

Three Essays in the Economics of Vaccination

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Abstract

Under-vaccination is a usual concern of disease control studies. However, the equilibrium vaccination pattern may not only deviates from social optimum by the number of vaccinations but also the type of individuals that gets vaccinated. This paper employs a vaccination game in a three-agent contagion network to show that it is only one of the three inefficient patterns. Chapter 2 shows that when the network structure is incomplete or individual characteristics are heterogeneous, there exist new types of Nash equilibrium outcomes with either the right number but wrong set of people getting vaccinated or too many vaccinations, and these equilibria are robust to standard refinements. However, if the pure-strategy Nash equilibrium assigns the vaccine to some agents but not to everyone, the vaccination game becomes anti-coordinative because everyone prefers the other agents to take the costly vaccine. Thus, agents achieve a mixed-strategy Nash equilibrium. Chapter 3 shows that in an incomplete network, the central player has a greater centrality but chooses a lower vaccination probability than the peripherals. These theoretical predictions differ from the traditional epidemiology models, and this paper tests the various models' predictions with U.S. workers' flu vaccine uptake. Chapter 4 finds that among all workers, high-centrality workers are more likely to get vaccinated than low-centrality workers. However, the difference diminishes as we exclude health care personnel. Both the theoretical and empirical results suggest that targeted vaccination policies on high-centrality people can improve social welfare.

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Chapter 1

Introduction

Fighting contagious disease is one of the biggest challenges for human beings. Though scientists have developed highly effective weapons such as vaccines, human beings only successfully eradicated smallpox in 1980, and the battle against contagious diseases are very likely to continue for the foreseeable future. Therefore, understanding the human behavior in the vaccine uptake is essential to control the contagious diseases. Thus, I develop a new theoretical model that incorporates people's strategic interactions and test the model's predictions empirically with data about U.S. workers' flu vaccine uptake.

Chapter 2 develops the theoretical model and investigates the vaccination pattern in a pure-strategy Nash equilibrium. Under-vaccination is a usual concern of disease control studies, but this chapter employs a simultaneous-move game in a three-agent contagion network to show that it is only one of the three inefficient patterns. When the network structure is incomplete or individual characteristics are heterogeneous, there exist new types of Nash equilibrium outcomes with either the right number but wrong set of people getting vaccinated or too many vaccinations, and these equilibria are robust to standard refinements. While untargeted policies can correct the standard under-vaccination problem, targeted policies are more palatable for correcting the new inefficiencies. Universal mandates can never improve on any Nash equilibria.

Chapter 3 extends the investigation to the mixed-strategy Nash equilibrium. If the pure-strategy Nash equilibrium assigns the vaccine to some agents but not to everyone, the vaccination game becomes anti-coordinative because everyone prefers the other agents to take

the costly vaccine. Thus, agents achieve a mixed-strategy Nash equilibrium, which has two implications. First, in a star network, everyone's vaccination probability rises as the number of players increases, but in each specific network, the central player has a greater centrality but chooses a lower vaccination probability than the peripherals. Second, in any network, a universal mandate produces the same social welfare a mixed-strategy Nash equilibrium does.

Chapter 4 empirically tests the model's predictions. High-centrality individuals have direct exposure to disease and interact with many people, so their vaccination generates a large social benefit. But whether they are more likely to uptake vaccines is unclear. Using data from the Occupational Information Network and the Behavioral Risk Factor Surveillance System with restricted information on industry and occupation, we construct a centrality measure for every occupation and estimate the effect of occupation centrality on influenza vaccine uptake. We find that among all workers, high-centrality workers are more likely to get vaccinated than low-centrality workers. However, the difference diminishes as we exclude health care personnel. Such pattern suggests that high-centrality non-health care workers are under-vaccinated, and targeted vaccination policies on them are needed to improve social welfare.

Chapter 2

Equilibrium Vaccination Patterns in Incomplete and Heterogeneous Networks

2.1 Introduction

When it comes to vaccinations, the primary focus of the general public, the medical profession, and academic researchers tends toward the problem of too few vaccinations.¹ For economists, under-vaccination is a straightforward example of free-riding. The individual receiving the vaccination bears the cost of the vaccination, but by keeping him from getting the disease, the benefits go not just to him but also to others with whom he interacts.² Free-riding provides one explanation for why too few individuals receive vaccinations, but some recent economic research has moved into other factors that might exacerbate this effect, with individuals not receiving vaccinations because of misinformation or behavioral biases.³

¹For instance, in 2015 the journal *Vaccine* published a special issue on the topic of vaccine hesitancy, the tendency of both patients and caregivers to become “hesitant” about vaccinations (see [Hickler et al. \(2015\)](#)).

²That vaccinations have a public-good component and lead to free-riding behavior was already well-known in public finance textbooks ([Stiglitz, 1988](#)), but [Brito et al. \(1991\)](#) were among the first to provide a formal treatment. Their paper looks at tax and subsidy schemes to get the socially-optimal number of vaccinations, and it was built upon by [Geoffard and Philipson \(1997\)](#) and [Francis \(1997\)](#). [Ward \(2014\)](#) and [White \(2018\)](#) find empirical evidence of vaccination externalities using data on influenza vaccines.

³Some recent experimental evidence includes [Ibuka et al. \(2014\)](#), which finds evidence of free-riding but also recency bias, and [Bronchetti et al. \(2015\)](#), which looks at attention, planning, and follow-through for vaccination behavior.

This paper focuses on a different problem. We show that in an asymmetric contagion network not only can too few people get vaccinated, but also the right number but the wrong set of people could get vaccinated, and the possibility even arises that too many people get vaccinated. As with free-riding, the intuition is straightforward. Suppose the socially-optimal vaccination pattern dictates that one particular individual should be among those vaccinated, perhaps she has the lowest vaccination cost or the highest likelihood to spread the disease, but in equilibrium, that person does not get vaccinated. Her forgoing the vaccine leads others with lower network externalities to get vaccinated as the best response, and sometimes it takes more than one person to make up for the missing vaccination. These new results show the importance not just of incentivizing vaccinations, but also of targeting the incentives to the right individuals in an asymmetric network.

The typical large, stochastic network models capture situations where diseases spread through random strangers. To analyze those models, researchers run simulations to find both the socially-optimal vaccination rate and the equilibrium vaccination rate in the presence of free-riding (see [Britton et al. \(2007\)](#) or [Miller and Hyman \(2007\)](#) for examples from the mathematics literature; see [Goyal and Vigier \(2015\)](#) for an example from the economics literature).⁴ In contrast, we adopt small, deterministic networks to describe situations where diseases spread among members who expect to interact. Though the networks are small, each member can be treated as a representative agent from a well-defined group. We then explicitly solve a non-cooperative game for the social optima and all pure-strategy Nash equilibria.⁵ These depend on the structure of the network, the cost of vaccination, the probabilities that the individuals become infected from outside the network, and the interpersonal transmission probabilities for the disease in the network.

Consistent with the goal of demonstrating that the problem exists, we establish it in the simplest possible cases. Three-person networks prove sufficient. We begin with a baseline case, a complete network in which three identical agents all have direct connections to each

⁴[Rao et al. \(2014\)](#) looks at a different question concerning vaccinations and networks, finding evidence of peer effects in vaccination behavior.

⁵Mixed-strategy equilibria also exist, but we do not pursue them in this paper for purposes of brevity, but the results are simple to summarize. When individuals in the network randomize between vaccinating and not, all possible outcomes are possible including the right set of vaccinations, too few, too many, and the right number but the wrong set. Furthermore, as with the chicken game, the mixed-strategy equilibrium has a lower expected total payoff than the pure-strategy ones do.

other. The only deviations from the socially optimal vaccination pattern arise when too few individuals get vaccinated in an equilibrium, which is the standard free-riding result. We then introduce asymmetry in the network structure by removing a link, creating a network in which two peripheral individuals are connected only through a central one. Vaccination for the central player generates a larger external benefit than vaccination for a peripheral player, and this asymmetry in the externalities leads to two new equilibrium outcomes.

In this 3-person star network, no one should get vaccinated when vaccinations are prohibitively expensive. As the costs come down, though, the central player should be the first to get vaccinated because he can spread the disease directly to two individuals whereas the peripheral players can spread to just one person. However, we show that there exist equilibria in which one of the peripheral players gets vaccinated instead of the central one, and thus the right number but the wrong set of people get vaccinated. Moreover, there also exist equilibria in which both of the peripheral players get vaccinated while the central player does not. They do so because getting vaccinated is the best response to the central player remaining unvaccinated, while the central player's choice is the best response to both peripheral players getting vaccinated. Under such circumstances, too many people get vaccinated.

These new patterns of wrong-vaccination and over-vaccination arise in cases where there are multiple equilibria, with the best equilibrium being the efficient one in which the central player takes the vaccine. However, we show that except on a set of measure zero the inefficient equilibria are trembling-hand perfect, and therefore survive the most common equilibrium refinement for normal-form games. Moreover, the same patterns can arise when the network is complete, but the individual parameters differ. Finally, we show that in a star network in which the central player is a healthy carrier, that is, one who can transmit the disease but suffers no ill effects of it herself, the new patterns uniquely emerge because a healthy carrier has no incentive to vaccinate.

All of this suggests that a successful pro-vaccine program must target the agent with the largest externality. We consider two targeted policies for the 3-person star network, a targeted subsidy which subsidizes the vaccine for the central agent, and a targeted fine which penalizes her for failure to vaccinate. Both policies, when administered appropriately, can

achieve the social optimum, and they avoid the problems of too many or the wrong set of vaccinations by making vaccination a dominant strategy for the central player. We go on to show that untargeted policies can also achieve the social optimum, but they do so in a much less-straightforward way. They address the problem of free-riding with a small subsidy or fine, but they address the problem of too many or the wrong set of vaccinations by *rewarding* nonvaccination (i.e., a negative untargeted fine) or *taxing* vaccination (i.e., a negative vaccination subsidy). These policies work by making nonvaccination a dominant strategy for the peripheral players, in which case the central player best-responds by vaccinating. However, policies incentivizing nonvaccination are unlikely to be palatable, either to policymakers or the public at large. Surprisingly, we also find that the straightforward policy of a universal vaccination mandate not only does worse than a targeted policy, but it also can never do better than no policy at all. In essence, the requirements of a Nash equilibrium leave too little room for improvement for a coarse policy like a universal mandate to work well.

Real-world policies include both subsidies and penalties, and many of them target specific, high-externality groups.⁶ For example, [California Senate Bill 277](#) mandates that after July 2016, all children in school from kindergarten through 12th grade, all incoming college students, and all hospital staff get certain vaccinations.⁷ All these individuals provide links between otherwise unrelated individuals. Children in school provide links between parents who would otherwise never interact, and on-campus college students provide links between households in different communities. Hospital workers can spread diseases from patient to patient. Also, many universities require international students to get vaccinated before arrival, and these students face different disease exposures than others inside the college network. Furthermore, effective July 2017 all sex workers in Germany must use condoms ([BGBI I No. 50](#), [Germany](#)), which is again a mandate targeting central players in the network that requires preventive actions against sexually transmitted diseases. Sex workers occupy central positions in a star network with their clients on the periphery, and the policy

⁶[Lawler \(2017\)](#) uses Canadian data to show that both government recommendations and government mandates have positive impacts on the propensity to vaccinate.

⁷Since 2013, Mississippi and West Virginia mandate vaccinations for K-12 students and recommend vaccinations for college students, but the mandate does not apply to hospital staff. See school immunization requirements for all states at the website of [National Conference of State Legislatures](#).

targets the sex workers. The analysis in this paper highlights an unrealized benefit from these targeted policies, which arises from avoiding inefficient behavior from the wrong people getting vaccinated in equilibrium.

The paper has substantial differences from the existing literature, all stemming from its explicit focus on individual behavior rather than the spread of the disease.⁸ We use a static game in which all players simultaneously choose whether to get vaccinated. This game differs from Francis (1997) in which the game is dynamic, and society eventually reaches the social optimum after enough people become infected. In our static game the disease is not yet present in the network, and so it best fits a situation where connected individuals make vaccination decisions in advance, as with measles vaccinations, juvenile HPV vaccinations, and early-season flu vaccinations.⁹

The paper proceeds as follows. Section 2 presents the general model and identifies conditions for a social optimum and a Nash equilibrium. Section 3 explores a 3-person homogeneous complete network to show that the only under-vaccination can arise. Section 4 introduces asymmetry through the network structure to examine a 3-person star network and finds that inefficiencies can arise from too few, too many, or the wrong person getting vaccinated and also establishes when these equilibria are trembling-hand perfect. Section 5 shows that the same patterns can arise in complete and star networks with heterogeneous payoffs and sometimes these patterns can be unique. Section 6 looks at policy implications of incentive programs using both targeted and untargeted subsidies for vaccinating or penalties for not vaccinating. Section 7 concludes.

⁸For example, Geoffard and Philipson (1997) look at policies for the complete eradication of contagious disease, sometimes called herd immunity, and Galeotti and Rogers (2013) look at disease spread when there are two groups and different matching protocols. Chen and Toxvaerd (2014) analyze the impacts of heterogeneity and strategic interaction on inefficiencies in a 3-person dynamic model. Goyal and Vigier (2015) look at the spread of disease when agents can immunize or protect themselves in a large random network, and Andrews and Bauch (2016) do the same using an agent-based model.

⁹We consider only diseases spread by human-to-human contact and not vector-borne diseases. For those, see Gersovitz and Hammer (2005).

2.2 The model: a contagion network

Consider a n -person network with members $N = \{1, \dots, n\}$.¹⁰ Connections among members are bi-directional. For two directly connected players i and j , if i catches the disease first then i can infect j , and if j catches it first j can infect i . Individuals can only catch the disease once.

Player i can contract the disease from outside the network with probability $\beta_i \in (0, 1)$, which is the channel of the initial invasion of the contagion. When an individual is not infected from outside, he still faces a probability $t_i \in (0, 1)$ that an infected player transmits the disease to him through a direct connection in the network. An infection imposes a cost of $D_i > 0$ on the infected individual.

Individuals can get vaccinated to protect themselves from the infection, and the vaccine is assumed to be perfectly effective, that is, a vaccinated individual cannot contract the infection whatsoever.¹¹ However, a vaccine is not free but costs $c_i \geq 0$ for each person. Obviously, if $c_i > D_i$ for every player, nobody gets vaccinated because the cost of the vaccination outweighs the cost of getting ill.

In the game, the n players simultaneously choose whether to get vaccinated to minimize their expected costs. The probability that individual i contracts the disease depend on who gets vaccinated. Let p_S^i denote the probability that player i gets infected given that the subset $S \subseteq N$ of the n players gets vaccinated. The perfect effectiveness of the vaccine means that $p_S^i = 0$ whenever $i \in S$.

We define S^{**} as the socially optimal vaccination set that minimizes the network's total expected cost. For a vaccinated agent i the expected cost is simply c_i because vaccines are 100% effective. For an unvaccinated individual, the expected cost is $p_S^i D_i$, which is the probability of infection multiplied by the illness cost. Total expected cost sums the expected costs over the set of individuals in the network. In cases where total expected cost remains the same whether player i vaccinates or not, we assume that S^{**} includes i .

¹⁰The setting in this section can be used for general, n -person networks, but in the subsequent sections, we restrict analysis to the case of $n = 3$, and each player can be a representative agent from a well-defined group, such as doctors and patients, teachers who move between schools and their students, or foreign travelers and non-travelers.

¹¹This assumption simplifies calculations but makes no difference to the qualitative results. To incorporate imperfect vaccines, we can add an effectiveness parameter to represent the vaccine matching rate.

Now consider an individual's incentive to get vaccinated when the vaccination set is S . In a noncooperative game, individual i conducts a cost-benefit analysis by comparing the vaccination cost c_i and the benefit of getting vaccinated. The benefit comes from not catching the disease and equals the expected cost of contracting the disease $p_{S-i}^i D_i$ given other players' vaccination set $S - i$, where $S - i$ denotes the subset S with i removed. Assume individuals are risk-neutral. If $c_i < p_{S-i}^i D_i$ agent i 's expected cost from remaining unvaccinated exceeds the cost of getting vaccinated, and so i chooses to vaccinate. If $c_i > p_{S-i}^i D_i$, then i chooses to remain unvaccinated because vaccination is too expensive. If $c_i = p_{S-i}^i D_i$, then i is indifferent between these two, and we assume that agents elect to vaccinate whenever they are indifferent.

Based on the above decision rules, a pure-strategy Nash equilibrium of the game consists of a subset $S^* \subseteq N$ of vaccinated individuals such that everyone in S^* weakly prefers to vaccinate, and everyone not in S^* weakly prefers not to. In other words, in a pure-strategy equilibrium, no vaccinated player would be better off forgoing vaccination, and no unvaccinated player would be better off getting vaccinated. Mathematically, the first condition means that if $i \in S^*$ then $c_i \leq p_{S^*-i}^i D_i$ so that i 's expected costs of going unvaccinated and possibly getting the disease exceed the cost of getting vaccinated. The second condition means that if $i \notin S^*$ then $c_i > p_{S^*}^i D_i$ so that for i the cost of vaccination exceeds the expected cost of catching the disease.

2.3 Symmetric structure: a complete network

We begin with the benchmark case of a 3-person homogeneous complete network in which everyone interacts with everyone else (completeness), and everyone has the same exogenous parameters, namely the infection probability β , the transmission probability t , the vaccination cost c , and the disease cost D . We refer to the case of identical exogenous parameters as homogeneity.

We can find complete networks in households, classrooms, and apartments. Individuals interact in small groups in these places, so they know the members. Moreover, though we explicitly refer to members as individuals, they can be representative agents from exclusive

groups. For example, at a community gathering, each member is a household representative. Connections exist among households, but only the representatives interact.

The complete network serves as a good benchmark for two reasons. The first is that it is entirely symmetric in that every player has the same number of connections and, in the absence of vaccinations, the same probability of illness. The second is that, as we will show, Nash equilibrium behavior can only deviate from the social optimum in one direction, with too few vaccinations.

The intuition behind the result is straightforward. Suppose that the vaccination cost c is low enough for it to be socially optimal to vaccinate two people but too high to vaccinate all three. Those two vaccinations benefit not only the people who get them but also the other one by eliminating his risk of getting infected from members in the network. The social optimum takes this external benefit into account, but individuals do not when deciding whether to get vaccinated in a noncooperative equilibrium. If the social benefit of vaccination makes it optimal for two players to get vaccinated but the private benefit does not, we end up with only one vaccinated, i.e., free-riding.

To establish the existence of free-riding in equilibrium, we compare the socially-optimal vaccination set S^{**} to the pure-strategy Nash equilibrium vaccination set S^* . If $\#S^* < \#S^{**}$, we have free-riding, where $\#S$ denotes the number of elements of S . The symmetry of both the network structure and the external infection probabilities means that only the number of players in S , and not which ones they are, matters for determining social costs. Vaccinated players have zero probability of infection, but pay the vaccination cost c . An unvaccinated player i does not pay c but has expected cost $p_S^i D$ when the set S of players get vaccinated. We now go on to compute p_S^i for different numbers of players in S .

First consider the case in which i is the only unvaccinated player, that is, $S = \{j, k\}$ and $\#S = 2$. Then i can only contract the disease by external infection, so $p_{\{j,k\}}^i = \beta$. If only one of the other two get vaccinated, say j , so that $\#S = 1$, i can contract the disease by external infection or through a one-step transmission from the other unvaccinated player ($k \rightarrow i$). Thus

$$p_{\{j\}}^i = \beta + (1 - \beta)\beta t.$$

The first term is the probability that i contracts the external infection himself (β). The second term is the probability that he does not get the external infection $(1 - \beta)$ times the probability that the other unvaccinated player k gets it (β) times the probability that k transmits the disease to him (t). Finally, if $\#S = 0$, i.e., none of the others get vaccinated, i can contract the disease by external infection or interpersonal transmission from j by one step ($j \rightarrow i$) or two steps ($j \rightarrow k \rightarrow i$). Hence, i 's probability of contracting the disease when $\#S = 0$ is

$$p_{\emptyset}^i = \beta + 2(1 - \beta)^2\beta(t + t^2 - t^3) + (1 - \beta)\beta^2(2t - t^2).$$

The first term is the exogenous infection (β). The second term accounts for when i and k are not exogenously infected ($(1 - \beta)^2$) but j is (β), i may get infected from j through $j \rightarrow i$ by one step (t) or $j \rightarrow k \rightarrow i$ by two steps (t^2) but not both (t^3). Since j can be any of the other two players, multiply this probability by 2. The third term accounts for when i is not exogenously infected $(1 - \beta)$ but both j and k are (β^2), i may get infected through $j \rightarrow i$ or $k \rightarrow i$ by one step ($2t$) but not both (t^2). Notice that in a 3-person homogeneous complete network, $p_{\{i\}}^i < p_{\{j,k\}}^i < p_{\{j\}}^i < p_{\emptyset}^i$.¹²

The social cost arising when the players in S get the vaccine is

$$\Pi_S = \begin{cases} 3c & \text{if } \#S = 3 \\ 2c + p_{\{j,k\}}^i D & \text{if } \#S = 2 \\ c + 2p_{\{j\}}^i D & \text{if } \#S = 1 \\ 3p_{\emptyset}^i D & \text{if } \#S = 0 \end{cases} \quad (2.1)$$

The first lemma shows the social optima for various vaccination costs.

