (67.05)	113.79# (60.25)	109.22* (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 benefits of vaccination and on other costs and benefits of immunization. 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.

Table 8: Probit estimates for effects on vaccination decisions of assignment to house with flu clinic and share of friends in houses with flu clinics.

	Vaccinated			
	With Overflow Dormitories		*Without Overflow Dormitories*	
Resident of a Treated House	0.2847*	0.2568*	0.2758*	0.2470*
	(0.1141)	(0.1167)	(0.1186)	(0.1212)
	[0.0995]	[0.0909]	[0.0962]	[0.0870]
Share of Friends in Treated Houses	0.3210#	0.3731*	0.3515#	0.4083*
	(0.1843)	(0.1887)	(0.1923)	(0.1967)
	[0.1083]	[0.1279]	[0.1187]	[0.1398]
Male Gender		-0.0432		-0.0721
		(0.0803)		(0.0841)
		[-0.0148]		[-0.0246]
Constant	-0.7517**	-0.7103**	-0.7642**	-0.7146**
	(0.0605)	(0.0691)	(0.0639)	(0.0723)
Observations	1173	1121	1077	1031
Log-likelihood	-696.8	-675.9	-640.2	-621.0
Pseudo-R^2	0.0218	0.0222	0.0230	0.0239

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

Table 9: Predicted vaccination rates by number of residential houses with flu clinics.

	Percentage of Students Vaccinated											
	With Overflow Dormitories						*Without Overflow Dormitories*					
	Without Gender Control			*With Gender Control*			*Without Gender Control*			*With Gender Control*		
Number of Treated Houses	*All Houses*	*Untreated Houses*	*Treated Houses*	*All Houses*	*Untreated Houses*	*Treated Houses*	*All Houses*	*Untreated Houses*	*Treated Houses*	*All Houses*	*Untreated Houses*	*Treated Houses*
0	22.61	22.61		23.31	23.31		22.24	22.24		22.83	22.83	
1	24.30	23.08	37.69	25.09	23.86	38.51	23.98	22.75	37.49	24.67	23.43	38.23
2	26.02	23.56	38.30	26.90	24.42	39.21	25.75	23.26	38.15	26.53	24.03	39.00
3	27.75	24.04	38.89	28.72	24.99	39.90	27.54	23.78	38.79	28.42	24.64	39.74
4	29.51	24.52	39.47	30.57	25.56	40.58	29.35	24.30	39.43	30.34	25.26	40.48
5	31.28	25.01	40.06	32.44	26.14	41.26	31.18	24.83	40.06	32.28	25.89	41.22
6	33.07	25.50	40.64	34.33	26.72	41.94	33.03	25.36	40.70	34.24	26.52	41.95
7	34.88	26.00	41.23	36.24	27.31	42.62	34.91	25.90	41.34	36.22	27.15	42.69
8	36.71	26.50	41.82	38.17	27.90	43.31	36.80	26.45	41.98	38.22	27.80	43.44
9	38.56	27.01	42.41	40.12	28.51	43.99	38.71	27.00	42.62	40.24	28.45	44.18
10	40.42	27.53	43.00	42.08	29.12	44.68	40.64	27.57	43.26	42.29	29.12	44.93
11	42.30	28.07	43.60	44.06	29.77	45.37	42.59	28.16	43.91	44.35	29.83	45.67
12	44.19		44.19	46.06		46.06	44.55		44.55	46.43		46.43

Note: The estimates are generated as follows. Every possible way of allocating flu clinics to the twelve residential houses is enumerated. For each combination of treated houses, the treatment statuses of all the students in the sample are determined based on their housing assignments. A student's vaccination probability is then predicted using the specifications from Table 8. The averages of the predictions are calculated for students in all houses, untreated houses, and treated houses. This procedure is repeated for every combination of treated houses. The means of the results are taken over all the combinations with a given number of treated houses.