¹² $p_{\emptyset}^i = \beta + 2(1 - \beta)^2\beta(t + t^2 - t^3) + (1 - \beta)\beta^2(2t - t^2) = p_{\{j\}}^i + (1 - \beta)\beta^2 t^2 + 2(1 - \beta) [(1 - t) - (1 - t)^2] + \beta^2 [1 - (1 - t)^2] > p_{\{j\}}^i$ because $1 > (1 - t) > (1 - t)^2$.

Lemma 2.1. Assume that $\beta t < 2/3$. In a 3-person homogeneous complete network, the socially-optimal set of vaccinated individuals is given by

$$S^{**} = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, p_{\{j,k\}}^i] \\ \{j, k\} & \text{if } \frac{c}{D} \in (p_{\{j,k\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i] \\ \{j\} & \text{if } \frac{c}{D} \in (2p_{\{j\}}^i - p_{\{j,k\}}^i, 3p_{\emptyset}^i - 2p_{\{j\}}^i] \\ \emptyset & \text{if } \frac{c}{D} \in (3p_{\emptyset}^i - 2p_{\{j\}}^i, \infty) \end{cases} \quad (2.2)$$

Proof. In appendix. □

The lemma contains some intuitive results, but also a less-intuitive one. As intuition would suggest when the normalized vaccination cost c/D is very low everyone should get vaccinated, and when it is very high, no vaccinations are efficient. As the cost of vaccination rises, fewer people should get the vaccine in the social optimum. The less-intuitive result is that vaccination may be efficient even when the vaccine costs more than the illness ($c/D > 1$) because one vaccination reduces the probability that the disease spreads in the network, and the social optimum internalizes this external benefit.¹³

The condition $\beta t < 2/3$ guarantees that $3p_{\emptyset}^i - 2p_{\{j\}}^i > 2p_{\{j\}}^i - p_{\{j,k\}}^i$, so $S = \{j\}$ can be socially optimal. It implies that the disease is not too communicable, but removing it does not affect the qualitative result.¹⁴

The next lemma shows the Nash equilibria for various vaccination costs.

¹³For example, when $\beta = 0.7$ and $t = 0.8$, the social optimum has everyone vaccinated when $c/D \leq 0.7$, two people vaccinated when $0.7 < c/D \leq 1.036$, one person vaccinated when $1.036 < c/D \leq 1.1381$, and no one vaccinated when $c/D > 1.1381$.

¹⁴If $\beta t \geq 2/3$, the inequality may not hold so $3p_{\emptyset}^i - 2p_{\{j\}}^i \leq 2p_{\{j\}}^i - p_{\{j,k\}}^i$. Then if $\frac{c}{D} \in (p_{\{j,k\}}^i, \frac{3}{2}p_{\emptyset}^i - \frac{1}{2}p_{\{j,k\}}^i]$, $S^{**} = \{j, k\}$; and if $\frac{c}{D} \in (\frac{3}{2}p_{\emptyset}^i - \frac{1}{2}p_{\{j,k\}}^i, \infty]$, $S^{**} = \emptyset$. Note $\frac{3}{2}p_{\emptyset}^i - \frac{1}{2}p_{\{j,k\}}^i \in (3p_{\emptyset}^i - 2p_{\{j\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i]$.

Lemma 2.2. *In a 3-person homogeneous complete network, the pure-strategy equilibrium set of vaccinated individuals is given by*

$$S^* = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, p_{\{j,k\}}^i] \\ \{j, k\} & \text{if } \frac{c}{D} \in (p_{\{j,k\}}^i, p_{\{j\}}^i] \\ \{j\} & \text{if } \frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i] \\ \emptyset & \text{if } \frac{c}{D} \in (p_{\emptyset}^i, \infty) \end{cases} \quad (2.3)$$

Proof. In appendix. □

Juxtaposing the two lemmas allows us to identify inefficient outcomes, that is, values of c/D for which the Nash outcome S^* differs from the socially-optimal outcome S^{**} . Figure 2.1 illustrates the inefficient outcomes with a numerical example by comparing the size of vaccination sets in the social optimum and the pure-strategy equilibrium.

The main result from this section of the paper confirms the conventional thinking, finding that in general, too few members may get vaccinated because individuals do not take the external benefit of getting vaccinated into consideration.

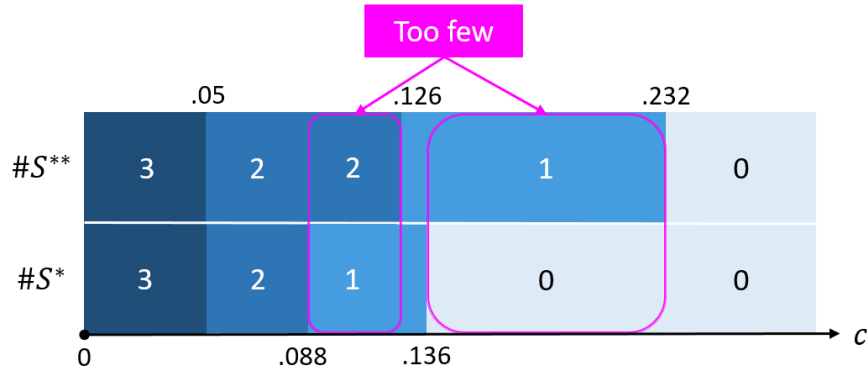


Figure 2.1: Inefficient outcomes in a 3-person homogeneous complete network with $\beta = .05$, $t = .8$, $D = 1$. The horizontal axis represents the vaccination cost from 0 to ∞ , and the numbered shadings represent the number of vaccinations, with the top shadings above the white midline corresponding to the social optimum and the bottom shadings below corresponding to the Nash equilibrium. Darker colors represent more vaccinations than lighter ones.

Proposition 2.3. *Assume that $\beta t < 2/3$. In a 3-person homogeneous complete network, too few individuals get vaccinated in a pure-strategy equilibrium when the vaccination cost $\frac{c}{D} \in \left(p_{\{j\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i\right] \cup \left(p_{\emptyset}^i, 3p_{\emptyset}^i - 2p_{\{j\}}^i\right]$. Otherwise, the correct number of individuals get vaccinated.*

Proof. In appendix. □

Proposition 2.3 is the result one would expect from the traditional theory of public goods when there are free riders. Furthermore, it emphasizes that individuals with full information may deliberately decline to get vaccinated. These are not new results, though. In the next two sections, we add asymmetries to the network to find sources of inefficiency different from free-riding.

2.4 Asymmetric structure: a star network

In a 3-person star network, player 1 directly connects to both players 2 and 3, but players 2 and 3 do not directly connect to each other. Player 2 can still pass a disease to player 3, and vice versa, but now the transmission must go through the central player 1. Central players can be doctors, nurses, teachers, flight attendants, international travelers, and people with multiple sexual partners.¹⁵ In particular, a doctor examines many patients while these patients do not directly interact. Furthermore, each player can be a representative agent from exclusive groups. When a patient goes to a hospital, he expects to meet some doctor from that hospital. Similarly, a doctor expects some patient from nearby communities.¹⁶

¹⁵Though we define the central player as the one who has the most connections to facilitate our analysis, solely comparing players' degree of connections can be problematic in a complex network. We can still calculate every player's infection probabilities under all vaccination sets to reveal whose vaccination generates the largest external benefit. However, such calculation can become exponentially complicated in an n -person network, since each player faces 2^{n-1} different vaccination sets. See Jackson (2008) for alternative centrality measures.

¹⁶Despite the fact that networks may be larger than the ones we consider and consequently network structure might also be more difficult to observe, we emphasize the positive aspects of our results rather than their normative aspects. The positive aspects highlight the potential over-vaccination in a Nash allocation, while the normative aspect emphasizes who should first vaccinate. (Section 6 goes on to illustrate normative conclusions from these results.) Regardless, in a complex network, we usually can find a central subgroup to demonstrate the relevance of positive aspects of our qualitative results.

In this section, we show that free-riding is not the only potential source of inefficiency in the contagion network. It is possible for the right number but the wrong set of people to get vaccinated in equilibrium, and it is also possible for too many people to get vaccinated in equilibrium.

Assume homogeneity, as in the benchmark model, that all players have the same exogenous infection probability β , the same transmission probability t , the same vaccination cost c , and the same disease cost D . The game is asymmetric, though, because of the network structure: the central player 1 has two connections, but the peripheral players 2 and 3 have only one each. This asymmetry affects who should get vaccinated in the social optimum. If only one person is vaccinated, it should be player 1 because all disease transmission must go through her. There exist equilibria, though, where player 1 chooses not to get vaccinated, but players 2 and 3 get vaccinated themselves as the best response, resulting in an inefficiently large number of vaccinations.

First, consider the central player 1's probability of contracting the disease. As before, if 1 gets vaccinated, her probability of infection is 0. If 1 remains unvaccinated, the probability depends on what the peripheral players 2 and 3 do. If both get vaccinated, then 1 can only catch the disease from outside the network, which occurs with probability β . If one of the two gets vaccinated, 1's probability of infection is $p_{\{i\}}^1 = \beta + (1 - \beta)\beta t$, which is the same as in the complete network when one person gets vaccinated. If none of the peripheral players get vaccinated, besides external infection, 1 can contract the disease by 1-step transmission from 2 or 3, but not both, so 1's probability of infection is

$$p_{\emptyset}^1 = \beta + (1 - \beta)(2\beta t - \beta^2 t^2)$$

where the term $2\beta t - \beta^2 t^2$ reflects that infection can be transmitted to 1 from two people ($2\beta t$) but cannot be transmitted from both ($\beta^2 t^2$). Notice that $p_{\{1\}}^1 < p_{\{2,3\}}^1 < p_{\{i\}}^1 < p_{\emptyset}^1$.¹⁷

Next, consider a peripheral player i 's probability of contracting the disease, $i = 2, 3$. If he vaccinates himself, his probability of infection is 0, and if player 1 gets vaccinated, his probability of infection is β . If 1 does not get vaccinated, but the other peripheral player j

¹⁷ $p_{\emptyset}^1 = \beta + (1 - \beta)(2\beta t - \beta^2 t^2) = p_{\{i\}}^1 + (1 - \beta)\beta t(1 - \beta t) > p_{\{i\}}^1$.

does, then the possible transmission exists between 1 and i . Player i can contract the disease either from outside the network or from player 1, for a probability of $p_{\{j\}}^i = \beta + (1 - \beta)\beta t$, which is the same as in a complete network with one vaccination. Finally, if neither 1 nor j gets vaccinated, then besides external infection, he can contract the disease by 1-step transmission from 1 ($1 \rightarrow i$) or by 2-step transmission from j ($j \rightarrow 1 \rightarrow i$), so his probability of infection is

$$p_{\emptyset}^i = \beta + (1 - \beta) [\beta t + (1 - \beta)\beta t^2]$$

where the term in brackets represents that i can get infected from 1 by one step ($1 \rightarrow i$) (βt) or from j by two steps ($j \rightarrow 1 \rightarrow i$), conditional on that 1 is not exogenously infected ($(1 - \beta)\beta t^2$). Notice that $p_{\{i\}}^i < p_{\{1\}}^i < p_{\{j\}}^i < p_{\emptyset}^i < p_{\emptyset}^1$.¹⁸

Summing over the three members of the network yields expected social costs:

$$\Pi_S = \begin{cases} 3c & \text{if } \#S = 3 \\ 2c + \beta D & \text{if } \#S = 2 \\ c + 2\beta D & \text{if } S = \{1\} \\ c + 2p_{\{j\}}^i D & \text{if } S = \{2\} \text{ or } \{3\} \\ (p_{\emptyset}^1 + 2p_{\emptyset}^i) D & \text{if } \#S = 0 \end{cases} \quad (2.4)$$

The next lemma shows the optimal allocation and the equilibrium allocation of vaccination programs for different values of the vaccination cost, holding β and t constant.

Lemma 2.4. *In a 3-person homogeneous star network, the socially optimal set of vaccinated individuals is given by*

$$S^{**} = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, \beta] \\ \{1\} & \text{if } \frac{c}{D} \in (\beta, p_{\emptyset}^1 + 2(p_{\emptyset}^i - \beta)] \\ \emptyset & \text{if } \frac{c}{D} \in (p_{\emptyset}^1 + 2(p_{\emptyset}^i - \beta), \infty) \end{cases} \quad (2.5)$$

Proof. In appendix. □

¹⁸ $p_{\emptyset}^i = \beta + (1 - \beta) [\beta t + (1 - \beta)\beta t^2] = p_{\{j\}}^i + (1 - \beta)^2 \beta t^2 > p_{\{j\}}^i$ and $p_{\emptyset}^1 = \beta + (1 - \beta)(2\beta t - \beta^2 t^2) = p_{\emptyset}^i + (1 - \beta)\beta t(1 - t) > p_{\emptyset}^i$.

When the vaccination cost is huge, no one gets vaccinated. When the cost falls enough for one individual to get the vaccine, the social optimum assigns it to player 1 because doing so removes any possibility of the disease spreading between players 2 and 3 if one of them gets sick. Vaccinating player 3 instead of player 1 raises the possibility that the disease spreads between 1 and 2. Thus, vaccinating a peripheral player instead of the central one increases expected social cost by $2(p_{\{j\}}^i - \beta) = 2(1 - \beta)\beta t > 0$. Also, as with the benchmark case of the complete network, it is possible that vaccination is efficient even when it costs more than the illness.¹⁹

The next lemma identifies the pure-strategy Nash equilibria for different values of the vaccination cost. In some cases, there are multiple equilibria.

Lemma 2.5. *In a 3-person homogeneous star network, the pure-strategy equilibrium set of vaccinated individuals is given by*

$$S^* = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, \beta] \\ \{1\} \text{ or } \{2, 3\} & \text{if } \frac{c}{D} \in \left(\beta, p_{\{j\}}^i\right] \\ \{1\} \text{ or } \{2\} \text{ or } \{3\} & \text{if } \frac{c}{D} \in \left(p_{\{j\}}^i, p_{\emptyset}^i\right] \\ \{1\} & \text{if } \frac{c}{D} \in \left(p_{\emptyset}^i, p_{\emptyset}^1\right] \\ \emptyset & \text{if } \frac{c}{D} \in \left(p_{\emptyset}^1, \infty\right) \end{cases} \quad (2.6)$$

Proof. In appendix. □

When the normalized vaccination cost c/D is below the probability of external infection β everyone gets vaccinated in equilibrium. When it is higher than the probability of infection with none vaccinated, $p_{\emptyset}^1$, nobody gets vaccinated. For values of c/D in between there is an equilibrium in which only the central player 1 takes the vaccine. But, when c/D is at the lower end of this interval, there are two Nash equilibria, the socially-efficient one in which 1 gets vaccinated and the socially-inefficient one where both 2 and 3 get vaccinated instead. In this range, $(\beta, p_{\{j\}}^i]$, there exists an equilibrium in which too many people get

¹⁹For example, when $\beta = 0.4$ and $t = 0.6$, the social optimum prescribes that player 1 get vaccinated when $0.4 < c/D \leq 1.0451$. The reason for this is player 1's vaccination creates a positive externality for players 2 and 3, and this externality lifts the entire benefit of the vaccination beyond the cost of a single illness.

vaccinated. Similarly, when c/D is in the middle of the interval there again exist two types of Nash equilibria, an efficient one vaccinating player 1 and an inefficient one vaccinating either player 2 or 3 instead. In the range $(p_{\{j\}}^i, p_{\emptyset}^i]$, then, there exists an equilibrium in which the right number but the wrong set of people get vaccinated. Figure 2.2 illustrates this for a star network in which $\beta = 0.05$, $t = 0.8$, and $D = 1$. And we generalize the results from this example in the following proposition.

Proposition 2.6. *In a 3-person homogeneous star network,*

- (a) *there exists a pure-strategy equilibrium in which too few individuals get vaccinated when $\frac{c}{D} \in (p_{\emptyset}^1, p_{\emptyset}^1 + 2(p_{\emptyset}^i - \beta)]$;*
- (b) *there exist pure-strategy equilibria in which the right number but the wrong set of individuals get vaccinated when $\frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i]$; and*
- (c) *there exists a pure-strategy equilibrium in which too many people get vaccinated when $\frac{c}{D} \in (\beta, p_{\{j\}}^i]$.*

Proof. In appendix. □

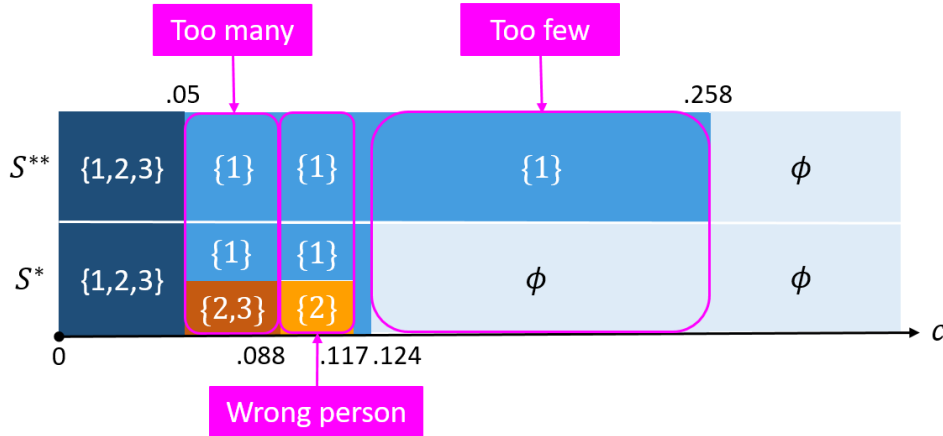


Figure 2.2: Inefficient outcomes in a 3-person homogeneous star network with $\beta = .05$, $t = .8$, $D = 1$. Same settings as in Figure 2.1 except that the shadings highlight the members in S^{**} and S^* ; the orange shading with $\{2\}$ also includes $\{3\}$.

Proposition 2.6 is the most novel finding of the paper. It shows that under an asymmetric network structure, for some range of the vaccination cost it is socially optimal to vaccinate only the central player 1, but there exist pure-strategy equilibria vaccinating one or both of the two peripheral players instead. Furthermore, the proposition shows that the asymmetries in a 3-person star network are sufficient to generate three patterns of inefficient vaccine allocations and not just the usual one of too few vaccinations.

Comparing Propositions 2.3 and 2.6 shows that the network structure has an impact on the incidence of free riding. In a complete network free riding occurs when the equilibrium vaccination set is one person smaller than the socially optimal set, and this can occur when there are either two or one socially-optimal vaccinations.²⁰ Lemma 2.4 shows that two vaccinations are never socially optimal in a star network, and three vaccinations are only socially optimal when the cost of the vaccination is lower than the external infection probability β . Thus, the only instance of free riding in the star network arises when player 1 is supposed to get vaccinated, but nobody takes the vaccine.

Because the existence of multiple equilibria drives the new sources of inefficiency in a vaccination network, it is worth exploring whether these inefficient equilibria are robust to standard refinements. The next proposition shows that, except at the right endpoints of the relevant intervals, all of the equilibria are trembling-hand perfect.

Proposition 2.7. *In a 3-person homogeneous star network,*

- (a) $S^* = \{1\}$ is trembling-hand perfect when $\frac{c}{D} \in (\beta, p_\emptyset^1)$;
- (b) $S^* = \{2\}$ or $\{3\}$ is trembling-hand perfect when $\frac{c}{D} \in (p_{\{j\}}^i, p_\emptyset^i)$; and
- (c) $S^* = \{2, 3\}$ is trembling-hand perfect when $\frac{c}{D} \in (\beta, p_{\{j\}}^i)$.

Proof. In appendix. □

At the right-hand limit of each of the intervals in the proposition the individuals in the equilibrium vaccination set are indifferent between vaccinating and not. For the case of $S^* = \{2, 3\}$, when $c/D = p_{\{j\}}^i$, if player 1 remains unvaccinated players 2 and 3 are indifferent

²⁰The equilibrium vaccination set is possible to be two members smaller than the socially optimal set. See the proof for Proposition 1.

between vaccinating and not. A tremble for player 1 consists of a small probability of vaccinating, and that small probability tips players 2 and 3 to strictly prefer to remain unvaccinated. Thus, the inefficient Nash equilibrium is not robust to trembles at that endpoint. To the left of the endpoint, though, players 2 and 3 strictly prefer vaccinating to not vaccinating, and a sufficiently small tremble by player 1 cannot overcome the strict preference. Consequently, except on a set of measure zero all of the Nash equilibria are also trembling-hand perfect equilibria.

2.5 Asymmetric payoffs in complete and star networks

Section 2.4 introduced asymmetry in the network structure, but the standard way to bring asymmetry into a game is through either the move timing or the payoffs. It is hard to imagine how a sequential vaccination game would play out, though, because no one can commit to no vaccination. There are usually opportunities to vaccinate later, in which case the choice is between “vaccinate now” or “do not vaccinate yet,” but not between “vaccinate now” or “never vaccinate.”²¹ Therefore this section explores the various channels of payoff-based asymmetries that give rise to the new types of inefficient outcomes, and also establishes scenarios in which these outcomes result in a unique Nash equilibrium.

Begin with a 3-person heterogeneous complete network by allowing individuals to have different disease costs D_i , but the same exogenous susceptibility, transmission probability, and vaccination cost. This setting reflects that people with poor health, such as seniors and children, are more likely to suffer a severe sickness when infected with a contagious disease than healthy adults. With this illness severity asymmetry, the social optimum first allocates a vaccination to the high-cost individual whenever the vaccination cost is low enough for at least one person to get vaccinated. As the next proposition shows, though, there exist inefficient allocations in which others get the vaccine instead.

²¹One can still address the question of whether making the game sequential has any impact on the results. The outcome depends on who moves first. If there is a Nash equilibrium in which (i) the first mover does not have a dominant strategy to vaccinate, and (ii) there exists of Nash equilibrium in which not some but not all players get vaccinated, then the first mover will choose not to get vaccinated. If the first mover is the one with the largest positive externalities, such as the central player in the star network, then letting that player move first guarantees an inefficient outcome. On the other hand, having that player move last guarantees that the individual generating the greatest external benefit takes the vaccine.

Proposition 2.8. *In a 3-person complete network with $D_1 > D_2 = D_3$, there exists a pure-strategy equilibrium in which the right number but the wrong set of individuals get vaccinated when $c \in \left(\beta D_1, p_{\{3\}}^2 D_2\right] \cup \left(p_{\{3\}}^2 D_1, p_{\emptyset}^2 D_2\right]$, given the existence of such intervals.*

Proof. In appendix. □

In the first interval two individuals take the vaccine in both the social optimum and the Nash equilibrium, and the inefficiency arises when the high disease-cost agent 1 is not among the vaccinated. In the second interval only one agent takes the vaccine, and the inefficiency arises when agent 1 is not the one who takes it. Unlike with the star network, there is no issue with too many vaccinations here because in a complete network there exist socially-optimal allocations with two vaccinations, but in a star network there do not.

Because the ratio between the disease cost and the vaccination cost determines the equilibria and the social optima, a similar outcome arises in the same network with heterogeneous vaccination costs c_i . In the social optimum the individual with the lowest vaccination cost takes the vaccine first, assuming that the cost is low enough for anyone to vaccinate. However, there exists equilibrium in which others get vaccinated instead. Such vaccination cost asymmetry captures differences in insurance status, travel cost, and philosophical beliefs.

Proposition 2.9. *In a 3-person complete network with $c_1 < c_2 = c_3$, there exists a pure-strategy equilibrium in which the right number but the wrong set of individuals get vaccinated when $\frac{c_1}{D}, \frac{c_2}{D} \in \left(\beta, p_{\{3\}}^2\right]$ or $\frac{c_1}{D}, \frac{c_2}{D} \in \left(p_{\{3\}}^2, p_{\emptyset}^2\right]$, given the existence of such intervals.*

Proof. In appendix. □

In the first interval two agents take the vaccine and in the second interval one agent does, and the inefficiencies arise because the low-cost agent 1 remains unvaccinated.

While the asymmetry in Proposition 2.6 comes from the shape of the network, the asymmetries in Propositions 2.8 and 2.9 involve individual costs. The asymmetries can also come from the transmission probabilities and the external infection probabilities. Consider heterogeneous transmission probabilities first. Let t_i denote the probability that the disease is transmitted to player i by one of the other two players, and assume that agent 1's

transmission probability is the highest. Such transmission heterogeneity might reflect that agent 1 is a highly susceptible individual who is at a high risk of becoming infected, such as seniors, children, and pregnant women. The transmission probability differences create an incentive for the social planner to vaccinate the individual with the greatest transmission probability. As the next proposition demonstrates, there exist Nash equilibria in which someone other than the most-susceptible person gets vaccinated.

Proposition 2.10. *In a 3-person complete network with $t_1 > t_2 = t_3$, there exists a Nash equilibrium in which the wrong person gets vaccinated when $\frac{c}{D} \in \left(p_{\{2\}}^1, p_{\emptyset}^2\right]$, given the existence of such an interval.*

Proof. In appendix. □

The inefficiency arises because either player 2 or 3 gets vaccinated in equilibrium but social cost is lower when the highly-susceptible player 1 gets vaccinated instead. Note that when two players get vaccinated transmission between agents becomes impossible, and so the proposition only concerns the case of one vaccination.

To complete the scope of asymmetry sources, suppose that the agents have different external infection probabilities, with agent 1 being most susceptible to infection from outside the network. Thus, agent 1 is the most likely individual to introduce the disease to the network, and the social optimum allocates a vaccination to him whenever the vaccination cost is sufficiently low. Such heterogeneity could arise because, for example, agent 1 travels more than the others or comes into contact with more strangers than the others. The next result shows that inefficiencies can arise in this setting as well.

Proposition 2.11. *In a 3-person complete network with $\beta_1 > \beta_2 = \beta_3$, there exists a pure-strategy equilibrium in which too many individuals get vaccinated when $c/D \in \left(\max\left\{\beta_1, 2p_{\{1\}}^2 - \beta_2\right\}, p_{\{2\}}^3\right]$, and the right number but the wrong set of individuals get vaccinated when $c/D \in \left(p_{\{2\}}^1, p_{\emptyset}^2\right]$, given the existence of such intervals.*

Proof. In appendix. □

This proposition shows that both types of inefficiency, either from the wrong set of vaccinations or from too many vaccinations, can occur in a complete network.

Propositions 2.6 and 2.8-2.11 demonstrate that any source of asymmetry in the network, whether from differences in the parameters or from the shape of the network itself, can lead to Nash equilibria with too many or the wrong set of vaccinations. In all of these cases the inefficiencies arise because there are multiple Nash equilibria, and the incorrect allocations can be avoided if the network selects a more efficient equilibrium. We finish this section with an example in which there are not multiple equilibria and the unique equilibrium vaccination allocations differ from the social optimum by having either too many or the wrong agents vaccinate.

To do this, we combine two types of asymmetry. Consider a 3-person star network in which the central player is a healthy carrier who remains healthy even after being infected, so her disease cost is zero but she still can transmit the disease to others.²² The healthy carrier does not have any incentive to vaccinate, so no Nash outcome includes her in the equilibrium vaccination set. However, the social planner prefers to vaccinate the carrier because of her central position in the star network. Because of this, the only Nash equilibrium outcomes are inefficient, as shown in the next proposition.²³

Proposition 2.12. *In a 3-person star network with $D_1 = 0 < D$, $c_1 = c - \beta D$ for $c > \beta D$, there exist unique inefficient equilibrium outcomes*

- (a) *that too many individuals get vaccinated when $\frac{c}{D} \in \left(\beta, p_{\{3\}}^2\right]$; and*
- (b) *that the right number but the wrong set of individuals get vaccinated when $\frac{c}{D} \in \left(p_{\{3\}}^2, p_{\emptyset}^2\right]$.*

Proof. In appendix. □

²²Typhoid Mary, who was the first person in the U.S. identified as a healthy carrier of the typhoid fever pathogen, infected 51 people but lived for nearly three decades in isolation. Also, for the human papillomavirus (HPV), which contains more than 100 types of sexually transmitted viruses, some infected people show no symptoms, but others are diagnosed with cancer.

²³When the number of members increases, we can obtain this outcome with homogeneous vaccination costs. In an n -person star network ($n > 3$) with the central player being a healthy carrier, holding other parameters identical, there exists a unique inefficient outcome that too many individuals get vaccinated in a pure-strategy equilibrium for $c/D \in \left(\frac{n-1}{n-2}\beta, \beta + (1-\beta)\beta t\right]$, which only requires $(1-\beta)t > \frac{1}{n-2}$.

2.6 Targeted and untargeted vaccination policies

Section 3 shows that when the network is complete and the parameters homogeneous, inefficiencies arise only from the familiar free-riding problem, with too few individuals taking the vaccine. Section 4 shows, however, that when the network is not complete, inefficiencies can arise with either the wrong individuals or too many individuals getting vaccinated. Section 5 demonstrates that the same patterns can arise when the network is complete, but the parameters reflecting disease or vaccination costs or transmission probabilities or exogenous susceptibilities are heterogeneous. In all cases, the inefficiencies arise because either the network structure or the parameter values make it least socially costly when one particular individual takes the vaccine, but that individual goes unvaccinated in the Nash equilibrium. Below we refer to this individual as the high-externality individual, reflecting that in the star network vaccinating the central player 1 provides larger positive externalities than vaccinating either of the two peripheral players. This suggests that targeting the central player could be a useful policy feature, and we explore targeted and untargeted policies in this section. In particular, we focus on the homogeneous star network.²⁴

Analyzing a targeted policy requires precise definitions of its objectives because there may exist two or more Nash equilibria but only one inefficient equilibrium for some parameter values. Therefore, we define the *worst* equilibrium $\bar{S}$ as the inefficient Nash allocation with the central player $1 \notin \bar{S}$ when multiple Nash outcomes exist. Since player 1 chooses not to vaccinate in $\bar{S}$, it must be the case that $c > p_{\bar{S}}^1 D$, that is, the vaccination cost is greater than his expected illness cost given members of $\bar{S}$ getting vaccinated.

However, a policymaker must motivate player 1 to get vaccinated because the efficient equilibrium requires vaccinating the central player. Two straightforward options are available to revert player 1's choice: subsidizing her vaccination or penalizing her for not getting vaccinated. To be specific, the subsidy s must be sufficient to motivate her to vaccinate anyway, or $c - s \leq p_{\bar{S}}^1 D$; and the penalty f also must be sufficient to prevent her from forgoing the vaccination, or $c \leq p_{\bar{S}}^1 D + f$.

²⁴Results similar to those in this section hold for the heterogeneous complete networks and the star network with a healthy carrier.

Motivating the central player is not sufficient to justify the policy, though, and the social planner must also demonstrate that the policy incurs smaller cost than benefit to the network. In particular, the administrative cost g to implement the policy must be no greater than the social cost savings, or $g \leq \Pi_{\bar{S}} - \Pi_{\{1\}}$.²⁵ Therefore, we define a policy as a *potential social improvement* if the Nash equilibrium with the policy generates a weakly smaller expected social loss than the *worst* Nash equilibrium without the policy.

Next, we use these criteria to analyze the subsidy first and then the fine. A targeted subsidy s constitutes a potential social improvement from the undesirable equilibrium allocation $\bar{S}$ if $s \geq c - p_{\bar{S}}^1 D$ and $g \leq \Pi_{\bar{S}} - \Pi_{\{1\}}$. That is, the subsidy is large enough to induce player 1's vaccination but incurs smaller administrative cost than the cost saving by that vaccination.

Proposition 2.13. *In a 3-person homogeneous star network, a subsidy s to the central player that incurs an administrative cost g constitutes a potential social improvement if*

- (a) $s \geq c - p_{\emptyset}^1 D$ and $g \leq [p_{\emptyset}^1 + 2(p_{\emptyset}^i - \beta)] D - c$ when $\frac{c}{D} \in (p_{\emptyset}^1, p_{\emptyset}^1 + 2(p_{\emptyset}^i - \beta)]$;
- (b) $s \geq c - p_{\{j\}}^i D$ and $g \leq 2(p_{\{j\}}^i - \beta) D$ when $\frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i]$;
- (c) $s \geq c - \beta D$ and $g \leq c - \beta D$ when $\frac{c}{D} \in (\beta, p_{\{j\}}^i]$.

Proof. In appendix. □

Proposition 2.13 is best understood by juxtaposing it with Proposition 2.6. The region in condition (a) corresponds to too few vaccinations, that is, where the socially efficient allocation is for player 1 to get vaccinated but in the unique Nash equilibrium, nobody gets it. Condition (b) concerns cost levels for which the right number but wrong set of individuals get vaccinated, and condition (c) looks at the region in which too many individuals get vaccinated. Proposition 2.13 shows that in all three cases a targeted subsidy can overcome the source of inefficiency throughout the region in which it occurs.

A targeted nonvaccination fine works in the same way. A targeted fine f constitutes a potential social improvement from $\bar{S}$ if $f \geq c - p_{\bar{S}}^1 D$ and $g \leq \Pi_{\bar{S}} - \Pi_{\{1\}}$. That is, the fine is

²⁵The government budget does not include the spending of the subsidy or the revenue of the fine because subsidies and fines are transfers within the network.

large enough to make getting the vaccine more attractive than forgoing it but incurs smaller administrative cost than the cost saving by that vaccination.

Proposition 2.14. *In a 3-person homogeneous star network, a fine f to the central player that incurs an administrative cost g constitutes a potential social improvement if*

- (a) $f \geq c - p_\emptyset^1 D$ and $g \leq [p_\emptyset^1 + 2(p_\emptyset^i - \beta)] D - c$ when $\frac{c}{D} \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$;
- (b) $f \geq c - p_{\{j\}}^i D$ and $g \leq 2(p_{\{j\}}^i - \beta) D$ when $\frac{c}{D} \in (p_{\{j\}}^i, p_\emptyset^i]$;
- (c) $f \geq c - \beta D$ and $g \leq c - \beta D$ when $\frac{c}{D} \in (\beta, p_{\{j\}}^i]$.

Proof. In appendix. □

Figure 2.3 illustrates the results of Propositions 2.13 and 2.14 using the same parameters as in Figure 2.2. The dashed magenta line shows the *worst* Nash equilibrium outcome for

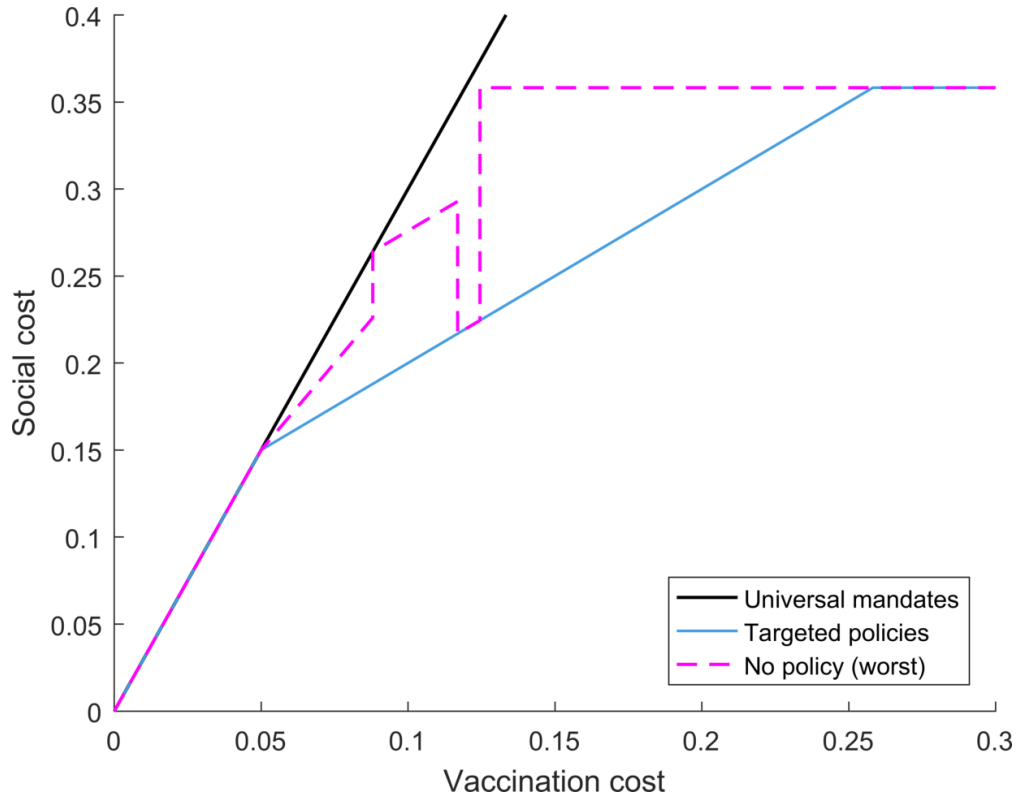


Figure 2.3: Policy comparisons in a 3-person homogeneous star network with $\beta = .05$, $t = .8$, $D = 1$. The y-axis is the expected social cost, and the x-axis is the vaccination cost.

various values of the vaccination cost.²⁶ The solid blue line shows the Nash equilibrium outcome with a targeted subsidy or fine, where it optimizes to be zero when the vaccination cost is either very low or very high, and it coincides with the social optimum. The distance between the magenta and blue lines demonstrates the upper bound of the administrative cost that can justify the targeted policy. Finally, the solid black line shows the social cost from a universal mandate where all members get vaccinated.

The figure does not show the *best* Nash equilibrium outcome because that line would always coincide with one of the other ones already shown. It coincides with the solid blue line from zero to the right-most vertical portion of the dashed magenta line, and it coincides with the magenta line from there on. The best Nash equilibrium has the central player 1 getting the vaccine until costs reach a level in which no one gets vaccinated. A targeted subsidy or penalty can correct player 1's failure to internalize the externalities.

Our policy analysis shows that both a targeted subsidy and a targeted fine can achieve the socially-optimal allocation of vaccinations. It is worth noting, though, that a subsidy can do this through a Pareto improvement, while a fine cannot. Player 1 prefers equilibria where others get vaccinated instead of her, while the peripheral players prefer the equilibrium where only player 1 vaccinates. A subsidy that induces player 1 to vaccinate instead of one or more peripheral players can make everyone better off. A fine, in contrast, makes the peripheral players better off by moving them to a preferred allocation, but even though she does not pay the fine in equilibrium, it makes player 1 worse off by moving her to a less-preferred one.

Both targeted policies avoid the problem of too many or the wrong vaccinations by making vaccination a dominant strategy for the central player 1, in which case the two peripheral players best-respond by remaining unvaccinated unless $c \leq \beta$. For untargeted policies, though, any policy that makes vaccination a dominant strategy for player 1 also makes it a dominant strategy for the two peripheral players. Because of this, untargeted vaccination policies allow for the same multiple-equilibrium inefficiencies that arise without a policy.

²⁶The figure is constructed so that when two or more lines coincide exactly, the dashed magenta line is always drawn on top and the solid black line is on the bottom, so if the black or blue lines are hidden, they coincide with the magenta one.

Figure 2.2 illustrates how this works for a subsidy. An untargeted subsidy s effectively lowers the vaccination cost from c to $c - s$ and therefore can be shown in the graph by a leftward movement. The problems of vaccinating too many or the wrong people arise when $(c - s)/D \in (\beta, p_\emptyset^i]$, where s is the subsidy, and there are multiple equilibria throughout this region. The only way to get a unique Nash equilibrium with only player 1 getting vaccinated is to have a negative subsidy, or a tax, on the vaccine. A tax would make vaccination more expensive, not less, and is quite counterintuitive.

The more intuitive notion of a positive subsidy improving social welfare arises when the vaccination cost is beyond $p_\emptyset^1$ so that the Nash equilibrium has no vaccinations, but the efficient outcome prescribes a vaccine to the central player. An appropriate untargeted subsidy can reduce the vaccination cost to between $p_\emptyset^i$ and $p_\emptyset^1$, in which case the central player vaccinates in the unique Nash equilibrium.

An untargeted fine for remaining unvaccinated works similarly. A fine of f raises the cost of remaining unvaccinated from $p_S^i D$ to $p_S^i D + f$, and the individual chooses to remain unvaccinated if $c > p_S^i D + f$, which is isomorphic to $c - f > p_S^i D$. So an untargeted fine works the same way as an equal-sized untargeted subsidy. As with the subsidy, a positive untargeted fine can improve the situation in which there are too few vaccinations, but the fine must be negative to avoid situations with too many or the wrong vaccinations. This negative fine would be a reward for those who remain unvaccinated, which is again counterintuitive.

Proposition 2.15. *In a 3-person homogeneous star network, assuming the administrative cost g is sufficiently small, the following policies constitute potential social improvements:*

- (a) *an untargeted vaccination subsidy or nonvaccination fine when $\frac{c}{D} \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$;*
- (b) *an untargeted vaccination tax or nonvaccination reward when $\frac{c}{D} \in (\beta, p_\emptyset^i]$.*

Proof. In appendix. □

Part (a) governs situations in which nobody gets vaccinated even though it is socially optimal for the central player 1 to take the vaccine. The untargeted vaccination subsidy or untargeted nonvaccination fine works by reducing the effective vaccination cost enough for player 1 to get vaccinated in equilibrium but not enough for the other, less efficient

equilibria to arise. Part (b) governs situations in which either too many or the wrong people take the vaccine, and the policies work by making nonvaccination a dominant strategy for the peripheral players 2 and 3 and inducing player 1 to best-respond by vaccinating.

Stark contrasts arise between the targeted and untargeted policies. The targeted policies avoid situations of too many or the wrong vaccinations by making vaccination a dominant strategy for player 1, and the policies do so through straightforward vaccination subsidies or nonvaccination fines. Untargeted policies avoid these same outcomes by making nonvaccination a dominant strategy for the peripheral players, and they do so through counterintuitive vaccination taxes or nonvaccination rewards. To address the new inefficient patterns identified in this paper, then, targeted policies have easy-to-understand and politically feasible parameters, while untargeted policies would be difficult for agencies to explain and sell to the public.

One policy that we briefly mentioned in Figure 2.3 is a universal mandate, which can be regarded as an untargeted fine large enough to induce everyone to vaccinate. The figure shows that the universal mandate can never do better than the worst Nash equilibrium. That it does worse than an appropriate targeted policy is no surprise because the universal mandate obtains more vaccinations than that are socially optimal. However, that it does no better than no policy at all may be a surprise to some. The next proposition shows that such relationship discovered in the homogeneous star network is completely general, covering any network with any amount of heterogeneity.

Proposition 2.16. *For any n -person network and any Nash equilibrium allocation S^* with $\#S^* < n$, the expected social cost is lower in the equilibrium than with a universal mandate; that is, $\Pi_{S^*} < \Pi_N$.*

Proof. In appendix. □

In a Nash equilibrium some agents go unvaccinated because for them the vaccination cost is higher than the expected cost of facing the disease. So their collective expected cost from facing the disease is lower than the sum of their vaccination costs, which they would have to pay under a universal mandate. Consequently, the only time a universal mandate can do as well as a Nash equilibrium is when everyone gets vaccinated in equilibrium, and

that only occurs when $c_i < \beta_i$ for everyone in the network. Thus, while universal mandates are straightforward to implement because everyone must make the same choice, they are far from the most efficient policy.

2.7 Conclusion

This paper departs from the conventional theoretical treatment of vaccination in contagion networks by examining small, explicit networks rather than large, random ones. Doing so allows us to identify all Nash equilibria of the vaccination game, and that in turn leads to some new results. The most striking result is that when the network has asymmetries, either from the structure of the network itself or heterogeneity in the agents' payoffs, under-vaccination is no longer the only possible inefficient outcome. In some cases there exist multiple equilibria, and while the efficient equilibria have the high-externality agent taking the vaccine, the inefficient equilibria have other, lower-externality agents taking it instead. Situations then arise in which the right number but wrong set of people get vaccinated, and also in which too many people get vaccinated. These results are new in the literature.²⁷

The potential problem of too many vaccinations arises from the existence of multiple equilibria, and it arises despite the fact that an individual vaccination might still be socially optimal even if the individual's cost of taking it exceeds his cost from actually catching the disease. The multiple equilibria arise because if the high-externality individual goes unvaccinated, others in the network best-respond by getting vaccinated, and it might take more than one of them to make up for the unvaccinated, high-externality person's choice.

The model allows for policy analysis, and the paper considers four: targeted subsidies, targeted fines, untargeted subsidies, and untargeted mandates. These policies can correct the allocation inefficiencies, but only the targeted policies do so in a straightforward manner by changing the behavior of the high-externality player. For example, a targeted subsidy can avoid the equilibrium in which the two peripheral players in a star network take the vaccine

²⁷In general, the literature relies on models with random networks where every possible connection is possible with a given probability. From the standpoint of our model, this makes the traditional network complete. When agents are otherwise homogeneous, the only inefficient equilibria involve too few vaccinations, a result consistent with our Proposition 2.3. Thus, the new results in our paper arise from departures from complete, homogeneous networks.

instead of the central player, and it does so by making vaccination a dominant strategy for the central player. Untargeted policies, on the other hand, may take a counterintuitive and unappealing form. Using the same example, the appropriated untargeted policy to avoid an equilibrium in which the peripheral players get vaccinated would take the form of an untargeted vaccination tax. This tax would make remaining unvaccinated a dominant strategy for the peripheral players, and the central player would best-respond by taking the vaccine.

The paper also shows that untargeted fines severe enough to induce everyone to vaccinate not only does worse than a targeted policy, they never perform better than no policy at all. While the analysis in this paper makes one wary of such universal mandates, in practice these mandates can have real effects. For example, [Carpenter and Lawler \(2017\)](#) find those mandatory vaccination requirements for middle schoolers in 46 U.S. states have increased not only vaccine take-up for the required diseases, but also for other diseases. The issue identified in this paper is that if we can identify the structure of the network, there are lower-cost solutions through targeting.

The paper provides proof-of-concept that asymmetric network structure can lead to new patterns of inefficient vaccination allocations, and future work can explore other networks. A fruitful path might begin with linked asymmetric networks, such as those in which the central players in two separate star networks connect to each other. For policy analysis, though, the primary implication of the paper is not that universal mandates lead to more vaccinations, but that they result in too many, and so policymakers should conduct a rational benefit-cost analysis of vaccination programs.

Chapter 3

Network Centrality and Vaccination Probability

3.1 Introduction

The network centrality measures an agent's importance in disease spread. A high-centrality agent usually has more connections and a greater infection risk than a low-centrality agent. If vaccines are available, a typical compartment model in epidemiology predicts that in a random network, the high-centrality agent is more likely to take the vaccine than the low-centrality agent.¹ However, vaccines are costly, and one's vaccination generates an external benefit to others. Thus, if agents have the incentive to avoid the vaccination cost and to gain the external benefit, they will forgo their vaccination to free ride others.² This paper applies a game-theoretical model to investigate the strategic interaction among agents with heterogeneous centralities.

This paper confirms a positive correlation between a player's centrality and vaccination probability as a network expands but finds a negative correlation across players in a specific network. Both results are derived in the star network where one central player directly

¹The simplest compartment model consists of three compartments: susceptible, infectious, and recovered. See an overview at [Hethcote \(2000\)](#).

²Classic public finance textbooks, such as [Stiglitz \(1988\)](#), have clearly identified the vaccination's external benefit. That is, an individual pays a private cost to be vaccinated, thus benefitting not only herself but also the public. [Ward \(2014\)](#) and [White \(2018\)](#) provide empirical evidence supporting the flu vaccine's externality. [Ibuka et al. \(2014\)](#) also find evidence in a lab experiment.

interacts with many peripheral players; thus, the central player has a greater centrality than peripheral players do. Adding one extra peripheral player increases all existing players' centrality and the probability of vaccination in the corresponding mixed-strategy Nash equilibria. However, in a specific star network, the central player chooses a *lower* probability of vaccination than peripheral players in the unique mixed-strategy Nash equilibrium. Such a result contradicts the compartment model's prediction.

This paper builds on [Neilson and Xiao \(2018\)](#)'s stylized network model. Network members are agents who expect to interact so they can form expectations about each other's response. Agents can contract the disease from either outside or inside the network, but they only consider the strategic response of agents in the network.³ Moreover, members can be individuals (e.g., relatives, friends, colleagues, and sexual partners) or representative agents from well-defined groups (e.g., service providers and customers as well as males and females in a heterosexual relationship). Finally, an agent can pay to vaccinate herself before the disease enters the network and spreads. The vaccination cost and the expected illness cost determine an agent's payoff. Agents simultaneously choose whether to vaccinate to maximize their payoffs.

The vaccination game is anti-coordinative within some range of the vaccination cost. Consider a network with two identical agents, i.e., a 2-person complete network. Each agent has two strategies: vaccinate or not vaccinate; thus, there are four potential outcomes: both are vaccinated, none is vaccinated, one is vaccinated but the other is not, and vice versa. Both want to get vaccinated if the cost is small, while none wants to get vaccinated if the cost is large. However, if the vaccination cost is in a medium range where no dominant strategy exists, in the equilibrium one agent gets vaccinated while the other does not. Since the pure-strategy Nash equilibrium prescribes one vaccination, if one agent knows the other

³The small, deterministic network can explain the behavior of individuals if they contract diseases from acquaintances, while the large, random network is suitable if infections spread among strangers. [Chen and Toxvaerd \(2014\)](#) proposes a three-person model, but their analysis stays within [Francis \(1997\)](#)'s dynamic framework and only investigates a complete network. [Cerdeiro \(2017\)](#) find that with a durable protection technology, such as a vaccine, the extent of protection monotonically increases in the population density. Epidemiologists use an agent-based model to simulate complex interaction patterns. For example, [DePasse et al. \(2017\)](#) consider that agents interact with family at home and with other households at the workplace or school. Mathematics studies, including [Britton et al. \(2007\)](#) and [Miller and Hyman \(2007\)](#), usually focus on the disease spread in a large network and the effective strategies to stop the spread.

is vaccinated, she will free ride; but if the other is not vaccinated, she will take the vaccine to avoid the high risk of infection. Both agents prefer the other person to take the vaccine, but it is impossible for both to free ride. Therefore, a conflict arises regarding who does free ride. Game theorists refer to games with such a conflict as the chicken game, and the conflict leads to the mixed-strategy Nash equilibrium whereby everyone wants to make the other agent indifferent.

An application of the 2-person network to the heterosexual relationship can best explain the mixed equilibrium's indifference property. Consider one male and one female interacting in a casual relationship.⁴ Both individuals can contract a sexually transmitted disease from each other or from sexual partners outside the network.⁵ Individuals can take a vaccine or use condoms to avoid the disease and to prevent transmitting the disease to each other, but vaccination or condom use is costly.⁶ Therefore, individuals desire an equilibrium in which they can balance the trade-off between the cost and the benefit of disease prevention, and such an equilibrium must be a mixed-strategy Nash equilibrium.

Agents' centralities are also the same in the symmetric equilibrium. However, if players have heterogeneous centralities, an asymmetric equilibrium arises. Consider a star network in which one central player directly interacts with many peripheral players while the peripherals do not interact with each other. The star network can be applied as a special case in which one female interacts with many males or vice versa. Thus, the central player has a greater centrality and a greater infection risk than the peripherals. First, as the number of players increases, both the central and the peripheral players' probabilities of vaccination increase. That result is consistent with the compartment model's prediction about a positive correlation between centrality and vaccination probability. However, in a specific star network, the central player chooses a *lower* probability of vaccination than the peripherals

⁴If assume males and females do not interact with agents of the same gender, the 2-person complete network is equivalent to a bipartite network with two sets of agents. See discussions about bipartite networks in [Galeotti and Rogers \(2013\)](#) and [Goyal and Vigier \(2015\)](#).

⁵An agent in the 2-person network considers other sexual partners' response as an exogenous parameter because they are outside the network. The 3-person star network endogenizes a third agent's strategic response.

⁶Vaccination against the sexually transmitted diseases are available, such as the Human papillomavirus (HPV) vaccine and the Hepatitis B vaccine. Also, consider condom use as a long-term commitment of using condoms in every sexual encounter since agents play a simultaneous-move game.

in a mixed-strategy Nash equilibrium. That result is driven by the equilibrium’s indifference property. To make everyone indifferent about either vaccinating or forgoing, the peripheral players must raise their probability of vaccination to offset the central player’s high infection risk; and the central player responds with a lower probability of vaccination. The negative correlation between centrality and vaccination probability within a star network is a novel result.

The equilibrium outcomes provide insights into empirical evidence about flu vaccination and condom use. First, workers in occupations with frequent public contact are more likely to be high-centrality individuals, but their flu vaccination coverage may be less than their customers’. For example, fewer workers in education, training, and library occupations get the flu vaccine than schoolchildren (38.8% vs. 55.6%) (CDC, 2013, O’Halloran et al., 2017); and if the vaccination is not required, fewer health care personnel get the flu vaccine than adult residents in long-term care facilities (44.7% vs. 73.7%) (CDC, 2016, 2017).⁷ Secondly, in the casual heterosexual relationship, condom uses frequency may not increase with the number of sexual partners. Anderson et al. (1999) find that in a casual relationship, U.S. adults with two to five partners are more likely to use condoms at the last sex encounter than those with one partner (68.8% vs. 53.5%). However, individuals with six or more partners do not use condoms more frequently (51.5%). In conclusion, the game-theoretical model provides insights into the observed negative correlation between centrality and vaccination probability in flu vaccination and condom use, that strategic interaction leads to unexpected results.

Targeting the vaccine to high-centrality agents prevents them from strategically free riding others and generates the greatest external benefit to society. However, if targeted policies are not politically feasible, a universal mandate becomes palatable because it treats

⁷If the health care personnel in long-term care facilities are required to get the flu vaccine, their vaccination rate is 87.4%. O’Halloran et al. (2017) also find that for the non-health care personnel, occupations with frequent public contact typically have a vaccination rate lower than the national adult average rate of 40%, including education, training, and library (38.8%), community and social services (38.3%), management (34.6%), personal care and service (29.3%), sales (27.3%), and food preparation and serving (21.9%). The sample mean vaccination coverage of non-health care personnel is 29.7%. The data are collected from 21 states using the 2013 Behavioral Risk Factor Surveillance System survey administered by Centers for Disease Control and Prevention (CDC). Luckhaupt et al. (2014) find similar results using the 2009 National H1N1 Flu Survey data.

everyone the same. Moreover, a universal mandate results in the same social welfare as a mixed-strategy Nash equilibrium. Based on the equilibrium’s indifference property, an individual must earn the same payoff whether she vaccinates or not. Thus, she earns the same payoff by either choosing the pure strategy to get vaccinated or choosing the probability mixture of vaccinating and forging. The same equality applies to everyone; therefore, whether everyone gets vaccinated or everyone chooses the probability mixture, the network’s aggregate payoffs are the same. To conclude, a universal mandate is desirable if individuals cannot coordinate, and policymakers prefer paying the fixed vaccination cost rather than facing the potential disease spread.⁸

This paper contributes to the economics literature of epidemics and protection in terms of three perspectives. First, this paper expands the understanding of the strategic interaction in the vaccination game. The earlier literature emphasizes vaccination programs cooperative feature that disease eradication requires policy intervention and international cooperation (Geoffard and Philipson, 1997, Barrett, 2003). Recent literature indicates the vaccination’s substitutability between groups (Galeotti and Rogers, 2013, Goyal and Vigier, 2015). This paper applies the chicken game to highlight the anti-coordinative aspect of the vaccination game .

Secondly, this paper broadens insight into the correlation between social activeness and protection incentives. Goyal and Vigier (2015) have developed a model to study the trade-off between interaction and protection and find a positive correlation between social activeness and disease protection. They also find that if two groups have heterogeneous returns from interaction, the high-return group is more socially active and invests more in protection than the low-return group. This paper finds not only a consistent result that an agent’s probability of vaccination increases as her centrality increases, but also a new result that in a star network, the high-centrality agent chooses a relatively low probability of vaccination.

Finally, this paper lends support to compulsory vaccination policies. Brito et al. (1991) argue that the competitive equilibrium is always better than the universal mandate because those who forgo the vaccine in the equilibrium are worse off under the mandate. Neilson

⁸A universal mandate is also preferable if the vaccination cost is very low, compared to the disease cost. In this case, vaccinating everyone is socially optimal. But since everyone has a dominant strategy to vaccinate, a universal mandate cannot improve the equilibrium.

and Xiao (2018) formally show that the argument holds if players coordinate. This paper finds that if they cannot coordinate, the universal mandate produces the same welfare that a mixed-strategy Nash equilibrium does.

This paper unfolds as follows. Section 3.2 introduces the 2-person benchmark model. Section 3.3 uses a 2-person network to demonstrate the vaccination game’s anti-coordination and the existence of a mixed-strategy Nash equilibrium. Section 3.4 introduces the 3-person star network. Section 3.5 finds the mixed equilibrium in the star network and presents the counter-intuitive outcome that the high-centrality agent chooses a lower probability of vaccination than low-centrality agents do. Section 3.6 analyzes the universal vaccination mandate and finds the same social welfare as in a mixed-strategy Nash equilibrium. Section 4.6 concludes the paper.

3.2 The benchmark model: a 2-person complete network

The benchmark model is a 2-person version of Neilson and Xiao (2018)’s network model, which is a complete network by definition because everyone interacts with everyone. Consider two risk-neutral players i and j in a network, $i, j = 1, 2, i \neq j$. Player i can contract the contagious disease from outside the network or from the other player j in the network. If player i involves in community activities or exposes to natural virus carriers, she may get infected and introduce the disease to the network. The probability of such infection is β . The infected player can transmit the disease to the healthy player j with a probability of t . Each player can catch the disease only once. Illness costs the infected player D . Meanwhile, individuals can choose to pay a cost c to vaccinate before the disease enters the network. For example, a flu vaccine is available before the flu season, a juvenile HPV vaccine is available for teenagers, and condoms are available all the time. Assume the vaccine is 100% effective.

Both players compare the cost and benefit of vaccination and decide whether to vaccinate simultaneously. The benefit depends on the expected cost of forgoing vaccination, which equals the probability of infection multiplied by the illness cost. p_S^i is defined as player

i 's probability of infection when players in S are vaccinated, and the vaccination set S determines the probability. Since the vaccine is perfect, if i is vaccinated, $p_{\{i\}}^i = 0$. However, if i forgoes vaccination, then j 's action determines the probability. If j is vaccinated, then

$$p_{\{j\}}^i = \beta,$$

where β implies that player i can only get infected from outside because j 's vaccination eliminates the risk that the disease transmits from j to i . However, if j is also not vaccinated, then

$$p_{\emptyset}^i = \beta + (1 - \beta)\beta t,$$

where β represents the exogenous susceptibility and $(1 - \beta)\beta t$ represents that if i is not infected exogenously, j gets the infection and transmits it to i . Since $(1 - \beta)\beta t$ is also the difference between $p_{\{j\}}^i$ and $p_{\emptyset}^i$, $(1 - \beta)\beta t D$ represents the external benefit for i of j 's vaccination. Notice that $p_{\{i\}}^i < p_{\{j\}}^i < p_{\emptyset}^i$. The payoff matrix is summarized:

		Player 2	
		V	N
Player 1	V	$-c, -c$	$-c, -p_{\{1\}}^2 D$
	N	$-p_{\{2\}}^1 D, -c$	$-p_{\emptyset}^1 D, -p_{\emptyset}^2 D$

In the matrix, V represents vaccinating while N represents not vaccinating. In each element, the first term is player 1's payoff while the second is player 2's. Notice that $p_{\{2\}}^1 = p_{\{1\}}^2 = \beta$.

Knowing the vaccination's cost and benefit, players choose the action that minimizes their costs. That action depends on the relative scale of c and D . If the vaccine cost is very low, or $c \leq \beta D$, then each player has a (weakly) dominant strategy to vaccinate because $c \leq p_{\{j\}}^i D < p_{\emptyset}^i D$. If the vaccine cost is very high, or $c > p_{\emptyset}^i D$, then each player has a dominant strategy to forgo vaccination because $c > p_{\emptyset}^i D > p_{\{j\}}^i D$. If the vaccine cost is in between, or $\beta D < c \leq p_{\emptyset}^i D$, then players do not have a dominant strategy. Also, players' preferences are unstable. If j is vaccinated, then i 's best response is to forgo the vaccination because $c > p_{\{j\}}^i D$. However, if j is not vaccinated, then i 's best response is to vaccinate because $c \leq p_{\emptyset}^i D$. This paper focuses on the last circumstance with no dominant strategies, which leads to the mixed-strategy Nash equilibrium (mixed-strategy NE).

3.3 The chicken game and the mixed equilibrium

First, consider the pure-strategy Nash equilibrium (pure-strategy NE) in the 2-person complete network, if no dominant strategy exists. In a pure-strategy NE, agents choose either to vaccinate or not with no incentive to deviate. For example, if $\beta D < c \leq p_\emptyset^i D$, two pure-strategy NEs exist: agent 1 vaccinates while 2 does not, and agent 1 forgoes while 2 vaccinates. In each equilibrium, the forgoing agent is better off than the vaccinated agent because $-p_{\{j\}}^i D > -c$. Thus, each agent prefers the equilibrium with her being a forgoing agent. Such ex-post preference indicates that both agents want to free ride. Economists categorize such anti-coordinative games as the chicken game.⁹

The anti-coordinative nature of the vaccination game leads to the mixed-strategy NE. If agents cannot coordinate, each agent chooses a strategy profile $(\theta_i, 1 - \theta_i)$, where θ_i is agent i 's probability of vaccination. Then the vector (θ_1^*, θ_2^*) defines a mixed-strategy NE such that both agents cannot be strictly better off by choosing a different probability mixture. To achieve the equilibrium, each agent must be indifferent about vaccinating and not against the other agent's strategy profile. The first proposition defines an equilibrium that satisfies such a condition.

Proposition 3.1. *In a 2-person homogeneous network, if $c/D \in (\beta, p_\emptyset^i]$, in a mixed-strategy Nash equilibrium both players choose the probability of vaccination*

$$\theta^* = 1 - \frac{c/D - \beta}{(1 - \beta)\beta t}.$$

Proof. By symmetry, let $\theta_1^* = \theta_2^* = \theta^*$. And θ^* solves the following equation:

$$\theta\beta D + (1 - \theta)[\beta + (1 - \beta)\beta t]D = c. \quad (3.1)$$

⁹In the chicken game, two players drive towards each other to challenge their nerves. If one player swerves but the other does not, the one who swerves is a “chicken”, while the other is a winner. However, if both go straight, they crash and both are injured. Thus, if a driver knows that the other will swerve, he wants to go straight to win; but if the other goes straight, he prefers to swerve to avoid a crash. Both the chicken and the vaccination games are anti-coordinative since players compete for a rivalrous resource and sharing the resource is costly. In the chicken game, winning is a rivalrous resource because only one player can win. However, if both players want to win, they are injured in the crash. Similarly, in the vaccination game, free-riding is a rivalrous resource because only one player can free ride. However, if both want to free ride, they face a greater risk of illness.

The full proof is in appendix. □

Proposition 3.1 highlights the mixed-strategy NE's existence in the vaccination game, thus laying the foundation for the rest of the paper. The proposition also provides two insights. First, an individual is more likely to vaccinate as the vaccination cost falls or as the illness cost rises if other parameters are constant. Such relationship is consistent with the intuition that people are more likely to take the vaccine as it becomes cheaper. Secondly, individuals are indifferent to choosing a probability mixture versus taking the vaccine. As equation (3.1) shows, the equilibrium requires player i to be indifferent about vaccinating and not against the player j 's strategy profile. Since the vaccine is perfect, her payoff is the negative vaccination cost, or $-c$, no matter she vaccinates or not. If player i mixes between vaccinating and forgoing, her payoff still is $-c$. Thus, player i 's expected payoff of choosing any probability mixture equals the vaccination cost if player j chooses the equilibrium strategy profile. Since i and j are substitutable, both players choose the same strategy profile in equilibrium.

An application of the 2-person network to the heterosexual relationship can best explain the mixed equilibrium's indifference property. Consider one male and one female interacting in a casual relationship. Both individuals can contract a sexually transmitted disease from each other or from sexual partners outside the network. However, an individual can take a vaccine or use condoms to avoid the disease and therefore not transmit the disease to the other individual. Thus, individuals desire an equilibrium in which they can balance the trade-off between the cost and the benefit of vaccination.

In a casual relationship, such an equilibrium must be a mixed-strategy Nash equilibrium. Assume that everyone prefers not to take a vaccine (or sex without condoms) if there is no infection risk and contraception concerns are irrelevant. Thus, individuals do not want to bear the vaccination cost if they can have safe sex in a casual relationship. Moreover, a female is unlikely to coordinate with a causal boyfriend on whether to take a vaccine. Furthermore, individuals desire an equilibrium in which they choose a vaccination probability to make each other indifferent about whether to vaccinate. For example, if the male's vaccination probability is too low, the female's infection risk is very high; thus, she must take a vaccine and let the male free rides her. However, if the male's vaccination probability is too high,

the female will never vaccinate so she can free ride the male; thus, the male dislikes the allocation. Therefore, everyone must choose the probability mixture that makes the other individual indifferent. In conclusion, individuals achieve a symmetric equilibrium if they have the same infection risk from outside the network, the same probability to transmit the disease within the network, the same vaccination cost, and the same illness cost.

3.4 A 3-person star network

Adding one player to the 2-person network creates a 3-person network. If everyone directly interacts with everyone, they form a complete network. But if only one player directly interacts with everyone else, they form a star network. The one interacting with two players is defined as the *central* player. The others, who directly interact with the central player but not with each other, are defined as the *peripheral* players. This section focuses on the star network.¹⁰

The central player has a greater centrality than the peripherals.¹¹ Central players usually can be found in socially active occupations, such as waitresses, teachers, and social workers. A waitress serves customers seated at separate tables. A teacher teaches students in various classrooms and schools. A social worker interacts with people from different households and communities.

Start with players' payoffs. Refer the central player as player 1 (female) and the peripheral players as players 2 and 3 (male). If player 1 takes the perfect vaccine, her payoff is $-c$ because $p_{\{1\}}^1 = 0$. However, if she forgoes vaccination, her expected payoff is the probability of infection multiplied by the illness cost, with the probability depending on the peripheral players' action. If both peripheral players are vaccinated, then $p_{\{2,3\}}^1 = \beta$ because she can only catch the disease from outside. If one of the peripherals is vaccinated, then $p_{\{i\}}^1 = \beta + (1-\beta)\beta t$ for $i = 2, 3$ because she can catch the disease either exogenously or from the other member.

¹⁰I skip the 3-person complete network because all results are qualitatively the same as those in a 2-person network.

¹¹Choosing which specific centrality measure does not matter in a star network since all measures assign a higher score to the central player. This paper essentially uses the probability of infection to rank the players, and the calculation is similar to the decay centrality (see [Jackson \(2008\)](#)).

If none of the players are vaccinated, then

$$p_{\emptyset}^1 = \beta + (1 - \beta)(2\beta t - \beta^2 t^2),$$

where $2\beta t - \beta^2 t^2$ represents the possibility that either of the two peripherals (but not both) can transmit the disease to player 1. Notice that $p_{\{1\}}^1 < p_{\{2,3\}}^1 < p_{\{i\}}^1 < p_{\emptyset}^1$.

Next, if a peripheral player $i = 2, 3$ takes the perfect vaccine, his payoff is $-c$ because $p_{\{i\}}^i = 0$. However, if he does not, his probability of infection depends on what player 1 and the other peripheral player j do. If player 1 is vaccinated, $p_{\{1\}}^i = \beta$ since player 1 is i 's only connection and her vaccination eliminates all interpersonal transmission in the network. If player 1 forgoes the vaccine but j takes it, then $p_{\{j\}}^i = \beta + (1 - \beta)\beta t$ because he can catch the disease either exogenously or from player 1. If none of the players are vaccinated, then

$$p_{\emptyset}^i = \beta + (1 - \beta)[\beta t + (1 - \beta)\beta t^2],$$

where $\beta t + (1 - \beta)\beta t^2$ represents that i gets the disease from other players by either one step ($1 \rightarrow i$) or two steps ($j \rightarrow 1 \rightarrow i$). Notice that $p_{\{i\}}^i < p_{\{1\}}^i < p_{\{j\}}^i < p_{\emptyset}^i < p_{\emptyset}^1$.

Players choose whether to vaccinate to minimize their costs. And their decisions may involve a conflict on coordination as in the chicken game. Consider the pure-strategy NEs outlined in [Neilson and Xiao \(2018\)](#):

$$S^* = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, \beta] \\ \{1\} \text{ or } \{2, 3\} & \text{if } \frac{c}{D} \in (\beta, p_{\{j\}}^i] \\ \{1\} \text{ or } \{2\} \text{ or } \{3\} & \text{if } \frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i] \\ \{1\} & \text{if } \frac{c}{D} \in (p_{\emptyset}^i, p_{\emptyset}^1] \\ \emptyset & \text{if } \frac{c}{D} \in (p_{\emptyset}^1, \infty) \end{cases} \quad (3.2)$$

First, consider the two extreme cases. Players have a dominant strategy to vaccinate if the normalized vaccination cost (c/D) is very low and a dominant strategy to forgo the vaccine if the cost is very high. These two circumstances correspond to the first and last equilibria in equation (3.2). As the cost falls below $p_{\emptyset}^1$ but is greater than $p_{\emptyset}^i$, the peripheral

players have a dominant strategy to forgo. Knowing that none of the others will vaccinate, the central player must take the vaccine. Thus, the equilibrium prescribes the vaccine to player 1 if the cost is in $(p_\emptyset^i, p_\emptyset^1]$.

Next, as the normalized vaccination cost continues to fall into $(\beta, p_\emptyset^i]$, no dominant strategies exist, resulting in multiple equilibria. Vaccinating the central player is socially optimal. However, in the lower part, the equilibria prescribes the vaccine either to the central player or to the two peripheral players. While in the upper part, any player taking the vaccine is a pure-strategy NE. In this circumstance, players cannot agree on which equilibrium to coordinate. Since a player forgoes the vaccine if the expected illness cost is smaller than the vaccination cost, all players must prefer an equilibrium with others vaccinated to the equilibrium with themselves vaccinated. The next section will show that the difficulty of coordinating results in a mixed-strategy NE, where the central player chooses a lower probability of vaccination than the peripherals.

3.5 The central player and equilibrium vaccination probability

Section 2 introduces the 2-person network. Section 3 shows that a mixed-strategy Nash equilibrium exists in the 2-person network. Section 4 suggests such a mixed-strategy NE can also exist in the 3-person star network. This section uses the equilibrium outcome to show the main result that the central player is less likely to vaccinate than the peripherals.

In a 3-person vaccination game with no dominant strategies, each agent chooses a strategy profile $(\theta_i, 1 - \theta_i)$ for $i = 1, 2, 3$. And the vector $(\theta_1^*, \theta_2^*, \theta_3^*)$ defines a mixed-strategy NE, whereby everyone must be indifferent to vaccinating and forgoing against the others' strategy profiles. The next proposition defines an equilibrium satisfying such a condition.¹²

¹²All players mix their strategies in this equilibrium, but asymmetric mixed-strategy solutions also exist. In such solutions, one player commits to non-vaccination, while the other two mix their strategies to achieve a Nash equilibrium. See details in Appendix B.1.

Proposition 3.2. *In a 3-person homogeneous star network, for $c/D \in (\beta, \bar{c}]$, there exists a mixed-strategy NE in which the central player chooses the probability of vaccination*

$$\theta_1^* = 1 - \frac{c/D - \beta}{(1 - \beta)(1 - \sqrt{(1 - c/D)(1 - \beta)})t},$$

and both peripheral players choose the probability of vaccination

$$\theta_2^* = \theta_3^* = 1 - \frac{1 - \beta - \sqrt{(1 - c/D)(1 - \beta)}}{(1 - \beta)\beta t},$$

where $\bar{c} = \beta + (1 - \beta)t - \frac{1}{2}(1 - \beta)^3 t^2 - \frac{1}{2}(1 - \beta)^2 t \sqrt{(1 - \beta)^2 t^2 + 4 - 4t}$ that solves $\theta_1^*(c/D) = 0$.

Proof. By symmetry, $\theta_2^* = \theta_3^*$. And θ_1^* and θ_2^* solve the following equations:

$$(\theta_2)^2 \cdot p_{\{2,3\}}^1 D + 2\theta_2(1 - \theta_2) \cdot p_{\{2\}}^1 D + (1 - \theta_2)^2 \cdot p_{\emptyset}^1 D = c, \quad (3.3)$$

$$\theta_1 \cdot p_{\{1\}}^2 D + (1 - \theta_1)\theta_2 \cdot p_{\{3\}}^2 D + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^2 D = c. \quad (3.4)$$

The full proof is in appendix. □

Proposition 3.2 offers similar insights as well as a significantly different insight into Proposition 3.1 of a 2-person network. The mixed-strategy NE's interval does not extend fully to $(\beta, p_{\emptyset}^i]$, where the multiple pure-strategy NEs exist, but is bounded above by some threshold below $p_{\emptyset}^i$ because as the normalized vaccination cost approaches the threshold from the left, the central agent's probability of vaccination goes to zero. However, the peripheral agents' probability is still positive.¹³ Thus, the central agent is less likely to vaccinate than the peripheral agents at the threshold. The next proposition shows that such a relationship holds whenever a mixed-strategy NE exists, which is the main result of this paper.

Proposition 3.3. *In a 3-person homogeneous star network, as in the mixed-strategy NE described in Proposition 3.2, the central player chooses a lower probability of vaccination than the peripheral players, that is*

$$\theta_1^* < \theta_2^* = \theta_3^*.$$

¹³Substitute $\theta_1 = 0$ in equation (3.4) and obtain $\theta_2 \cdot p_{\{3\}}^2 D + (1 - \theta_2) \cdot p_{\emptyset}^2 D = c$. Since $p_{\{3\}}^2 D < c < p_{\emptyset}^2 D$, one can verify that $0 < \theta_2 < 1$.

Proof. In appendix. □

Figure 3.1 illustrates Proposition 3.2 and 3.3's results using parameters $\beta = .05, t = .8, D = 1$. The dashed magenta curve shows the central player's probability of vaccination, and the solid blue curve shows the peripherals'. The two curves highlight a surprising result: the central player's probability of vaccination is always smaller than the peripherals', though she faces a relatively greater infection risk than the peripherals. The intuition is that everyone's expected illness cost must equal the vaccination cost because of the equilibrium's indifference property (equations (3.3) and (3.4)). To make the central player indifferent between vaccinating and forgoing, the peripheral players must raise their probabilities of vaccination to offset the central player's high infection risk; and the central player reduces her probability of vaccination to best respond. Thus, the central player has a higher network centrality but a lower equilibrium vaccination probability than the peripheral players.

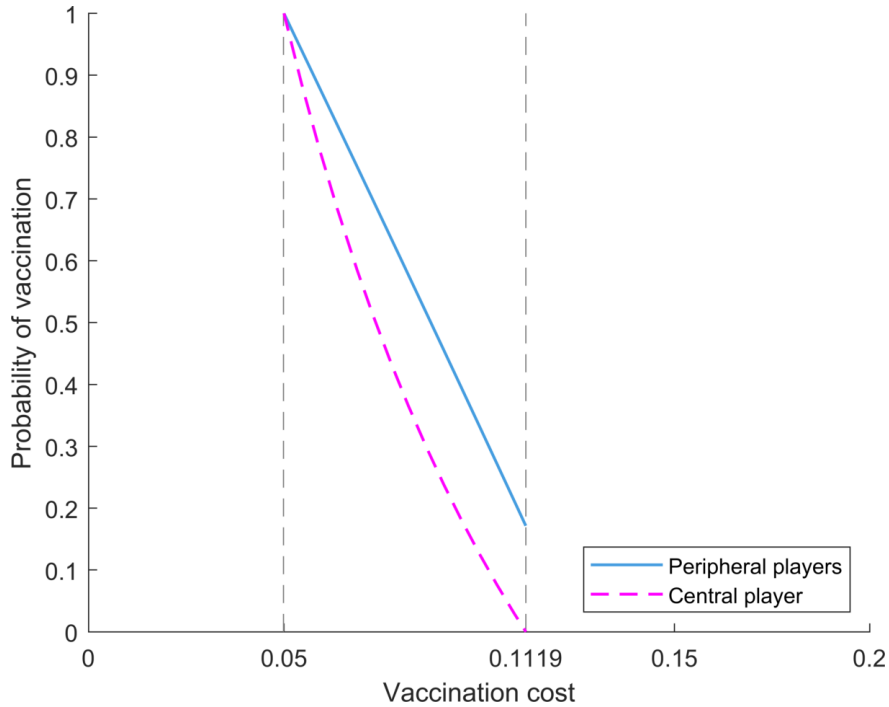


Figure 3.1: The central and peripheral players' probabilities of vaccination in a 3-person homogeneous star network with $\beta = .05, t = .8, D = 1$. The horizontal axis is the vaccination cost, with a domain $c \in (.05, .1119]$. The vertical axis is the probability of vaccination, with ranges $\theta_1 \in [0, 1)$ and $\theta_2 \in [.1714, 1)$.

Moreover, such relationship persists as the number of players increases because the central player always faces a greater infection risk than the peripherals. Thus, the peripheral players must still choose a greater probability of vaccination than the central player to make her indifferent. The next proposition generalizes the result to an n -person star network.

Proposition 3.4. *In an n -person homogeneous star network, for $c/D \in (\beta, \bar{c}]$, there exists a mixed-strategy NE in which the central player chooses a lower probability of vaccination than all peripheral players, that is*

$$\theta_1^* < \theta_i^*,$$

where $i = 2, \dots, n$ and $\bar{c}$ solves $\theta_1^*(c/D) = 0$.

Proof. In appendix. □

Figure 3.2 illustrates Proposition 3.4's result by simulating the 3-person to 20-person star networks using parameters $\beta = .05, t = .8, D = 1, c = .1$. The dashed magenta curve shows the central player's probability of vaccination, and the solid blue curve shows the peripherals'. Both curves increase as the number of players increases, which means that for either a central or peripheral player, the probability of vaccination increases as the player's centrality increases.¹⁴ Such a positive correlation is consistent with the intuition that as an individual becomes more socially active, she is more likely to get vaccinated. Propositions 3.3 and 3.4 consider a different question. That is, if players interact in a given star network but cannot coordinate, the high-centrality player strategically chooses a lower probability of vaccination than the low-centrality player.

Furthermore, the gap between the two curves expands as the number of players increases, which shows the difference between the central and peripheral players' probabilities of vaccination. To understand the expansion, consider adding one peripheral player to the existing star network. Since the added player only directly interacts with the central player, the central player's infection risk is increasing faster than an existing peripheral player's. Thus, under the equilibrium's indifference property, the peripheral players must raise their

¹⁴Most centrality measures assign a higher score for both central and peripheral players as the number of players increases. Except for the degree centrality, which considers the number of connections, so the peripheral player's degree centrality is always 1.

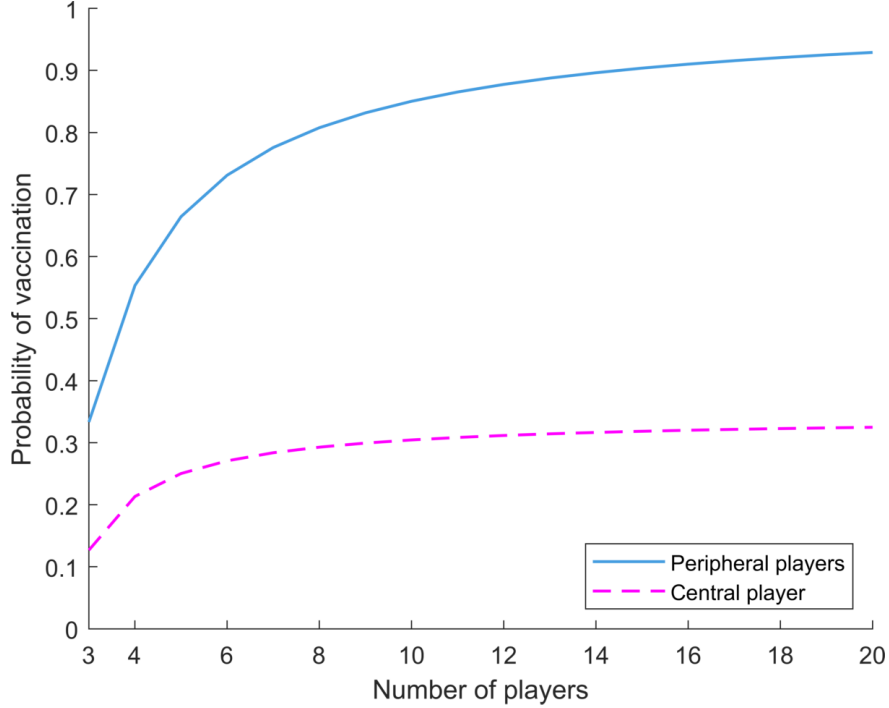


Figure 3.2: The central and peripheral players' probabilities of vaccination in a homogeneous star network with $\beta = .05, t = .8, D = 1, c = .1$. The horizontal axis is the number of players, which ranges from 3 to 20. The vertical axis is the probability of vaccination.

probabilities of vaccination faster to compensate the central player's extra increment of infection risk.

3.6 Policy analysis: a universal vaccination mandate

The above sections show that in a 3-person star network, the central player is the least likely to vaccinate in a mixed-strategy NE, though she should be the first to vaccinate. This section shows that a targeted policy can achieve the optimal allocation, while a universal mandate produces the same welfare as in a mixed-strategy NE.

Neilson and Xiao (2018) suggest that targeted subsidies and fines can improve the welfare of a suboptimal pure-strategy NE. The subsidies and fines ensure that the targeted player has a dominant strategy to vaccinate, and the others' best response is to forgo the vaccine. Thus, players achieve the unique optimal allocation under the targeted policy. Moreover, the

targeted policy eliminates the possibility of a mixed-strategy NE. Therefore, the targeted policy can achieve the social optimum, whether players coordinate or not.

The authors also show that a universal mandate cannot improve any pure-strategy NEs in any network. A universal mandate requires all players to take the vaccine; but in a pure-strategy NE, some players forgo the vaccine if their expected illness cost is smaller than the vaccination cost. Thus, a pure-strategy NE produces a greater welfare than a universal mandate.¹⁵ However, the next two propositions show that in both a 2-person network and a 3-person star network, a universal mandate performs the same as the mixed-strategy NE.

Proposition 3.5. *In a 2-person homogeneous network, if $c/D \in (\beta, p_\emptyset^1]$, a universal mandate produces the same expected social welfare a mixed-strategy NE does.*

Proof. In appendix. □

Proposition 3.6. *In a 3-person homogeneous star network, if $c/D \in (\beta, \bar{c})$, a universal mandate produces the same expected social welfare as in a mixed-strategy NE.*

Proof. In appendix. □

The indifference property drives the welfare equivalence in the propositions above. Since players are indifferent to whether to take or forgo the vaccine, a probability mixture of these two strategies generates the same payoff.¹⁶ Moreover, such an indifference property always exists in a mixed-strategy NE. Thus, the next proposition generalizes the welfare equivalence to any n -person network.

Proposition 3.7. *For any n -person network, if a mixed-strategy NE exists, a universal mandate produces the same expected social welfare a mixed-strategy NE does.*

Proof. In appendix. □

¹⁵Again, the social welfare is the same if the vaccination cost is lower than the exogenous susceptibility.

¹⁶Notice the two important assumptions for the equivalence result: (1) individuals cannot coordinate and (2) individuals are risk-neutral. In the equilibrium, loss-averse players choose a lower probability to vaccinate than risk-neutral players. Given the same expected loss, loss-averse individuals prefer facing the uncertain infection risk than taking the vaccine. Thus, to make them indifferent, the equilibrium must reduce the probability of vaccination as well as the chance of gaining the free-riding benefit.

Though a universal mandate cannot achieve the social optimum, dealing with a mixed-strategy NE is useful. A targeted policy may not be feasible or politically palatable, while a universal mandate can be because everyone makes the same choice. Moreover, policymakers usually prefer paying a fixed vaccination cost to prevent a possible epidemic.¹⁷ Above all, a universal mandate is a practical policy option if targeting is infeasible and coordination is difficult.

3.7 Conclusion

This paper builds on [Nelson and Xiao \(2018\)](#)'s stylized network model and establishes the vaccination game's mixed-strategy Nash equilibrium in a 2-person complete network and a 3-person star network. The mixed equilibrium allocation leads to new results. The most surprising one is that in a star network, the central player has a greater centrality but chooses a lower probability of vaccination than the peripheral players. Such result is consistent with empirical evidence about flu vaccination coverage of workers in occupations with frequent public contact and individuals' condom use behavior in a causal relationship.

This finding is based on an understanding of the anti-coordinative nature of the vaccination game. If the pure-strategy Nash equilibrium assigns the vaccine to some agents but not to everyone, then multiple equilibria arise. Each agent prefers the other agents to take the vaccine; thus, they cannot agree on which equilibrium to achieve. Instead, everyone chooses a probability mixture to achieve a mixed-strategy Nash equilibrium.

The model also provides policy implications, especially for the universal mandate. Though a universal mandate cannot improve a pure-strategy Nash equilibrium, it generates the same social welfare as in a mixed-strategy Nash equilibrium. The welfare equivalence holds in any network where a mixed-strategy Nash equilibrium exists. Thus, a universal mandate is a practical option for policymakers if targeting is infeasible and coordination is difficult. Empirical research finds that government mandates increase individuals' incentive

¹⁷In the equilibrium, a loss-averse player's expected loss is greater than the vaccination cost. In that case, the universal mandate can reduce the aggregate expected loss and prevent the relatively more probable under-vaccination outcome, while leaving the aggregate utility unchanged.

to vaccinate and that the effects spill over to other types of vaccines (Lawler, 2017, Carpenter and Lawler, 2017).

Future research can exploit various occupations' social activeness as a measure to proximate individuals centrality and investigate workers flu vaccination decisions to test which equilibrium allocation is realized. Also, the relationship between players' centrality and vaccination probability in a complex network worths exploring. That is, whether a high-centrality agent always choose a lower vaccination probability in an arbitrary network. Lastly, researchers can investigate the evolutionary game theory's interpretation. In a 2-person game, two types of players are involved (e.g., one being aggressive and the other being conservative). Both approaches can help in understanding the heterogeneity of different groups' behavior.

Chapter 4

Influenza Vaccination and Occupation Centrality: Evidence from U.S. Workers

4.1 Introduction

Vaccination yields benefits for the vaccinated individuals but also others who interact with them in the contagion network. For example, people obtain seasonal influenza vaccines so they are less likely to contract flu than if they were unvaccinated. Moreover, those who interact with the vaccinated individual are also less likely to be sick than before. The Centers for Disease Control and Prevention (CDC) estimates that in the 2017-2018 season, 37.1% of adults and 57.9% of children received influenza vaccination, which prevented 7.1 million illnesses, 109,000 hospitalizations, and 8,000 deaths in the United States ([CDC, 2018a,b](#), [Rolfes et al., 2019](#)).¹

Because not everyone is vaccinated, policymakers may be disproportionately interested about the flu vaccination coverage of socially active people who are at more central positions in the contagion network. We refer to them as high-centrality individuals.² Their vaccination

¹Adults are people aged 18 or older, children are people aged 6 month through 17 years during the 2017-2018 flu season.

²The definition of centrality here is closest to degree centrality in network theory, which refers to the number of links each node has. See examples of centrality definitions in [Jackson \(2008\)](#).

generates a large social benefit, which is the sum of the private benefit to the vaccinated people and the external benefit to others who interact with them. The private benefit depends on the avoided sickness cost and the probability that an individual becomes sick. The external benefit depends on the extent that an individual can spread the disease, which is positively correlated with the individual’s social activeness. Therefore, vaccinating socially active people with a higher centrality can generate large social benefits relative to less socially active people. However, whether high-centrality individuals are more likely to get vaccinated than low-centrality individuals is an open empirical question.

This paper investigates the empirical evidence about the correlation between individuals’ social centrality and probability of flu vaccine uptake. The ex-ante theoretical predictions for the correlation is mixed. A typical epidemiology model considers a complete random network and predicts that a high-centrality individual is more likely to obtain the vaccine than a low-centrality individual (Hethcote, 2000). Recent economic theories consider strategic vaccination choices in various network models but draw contradictory predictions about high-centrality individuals’ vaccination decision. First, Goyal and Vigier (2015) develop a bipartite network model and find that agents who gain a higher return from interaction have a higher centrality and invest more in protection, compared to low-return individuals. Secondly, Neilson and Xiao (2018) find that in an incomplete network, if players do not have dominant strategies but can coordinate, high-centrality player can get vaccinated in one equilibrium but forgo vaccination in the other. In addition, Xiao (2018) find that in an uncoordinated equilibrium, the high-centrality player is less likely to get vaccinated than the low-centrality player within an incomplete network. Therefore, the conflicting theoretical predictions call for empirical evidence.

This is the first paper to investigate whether individuals with a greater centrality are more likely to get vaccinated than less socially active individuals. Though it is unclear whether high-centrality individuals received sufficient vaccination, economics scholars measured the marginal size of externality when policies motivate potential high-centrality people to get vaccinated. White (2018) found that when California mandates health care personnel to receive the flu vaccine, a 10.3 percent increase in their vaccination coverage reduces influenza diagnosis in inpatient hospitalizations by 20.1 percent and emergent outpatient visits by 8.1

percent. Similarly, [Ward \(2014\)](#) found that when Ontario expands flu vaccine subsidies, which originally targeted seniors aged 65+, a 10.8 percentage point increase in younger adults' vaccination coverage reduces at least 20 percent of seniors' influenza and pneumonia admissions during the epidemic period. Therefore, vaccinating health care personnel in California and younger adults in Ontario generates considerable external benefit, but those people on the margin would not obtain flu vaccines if they were not mandated or must pay out of pocket.

Social centrality can vary on multiple dimensions. Thus, identifying individuals who are at the center of their respective networks is very difficult. However, workplace-specific social activeness is an important measure because workplaces are a common space where many people interact and spread the flu. Economics literature provides evidence that workers are the important source of disease spread, whereas policies restricting interpersonal interactions in workplaces are an effective disease control method.³ Moreover, policymakers implement targeted vaccination policies based on occupation, age, and health status. The U.S. Department of Health and Human Services and Department of Homeland Security provide pandemic influenza guidance that prioritizes vaccine to selected occupational groups who provide critical services and groups with fragile health status when the flu is widely spread and vaccine supplies are limited. Similarly, the U.S. Advisory Committee on Immunization Practices recommends an annual flu shot for all people who are 6 months or older but also emphasizes the importance on vaccinating higher-risk people and people who have direct contact with them, such as doctors, nurses, and caregivers ([Grohskopf et al., 2018](#)). Therefore, we focus on workers and exploit every occupation's characteristics to identify their centrality.

We implement the investigation on whether workers with higher centrality are more likely to get vaccinated in three steps. First, we apply principal component analysis to construct the centrality score for every occupation with selected descriptors from the Occupational

³[Markowitz et al. \(2010\)](#) find that employment and flu-related doctor visits are strongly positively correlated, especially for those occupations with frequent public contact. [Pichler and Ziebarth \(2017\)](#) find that the flu-related admissions in states without sick leave insurance mandate are greater than the states with the mandate, which suggests that workers are more likely to be present at work if they do not have sick pay. [Adda \(2016\)](#) finds that policies restricting interpersonal interactions in workplaces effectively control disease spread, such as schools and public transportation networks.

Information Network (O*NET). Secondly, we utilize the centrality score to augment the Behavioral Risk Factor Surveillance System (BRFSS) with restricted information on industry and occupation. Finally, we run regressions to estimate the correlation between worker’s centrality and flu vaccine uptake, while controlling for other relevant variables.

We find that high-centrality workers are more likely to get vaccinated than low-centrality workers, but the positive correlation between centrality and vaccine uptake becomes statistically insignificant if we control for health care personnel. Furthermore, workers who face direct exposure to diseases are more likely to get vaccinated than those who do not, no matter they are health care personnel or not. Lastly, vaccine uptake is not monotonically increasing in centrality across all specifications, which is consistent with the incomplete network model’s predictions. The result suggests that while all workers consider the risk of direct exposure to diseases, only health care personnel pay attention to the infection risk in social interactions. Thus, there is room for targeted vaccination policies that generate potentially large social benefits.

This paper contributes to the economics literature about externality and vaccination. We provide the first empirical evidence for the various theoretical predictions ([Galeotti and Rogers, 2013](#), [Goyal and Vigier, 2015](#), [Neilson and Xiao, 2018](#), [Xiao, 2018](#)). The general result is consistent with the complete and bipartite network models, and more specific findings can be explained by incomplete network models.

This paper also contributes to the public health literature about flu vaccination. Existing literature shows that many occupations with frequent public contact have lower flu vaccination coverage than the population average ([Luckhaupt et al., 2014](#), [O’Halloran et al., 2017](#)). And this paper is the first to investigate the correlation between individuals’ social centrality and vaccine uptake. Our result is consistent with the literature that high-centrality non-health care workers are under-vaccinated.

Lastly, this paper constructs a novel centrality measure to quantify the social-activeness for every occupation. Mathematicians and network scientists utilize centrality to describe the importance of different nodes in visual or simulated networks (see an example in [Dekker \(2013\)](#)), and this is the first attempt to measure the social-activeness for the interpersonal contact of all workers.

4.2 Data

Our primary data are the individual-level cross-sectional data from the Behavioral Risk Factor Surveillance System (BRFSS) for the year 2013. BRFSS uses telephone survey to collect information about U.S. residents on their health-related risk behaviors, chronic health conditions, and preventive services utilizations. BRFSS started to support an optional industry/occupation module in 2013, and 21 states included the module.⁴ BRFSS interviews more than 400,000 adults every year, and we restrict the sample to 75,712 employed non-military adults. We can observe their flu vaccine uptake, demographics, health conditions, insurance coverage, and the restricted industry/occupation information. Table 4.1 presents the summary statistics.

Table 4.1: Summary Statistics of Variables in Main Regressions

Variable	Mean	Std. Dev.	Min	Max
Flu vaccine uptake	0.39	0.49	0	1
Health care personnel	0.16	0.37	0	1
Female	0.54	0.50	0	1
Age group	3.85	1.35	1	6
Race/ethnicity group	1.37	0.83	1	4
Education level	3.13	0.91	1	4
Income level	4.12	1.26	1	5
Married	0.60	0.49	0	1
High-risk conditions	0.23	0.42	0	1
Have personal health care provider	0.80	0.40	0	1
Have medical insurance	0.87	0.33	0	1
Centrality	0.88	3.09	-7.71	8.32
Exposure	0	1	-0.96	2.87
Sampling weight	522.86	977.30	1.27	30576.48
Observations	75,712			

Source: BRFSS 2013 and O*NET. Age group includes 18-24, 25-34, 35-44, 45-54, 55-64, and 65+. Race/ethnicity group includes white, black, Hispanic, and other. Education level includes less than high school, high school graduate or GED, some college or technical school, and college graduate. Income level includes less than 15K, 15-25K, 25-35K, 35-50K, and 50K+.

⁴The 21 states are California, Florida, Illinois, Louisiana, Missouri, Massachusetts, Michigan, Minnesota, Mississippi, Montana, Nebraska, New Hampshire, New Jersey, New Mexico, New York, North Dakota, Oregon, Utah, Washington, Wisconsin, and Wyoming.

We observe the key outcome variable, whether the respondent receives a flu vaccine in the past 12 months. An individual can get vaccinated by either a flu shot with a needle or a spray in the nose. We can also observe the time of vaccine uptake, which ranges from Jan 2012 to Feb 2014. Though the vaccination timing spans across three flu seasons, we do not distinguish which flu season the respondent gets vaccinated for three reasons. First, there are no significant events related to flu or flu vaccine during that period, such as a pandemic or vaccine shortages. Secondly, the flu prevalence and vaccine effectiveness are similar across these flu seasons. The flu severity is either low (2011-2012) or moderate (2012-2013, 2013-2014) among adults and overall population (Biggerstaff et al., 2017), and the vaccine effectivenesses are around 50% (CDC, 2018c). Lastly, researchers compare the calendar-year estimates versus season-specific estimates from 2010-2013 and find no significant differences in the overall estimates for adults' flu vaccination coverage (Lu et al., 2013).

The most important variable is the workers' occupation, and our sample contains 492 unique occupations. We classify these occupations into 22 major groups, 93 minor groups, and 412 broad occupations based on the 2000 Standard Occupational Classification (SOC) codes.⁵ Our sample covers all non-military major and minor groups and over 90% of non-military broad occupations.⁶ The SOC codes allow us to supplement the BRFSS data with a centrality score for each occupation.

We use the Occupational Information Network (O*NET) data to construct the occupation centrality. O*NET surveys workers and provides data about specific job descriptions and requirements, which include numeric measures about work contexts and activities, i.e., *descriptors*. First, we select 6 descriptors about work context and 16 descriptors about work activities that are related to interpersonal interactions. Table 4.2 presents the summary statistics of the 22 descriptors for 492 occupations. Then we standardize the descriptors as mean zero and standard deviation one and apply the principal component analysis to construct the centrality score. We choose the first principal component as the centrality score, which represents the greatest variance of all descriptors among all components. The

⁵BRFSS originally coded the industry/occupation module in the Census code, and O'Halloran et al. (2017) convert the Census codes to equivalent 2000 Standard Occupational Classification (SOC) codes and 2002 North American Industry Classification System (NAICS) industry codes.

⁶The 2000 Standard Occupational Classification (SOC) specifies 22 major groups, 93 minor groups, 446 broad occupations, and 801 detailed occupations of non-military occupations.

Table 4.2: Summary Statistics of 22 Occupational Descriptors

Descriptors	Mean	Std. Dev.	Min	Max	Weight (%)
Work Context					
Physical Proximity	60.71	15.46	17	100	1.27
Contact With Others	83.57	10.71	50	100	3.90
Coordinate or Lead Others	61.81	13.24	15	91	4.81
Deal With External Customers	60.00	21.57	5	99	3.82
Face-to-Face Discussions	88.25	8.45	39	100	3.55
Work With Work Group or Team	78.10	11.24	25	100	4.15
Work Activities					
Assisting and Caring for Others	45.57	18.56	10	97	3.20
Coaching and Developing Others	48.03	13.04	7	87	5.54
Communicating with Persons Outside Organization	54.63	18.84	8	94	4.82
Communicating with Supervisors, Peers, or Subordinates	73.10	10.21	34	95	4.91
Coordinating the Work and Activities of Others	51.01	13.38	9	89	5.56
Developing and Building Teams	48.88	13.74	10	89	5.85
Establishing and Maintaining Interpersonal Relationships	65.55	12.45	21	97	5.30
Guiding, Directing, and Motivating Subordinates	44.94	15.06	6	90	5.56
Interpreting the Meaning of Information for Others	53.90	14.79	19	93	4.67
Performing Administrative Activities	43.54	15.36	6	89	4.72
Performing for or Working Directly with the Public	48.49	23.19	3	94	3.44
Provide Consultation and Advice to Others	44.39	13.93	10	96	5.26
Resolving Conflicts and Negotiating with Others	49.76	15.10	5	93	5.61
Selling or Influencing Others	37.26	16.92	5	99	4.00
Staffing Organizational Units	26.99	13.79	3	73	5.44
Training and Teaching Others	54.12	12.62	8	91	5.53
Observations	492				

Source: O*NET. The “importance” score reported for descriptors under Work Activities. Each descriptor’s impact on centrality reported in percentage as “Weight” and summed up to 100. All descriptors standardized before applying the principal component analysis.

centrality ranges from -7.71 to 8.32 , which is a cardinal measure of the representative worker’s social activeness. Finally, we merge the centrality dataset with the BRFSS data.⁷

Another important variable is the workers’ industry. It is necessary to distinguish whether people work in a healthcare-related industry or not because these workplaces are likely to require employees to obtain a flu vaccine. We follow O’Halloran et al. (2017) and define health care personnel as people working in a clinical setting based on the 2002 North American Industry Classification System (NAICS) industry code, who are clinical and nonclinical staff working in hospitals (NAICS 622), outpatient care and physician offices (NAICS 6214 and 6211), long-term care facilities (NAICS 6216, 6231, 6232, 6233, and 6239), and other clinical settings (NAICS 6212, 62131, 62132, 6213, 6215, and 6219). Figure 4.1 is the histogram of the number of workers by major occupation groups, which are ranked from the highest average centrality. Each group is decomposed to health care personnel and non-health care personnel. Health care personnel exists in all major groups except the “farming, fishing and forestry” group.

Lastly, we select three descriptors from O*NET as additional controls. “Exposed to disease or infections (exposure)” from the work context category controls for workers’ direct exposure to disease. “Concern for others (concern)” from the work style category describes workers’ altruistic motivation. “Social” from the work style category represents workers’ social skills required for the job. All three variables are standardized.

Figure 4.2 and 4.3 plot the flu vaccination coverage by the centrality of the 22 major occupation groups and of the 492 specific occupations. The blue dots represent occupations that contain a majority of health care personnel. Both figures include two upward sloping fitted lines, with the solid one using the full sample while the dashed one excludes the blue dots. The upward sloping lines show that workers’ social centrality and flu vaccine coverage are positively correlated. In both figures, the dashed lines are flatter than the corresponding

⁷O*NET uses the 2010 SOC codes, so we follow the crosswalk guide provided by the U.S. Bureau of Labor Statistics (2012) to convert the codes to 2000 SOC. If multiple 2010 SOC codes are matched with a single 2000 SOC codes, we take the simple average of the descriptors. When merging with BRFSS, we find 335 matches of detailed occupations. For the remaining more general occupations, we take the simple average of the descriptors of all detailed occupations under the corresponding category to impute descriptors for 157 general occupations. See detailed explanations about the construction of centrality in the Appendix.

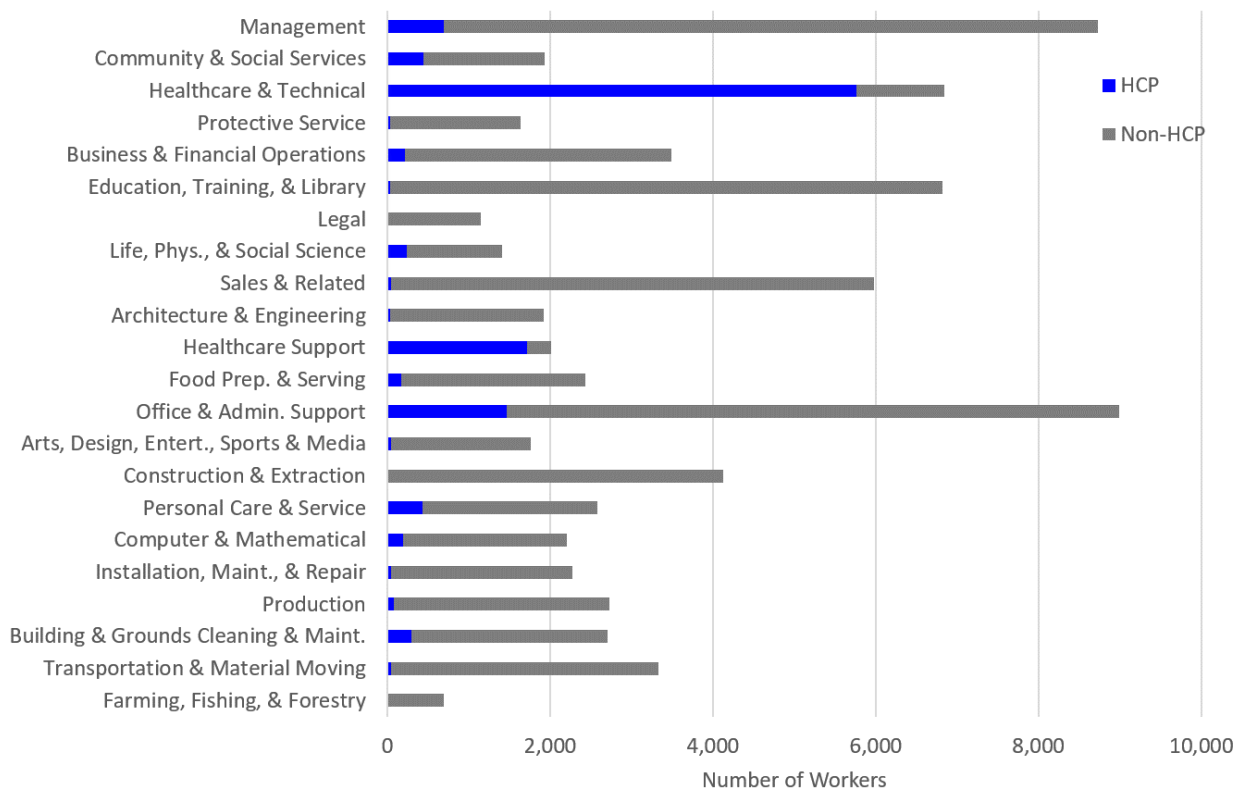


Figure 4.1: The Number of Workers of 22 Major Occupation Groups: Listed from the Group with Highest Centrality

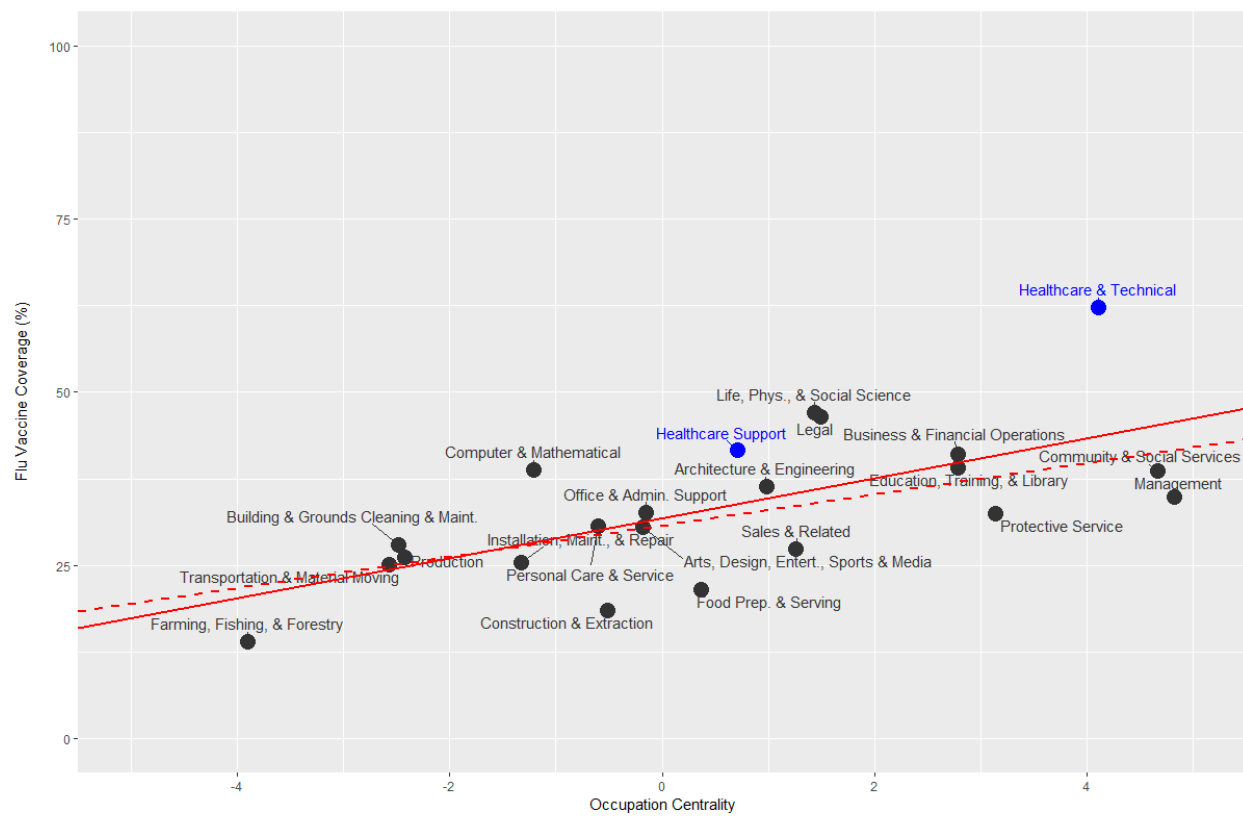


Figure 4.2: The Flu Vaccine Coverage by Centrality of 22 Major Occupation Groups

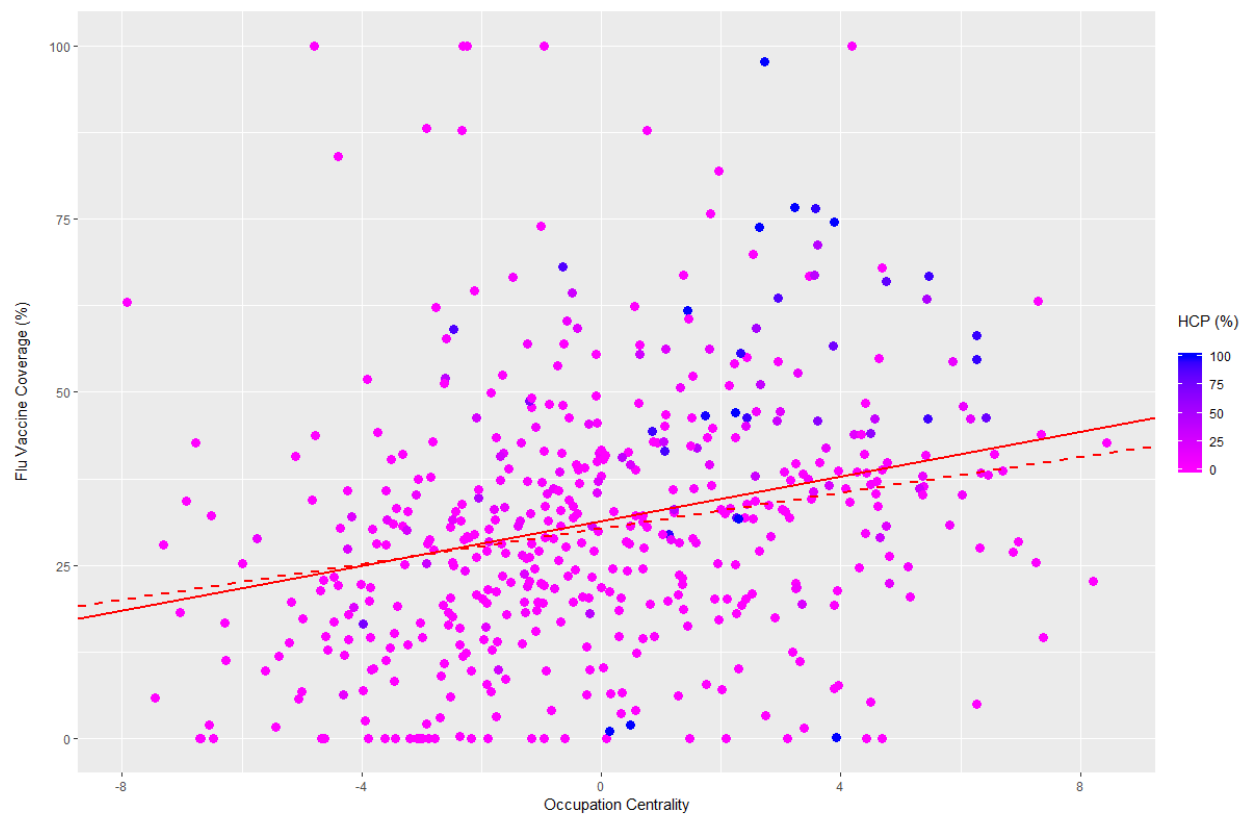


Figure 4.3: The Flu Vaccine Coverage by Centrality of 492 Occupations: Dots in Lighter Blue Contain More Health Care Personnel than Dots in Darker Blue

solid lines, which shows that non-health care personnel’s vaccine uptake is less sensitive to centrality than health care personnel.

4.3 Methods

We first estimate a linear probability model. Specifically, we run the following regression:

$$\mathbf{1}.vax_i = \beta_0 + \beta_1 centrality_i + \beta_2 exposure_i + \beta_3 \mathbf{1}.hcp_i + \gamma \mathbf{X}_i + state_i + \epsilon_i \quad (4.1)$$

where $\mathbf{1}.vax_i$ is the vaccine uptake indicator, $centrality_i$ is the occupation’s centrality, $exposure_i$ is the occupation’s standardized disease exposure, $\mathbf{1}.hcp_i$ is the health care personnel indicator, X_i is a vector of the demographics and health-related characteristics, $state_i$ is the state fixed effects, and ϵ_i is the error term. We report estimates with BRFSS sampling weights and state-level cluster-robust standard errors.

We also estimate a linear probability model with centrality bins to allow flexible coefficients and to facilitate direct comparison across bins. The occupation centrality is a linear measure, but its relationship with an individual’s flu vaccine uptake is not necessarily linear. Thus, we use discrete changes on the integer-level to categorize centrality into seventeen bins in $(-8, 9)$. Figure 4.4 is the histogram of the number of workers by centrality bin, which shows that the health care personnel’s centrality varies from -5 to 6 . We specify bin $[0, 1)$ as the base level which contains both weighted mean and median. Specifically, we run the regression with centrality bins:

$$\mathbf{1}.vax_i = \beta_0 + \beta_{1(bin)} \mathbf{1}.centrality_{i(bin)} + \beta_2 \mathbf{1}.hcp_i + \beta_3 X_i + state_i + \epsilon_i \quad (4.2)$$

where $\mathbf{1}.vax_i$ is the vaccine uptake indicator, $\mathbf{1}.centrality_{i(bin)}$ is the centrality bin indicator for every bin but the base level, $exposure_i$ is the occupation’s standardized disease exposure, $\mathbf{1}.hcp_i$ is the health care personnel indicator, X_i is a vector of the demographics and health-related characteristics, $state_i$ is the state fixed effects, and ϵ_i is the error term. We report estimates with BRFSS sampling weights and state-level cluster-robust standard errors.

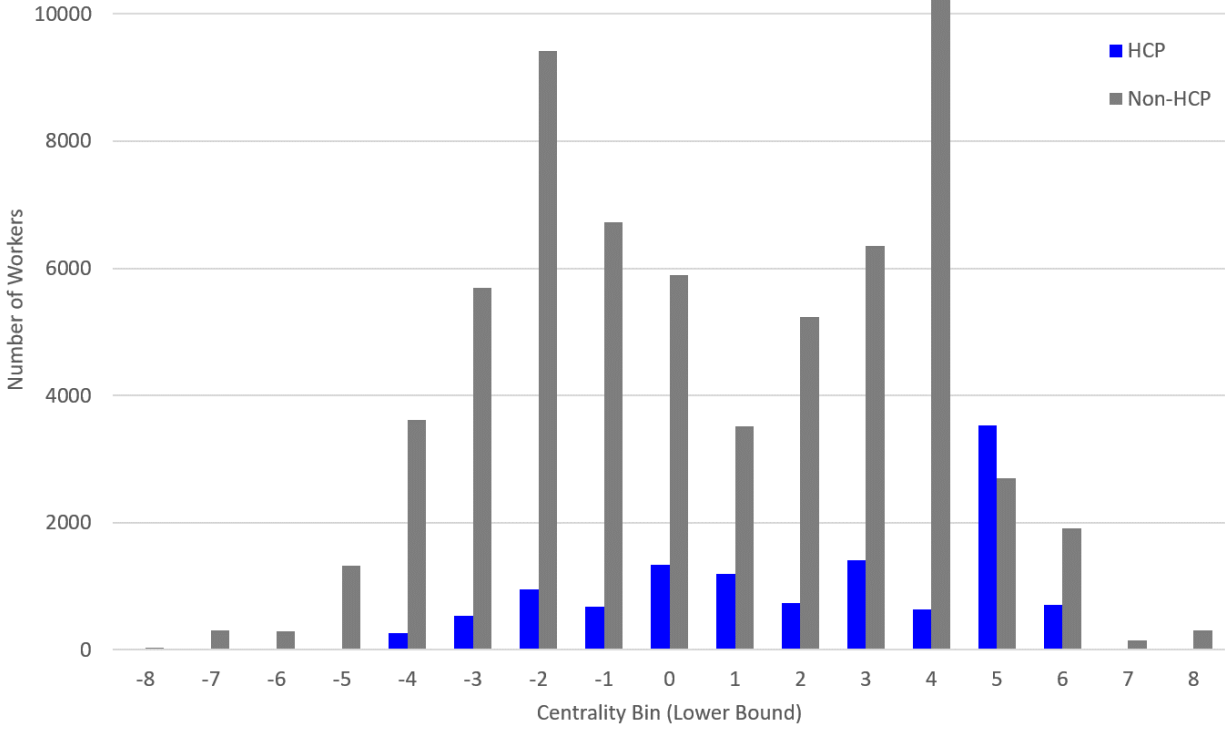


Figure 4.4: The Number of Workers by Centrality Bin: Health Care Personnel (HCP) vs. Non-HCP

The key assumption is that an individual’s flu vaccine uptake does not affect her occupation choice. The challenge to the assumption is that there may be unobservables that simultaneously influence vaccine uptake and career choice. For example, certain occupations require workers to get vaccinated, such as doctors and nurses, and people who hold strong beliefs against vaccines may self-select to avoid these occupations. Moreover, if these anti-vaccine people randomly self-select to non-health care occupations, their average centrality is likely to be lower than the health care workers’, which biases the estimated impact of occupation centrality on vaccine uptake upward. That is if vaccination and centrality are positively correlated, and “positive self-selection” exists, we overestimate a positive coefficient and underestimate a negative coefficient in terms of the magnitude.

We control individuals’ heterogeneous vaccination cost and potential illness cost by X_i . X_i includes demographics, such as gender, age, race, education, income, and marital status, and health-related characteristics, such as high-risk condition, insurance status, access to

health care provider. Income and health-related information describe a person’s vaccination cost and potential illness cost if she contracts flu.

4.4 Results

Table 4.3 reports the main results of the effect of centrality on flu vaccine uptake. Columns (1)-(4) use the full sample. Column (5) includes health care personnel only. Column (6) excludes health care personnel. Table 4.4 presents estimates of the same regression models except specifying centrality as bins. Columns (1)-(3) use the full sample. Column (4) includes health care personnel only. Column (5) excludes health care personnel. All columns include seventeen bins for centrality while omitting the base level bin $[0, 1)$. Each coefficient of centrality bin is the point estimate of the difference in the probability of flu vaccine uptake between workers in that bin and workers at the base level. And the constant in column (1), 28.4%, represents the base-level workers’ average flu vaccination coverage. Figures C.2 to C.6 plot these coefficients of centrality bin.

First, centrality and flu vaccine uptake are positively correlated across all specifications in Table 4.3, which is consistent with the predictions of models assuming a complete network. However, if we control for whether the worker is a health care personnel (columns (3)-(6)), the coefficient is no longer statistically significant. Also, the coefficient of health care personnel in column (3) suggests that they are 18.39% more likely to get vaccinated than others, which is statistically significant at 1% level. Such finding suggests that health care personnel contributes significantly to the positive correlation. Plots of the coefficient estimates in Table 4.4 (Figures (C.2)-(C.6)) confirms the finding.

Secondly, Table 4.3 column (4) shows that the coefficient of the interaction term between centrality and health care personnel is positive and significant both statistically and economically, which means that health care personnel are more sensitive to centrality than non-health care personnel at the same centrality level. The reason could be that health care personnel have a good knowledge about the infection risk in social interactions and thus pay more attention to the risk.

Table 4.3: The Linear Model Estimates of the Effect of Centrality on Flu Vaccine Uptake

Dependent: Flu Vaccine Uptake						
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Full Sample	Full Sample	Full Sample	HCP	Non-HCP
Centrality	0.0189*** (0.0010)	0.0024** (0.0011)	0.0015 (0.0011)	0.0008 (0.0011)	0.0040 (0.0038)	0.0009 (0.0011)
Exposure		0.0575*** (0.0036)	0.0207*** (0.0033)	0.0193*** (0.0034)	0.0252*** (0.0065)	0.0161*** (0.0041)
Health Care Personnel			0.1839*** (0.0089)	0.1743*** (0.0125)		
Centrality X HCP				0.0054* (0.0031)		
Constant	0.3182*** (0.0157)	0.0459** (0.0215)	0.0425* (0.0222)	0.0417* (0.0219)	0.0564 (0.0785)	0.0463** (0.0222)
Controls	No	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Observations	75712	75712	75712	75712	11997	63715

Source: BRFSS 2013 and O*NET. Controls include gender, age group, race/ethnicity group, income level, marital status, and indicators for high-risk conditions, having personal health care provider, and having medical insurance. ***, **, * means that the coefficient is statistically different from zero at the 1%, 5%, and 10% level. All models weighted with BRFSS weights. Standard errors clustered at the state-level and reported in parentheses. Mean calculated as the weighted mean of flu vaccine uptake. Percentage change calculated as the fraction of the coefficient of centrality over mean and multiplied by 100.

Table 4.4: The Bin Model Estimates of the Effect of Centrality on Flu Vaccine Uptake

Dependent: Flu Vaccine Uptake					
	(1)	(2)	(3)	(4)	(5)
	Full Sample	Full Sample	Full Sample	HCP	Non-HCP
Centrality					
[-8, -7)	-0.1564*** (0.0326)	-0.1333*** (0.0240)	-0.1276*** (0.0252)		-0.1222*** (0.0234)
[-7, -6)	-0.0135 (0.0287)	0.0316 (0.0373)	0.0354 (0.0350)		0.0322 (0.0344)
[-6, -5)	-0.1087*** (0.0335)	-0.0892** (0.0323)	-0.0668** (0.0278)	0.0889 (0.1405)	-0.0673** (0.0289)
[-5, -4)	-0.0724*** (0.0241)	-0.0057 (0.0239)	-0.0074 (0.0263)	0.0370 (0.0765)	-0.0100 (0.0304)
[-4, -3)	0.0172 (0.0259)	0.0143 (0.0275)	0.0373 (0.0279)	-0.0260 (0.0506)	0.0420 (0.0331)
[-3, -2)	-0.0419** (0.0166)	-0.0020 (0.0189)	0.0052 (0.0203)	-0.0582* (0.0286)	0.0127 (0.0235)
[-2, -1)	0.0076 (0.0176)	0.0125 (0.0196)	0.0215 (0.0206)	0.0286 (0.0704)	0.0218 (0.0253)
[-1, 0)	0.0593*** (0.0202)	0.0532** (0.0192)	0.0567*** (0.0189)	0.0911*** (0.0290)	0.0535** (0.0197)
[1, 2)	0.0486** (0.0222)	0.0114 (0.0197)	0.0108 (0.0201)	-0.0537 (0.0455)	0.0237 (0.0286)
[2, 3)	0.1220*** (0.0330)	0.0409 (0.0283)	0.0627** (0.0283)	0.0184 (0.0296)	0.0654* (0.0319)
[3, 4)	0.1021*** (0.0124)	0.0290** (0.0122)	0.0290** (0.0127)	0.0204 (0.0450)	0.0280* (0.0156)
[4, 5)	0.0684*** (0.0170)	-0.0071 (0.0159)	0.0117 (0.0170)	-0.0290 (0.0663)	0.0141 (0.0211)
[5, 6)	0.2231*** (0.0188)	0.0584*** (0.0184)	0.0509** (0.0209)	0.0529 (0.0349)	0.0290 (0.0337)
[6, 7)	0.1381*** (0.0249)	0.0321 (0.0238)	0.0150 (0.0261)	-0.0225 (0.0621)	0.0256 (0.0329)
[7, 8)	0.0207 (0.0909)	-0.0429 (0.0771)	-0.0026 (0.0747)	0.1350 (0.1589)	0.0027 (0.0801)
[8, 9)	0.1295** (0.0504)	0.0848* (0.0446)	0.0961** (0.0442)	0.6663*** (0.0567)	0.0953** (0.0420)
Health Care Personnel			0.1865*** (0.0100)		
Constant	0.2840*** (0.0213)	0.0335 (0.0290)	0.0248 (0.0303)	0.0777 (0.0852)	0.0258 (0.0341)
Controls	No	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	75712	75712	75712	11997	63715

Source: BRFSS 2013 and O*NET. Controls include gender, age group, race/ethnicity group, income level, marital status, and indicators for high-risk conditions, having personal health care provider, and having medical insurance. ***, **, * means that the coefficient is statistically different from zero at the 1%, 5%, and 10% level. All models weighted with BRFSS weights. Standard errors clustered at the state-level and reported in parentheses.

Thirdly, Table 4.4 shows that coefficients of centrality bins are not monotonically increasing in centrality, which is not consistent with the complete network models' predications. The non-monotonicity allows room for incomplete network models' explanations that some workers may behave strategically on vaccination decisions.

Lastly, Table 4.4 shows that variations are mostly driven by the end bins. The coefficient of bin $[-8,-7)$ is at least 12% smaller than the base level, while the coefficient of bin $[8,9)$ is at least 8% greater than the base level; both estimates are statistically significant. On the contrary, the middle bins' magnitudes of coefficients are relatively small. For example, in column (3), the differences in the coefficients of bins from -5 to 5 are within 10%, and these bins constitute 86.7% of all workers and 91.5% of non-health care workers.

4.5 Robustness checks

We choose two different subsets of the 22 descriptors mentioned in Table 4.1 to construct alternative centrality measures to check the robustness. We construct the “context” measure with 6 descriptors about work context and the “activity” measure with 16 descriptors about work activities. Table 4.5 replicates Table 4.3 by substituting centrality with the “context” measure. Table 4.6 does the same exercise with the “activity” measure. We find that the coefficient estimates are generally consistent with our finding with the original centrality measure. Column (1) shows that all three centrality measures are positively correlated with vaccine uptake in the baseline estimation. Columns (2-4) show that the coefficient of centrality moves closer to zero if we add more controls, while the coefficients of exposure and health care personnel indicator are always statistically significant at 1% level.

4.6 Conclusion

Our major finding is that workers' social centrality and flu vaccine uptake are positively correlated, which confirms the hypothesis that high-centrality individuals are more likely to get vaccinated than low-centrality individuals. The finding is consistent with the complete network models' predictions (Hethcote, 2000, Goyal and Vigier, 2015). Moreover, we find

Table 4.5: The Linear Model Estimates of the Effect of Centrality (Context) on Flu Vaccine Uptake

Dependent: Flu Vaccine Uptake						
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Full Sample	Full Sample	Full Sample	HCP	Non-HCP
Centrality (Context)	0.0312*** (0.0031)	-0.0021 (0.0036)	-0.0023 (0.0038)	-0.0035 (0.0038)	-0.0013 (0.0122)	-0.0032 (0.0038)
Exposure		0.0599*** (0.0043)	0.0225*** (0.0039)	0.0199*** (0.0040)	0.0292*** (0.0078)	0.0177*** (0.0046)
Health Care Personnel			0.1846*** (0.0088)	0.1686*** (0.0150)		
Centrality X HCP				0.0147 (0.0087)		
Constant	0.3176*** (0.0157)	0.0402* (0.0216)	0.0383 (0.0222)	0.0375 (0.0221)	0.0428 (0.0788)	0.0429* (0.0224)
Controls	No	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Observations	75712	75712	75712	75712	11997	63715

Source: BRFSS 2013 and O*NET. Controls include gender, age group, race/ethnicity group, income level, marital status, and indicators for high-risk conditions, having personal health care provider, and having medical insurance. ***, **, * means that the coefficient is statistically different from zero at the 1%, 5%, and 10% level. All models weighted with BRFSS weights. Standard errors clustered at the state-level and reported in parentheses. Mean calculated as the weighted mean of flu vaccine uptake. Percentage change calculated as the fraction of the coefficient of centrality over mean and multiplied by 100.

Table 4.6: The Linear Model Estimates of the Effect of Centrality (Activity) on Flu Vaccine Uptake

Dependent: Flu Vaccine Uptake						
	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Full Sample	Full Sample	Full Sample	HCP	Non-HCP
Centrality (Activity)	0.0195*** (0.0008)	0.0031*** (0.0010)	0.0020** (0.0010)	0.0014 (0.0010)	0.0044 (0.0037)	0.0015 (0.0009)
Exposure		0.0576*** (0.0035)	0.0207*** (0.0033)	0.0197*** (0.0033)	0.0256*** (0.0063)	0.0162*** (0.0041)
Health Care Personnel			0.1835*** (0.0089)	0.1765*** (0.0118)		
Centrality X HCP				0.0048 (0.0031)		
Constant	0.3208*** (0.0157)	0.0469** (0.0212)	0.0433* (0.0219)	0.0426* (0.0216)	0.0567 (0.0773)	0.0473** (0.0219)
Controls	No	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes	Yes
Observations	75712	75712	75712	75712	11997	63715

Source: BRFSS 2013 and O*NET. Controls include gender, age group, race/ethnicity group, income level, marital status, and indicators for high-risk conditions, having personal health care provider, and having medical insurance. ***, **, * means that the coefficient is statistically different from zero at the 1%, 5%, and 10% level. All models weighted with BRFSS weights. Standard errors clustered at the state-level and reported in parentheses. Mean calculated as the weighted mean of flu vaccine uptake. Percentage change calculated as the fraction of the coefficient of centrality over mean and multiplied by 100.

that flu vaccine uptake is not monotonically increasing in centrality, which allows room for incomplete network models' explanations (Neilson and Xiao, 2018, Xiao, 2018).

We also find that health care personnel contributes significantly to the the positive correlation because the coefficient of centrality moves closer to zero if we control for whether the worker is a health care personnel. Such result suggests that high-centrality non-health care workers are under-vaccinated, which indicates potential targeting options for future vaccination policies and campaigns.

Finally, we call for a more sophisticated method to develop the centrality scores. Though we apply an effective method to construct the centrality measure, the primary objective of O*NET is not for the study of contagious diseases. Thus, authorities and researchers should work together to collect data related to disease exposure and social activeness. Moreover, a comprehensive survey should also consider the behavioral response to flu contraction. For example, whether the workplace will be closed once there is an epidemic, such as schools; and whether the worker will be stay at home once she catches the flu.

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Appendices

A Chapter 2 Appendix

A.1 Proofs

Lemma .1. *Assume that $\beta t < 2/3$. In a 3-person homogeneous complete network, the socially-optimal set of vaccinated individuals is given by*

$$S^{**} = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, p_{\{j,k\}}^i] \\ \{j, k\} & \text{if } \frac{c}{D} \in (p_{\{j,k\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i] \\ \{j\} & \text{if } \frac{c}{D} \in (2p_{\{j\}}^i - p_{\{j,k\}}^i, 3p_{\emptyset}^i - 2p_{\{j\}}^i] \\ \emptyset & \text{if } \frac{c}{D} \in (3p_{\emptyset}^i - 2p_{\{j\}}^i, \infty) \end{cases} \quad (2.2)$$

Proof. Without loss of generality, we can normalize $D = 1$. It is straightforward to show that $\Pi_{\{1,2,3\}} \geq \Pi_{\{j,k\}}$ if and only if $c \geq p_{\{j,k\}}^i$, that $\Pi_{\{j,k\}} \geq \Pi_{\{j\}}$ if and only if $c \geq 2p_{\{j\}}^i - p_{\{j,k\}}^i$, and that $\Pi_{\{j\}} \geq \Pi_{\emptyset}$ if and only if $c \geq 3p_{\emptyset}^i - 2p_{\{j\}}^i$.

It remains to show that $p_{\{j,k\}}^i < 2p_{\{j\}}^i - p_{\{j,k\}}^i < 3p_{\emptyset}^i - 2p_{\{j\}}^i$. The first inequality holds because $p_{\{j,k\}}^i < p_{\{j\}}^i$ implies $p_{\{j,k\}}^i < p_{\{j,k\}}^i + 2(p_{\{j\}}^i - p_{\{j,k\}}^i) = 2p_{\{j\}}^i - p_{\{j,k\}}^i$. For the second inequality, compute

$$\begin{aligned} 3p_{\emptyset}^i - 2p_{\{j\}}^i - (2p_{\{j\}}^i - p_{\{j,k\}}^i) &= 3p_{\emptyset}^i - 4p_{\{j\}}^i + p_{\{j,k\}}^i \\ &= 3(2(1-\beta)^2\beta(t+t^2-t^3) + (1-\beta)\beta^2(2t-t^2)) - 4(1-\beta)\beta t \\ &= \beta(1-\beta)t(6t-9t\beta-6t^2+6t^2\beta+2) \\ &= \beta(1-\beta)t[6(t-t^2)(1-\beta) + (2-3\beta t)]. \end{aligned}$$

The last line is positive because $t > 0$, $0 < \beta < 1$, and $\beta t < 2/3$. □

Lemma .2. *In a 3-person homogeneous complete network, the pure-strategy equilibrium set of vaccinated individuals is given by*

$$S^* = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, p_{\{j,k\}}^i] \\ \{j, k\} & \text{if } \frac{c}{D} \in (p_{\{j,k\}}^i, p_{\{j\}}^i] \\ \{j\} & \text{if } \frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i] \\ \emptyset & \text{if } \frac{c}{D} \in (p_{\emptyset}^i, \infty) \end{cases} \quad (2.3)$$

Proof. This follows immediately from the definition of the Nash equilibrium: $i \in S^*$ when $c \leq p_{S^*-i}^i D$ and $i \notin S^*$ when $c > p_{S^*}^i D$. $\square$

Proposition .3. *Assume that $\beta t < 2/3$. In a 3-person homogeneous complete network, too few individuals get vaccinated in a pure-strategy equilibrium when the vaccination cost $\frac{c}{D} \in (p_{\{j\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i] \cup (p_{\emptyset}^i, 3p_{\emptyset}^i - 2p_{\{j\}}^i]$. Otherwise, the correct number of individuals get vaccinated.*

Proof. First show that $p_{\{j\}}^i < 2p_{\{j\}}^i - p_{\{j,k\}}^i$ and $p_{\emptyset}^i < 3p_{\emptyset}^i - 2p_{\{j\}}^i$. To establish the first inequality, note that $2p_{\{j\}}^i - p_{\{j,k\}}^i = p_{\{j\}}^i + (p_{\{j\}}^i - p_{\{j,k\}}^i) > p_{\{j\}}^i$. And for the second inequality, note that $3p_{\emptyset}^i - 2p_{\{j\}}^i = p_{\emptyset}^i + 2(p_{\emptyset}^i - p_{\{j\}}^i) > p_{\emptyset}^i$.

Then we show that different relationships between the two bounds in the middle can lead to consistent results. If $2p_{\{j\}}^i - p_{\{j,k\}}^i \leq p_{\emptyset}^i$, then for the first interval, $(p_{\{j\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i] \subset (p_{\{j\}}^i, p_{\emptyset}^i]$ with $S^* = \{j\}$ on this interval, and $(p_{\{j\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i] \subset (p_{\{j,k\}}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i]$ with $S^{**} = \{j, k\}$ on this interval. And the second interval follows from direct comparison of expressions (2.2) and (2.3). If $2p_{\{j\}}^i - p_{\{j,k\}}^i > p_{\emptyset}^i$, then the union of the two intervals is $(p_{\{j\}}^i, 3p_{\emptyset}^i - 2p_{\{j\}}^i]$. Break it down into three regions. For $\frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i]$, we know $S^{**} = \{j, k\}$, but $S^* = \{j\}$. For $\frac{c}{D} \in (p_{\emptyset}^i, 2p_{\{j\}}^i - p_{\{j,k\}}^i]$, again $S^{**} = \{j, k\}$, but $S^* = \emptyset$. For $\frac{c}{D} \in (2p_{\{j\}}^i - p_{\{j,k\}}^i, 3p_{\emptyset}^i - 2p_{\{j\}}^i]$, we know $S^{**} = \{j\}$, but $S^* = \emptyset$. And $\beta t < 2/3$ guarantees the existence of the last interval, as shown in the proof of Lemma 1. $\square$

Lemma .4. *In a 3-person homogeneous star network, the socially optimal set of vaccinated individuals is given by*

$$S^{**} = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, \beta] \\ \{1\} & \text{if } \frac{c}{D} \in (\beta, p_\emptyset^1 + 2(p_\emptyset^i - \beta)] \\ \emptyset & \text{if } \frac{c}{D} \in (p_\emptyset^1 + 2(p_\emptyset^i - \beta), \infty) \end{cases} \quad (2.5)$$

Proof. Begin by showing that if $\Pi_{\{i,j\}} < \Pi_{\{1\}}$ then $\Pi_{\{i,j\}} > \Pi_{\{1,2,3\}}$. The former occurs if $2c + \beta D < c + 2\beta D$ which holds if and only if $c < \beta D$. But then $3c < 2c + \beta D$, and therefore vaccinating two people cannot be optimal. Next, note that $\Pi_{\{i\}} = c + 2p_{\{j\}}^i D > c + 2\beta D > \Pi_{\{1\}}$ since $p_{\{j\}}^i > \beta$, so it is never socially optimal for player $i \neq 1$ to get vaccinated when player 1 does not. That leaves the potential socially-optimal vaccination sets to be $S^{**} = \{1, 2, 3\}$, $S^{**} = \{1\}$, and $S^{**} = \emptyset$. The remainder of the proof follows from expression (4). $\square$

Lemma .5. *In a 3-person homogeneous star network, the pure-strategy equilibrium set of vaccinated individuals is given by*

$$S^* = \begin{cases} \{1, 2, 3\} & \text{if } \frac{c}{D} \in [0, \beta] \\ \{1\} \text{ or } \{2, 3\} & \text{if } \frac{c}{D} \in (\beta, p_{\{j\}}^i] \\ \{1\} \text{ or } \{2\} \text{ or } \{3\} & \text{if } \frac{c}{D} \in (p_{\{j\}}^i, p_\emptyset^i] \\ \{1\} & \text{if } \frac{c}{D} \in (p_\emptyset^i, p_\emptyset^1] \\ \emptyset & \text{if } \frac{c}{D} \in (p_\emptyset^1, \infty) \end{cases} \quad (2.6)$$

Proof. Without loss of generality, we can normalize $D = 1$. As in Lemma 2.2, when $c \leq \beta$ everyone has a dominant strategy of vaccinating, and when $c > p_\emptyset^1$ everyone has a dominant strategy of not vaccinating.

When $\beta < c \leq p_\emptyset^1$ there exists an equilibrium in which only player 1 gets vaccinated. To see this, note that if 2 and 3 remain unvaccinated, if 1 also remains unvaccinated his probability of infection is $p_\emptyset^1 \geq c$, and so his best response is to vaccinate. When 1 vaccinates 2 and 3 each face the infection probability of $p_{\{1\}}^i = \beta < c$, and so they remain unvaccinated.

When $\beta < c \leq p_{\{j\}}^i$ there exists an equilibrium in which players 2 and 3 get vaccinated. When 1 does not get vaccinated but player j does, player i 's probability of infection is $p_j^i \geq c$ and so player i 's best response is to vaccinate. When both 2 and 3 vaccinate player 1's probability of infection is $\beta < c$ and so player 1's best response is to not vaccinate.

When $p_{\{j\}}^i < c \leq p_{\emptyset}^i$ there exist equilibria in which one of the peripheral players gets vaccinated and player 1 does not. The proof treats player 2 as the vaccinated player. If 1 and 3 remain unvaccinated, 2's infection probability is $p_{\emptyset}^i \geq c$ and so 2's best response is to vaccinate. If 2 gets vaccinated and 1 does not, 3's infection probability is $p_{\{j\}}^i < c$ and therefore player 3 remains unvaccinated. Finally, if 2 gets vaccinated and 3 does not, 1's probability of infection is $p_{\{j\}}^1 = p_{\{j\}}^i < c$ and so 1's best response is to remain unvaccinated. $\square$

Proposition .6. *In a 3-person homogeneous star network,*

- (a) *there exists a pure-strategy equilibrium in which too few individuals get vaccinated when $\frac{c}{D} \in (p_{\emptyset}^1, p_{\emptyset}^1 + 2(p_{\emptyset}^i - \beta)]$;*
- (b) *there exist pure-strategy equilibria in which the right number but the wrong set of individuals get vaccinated when $\frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i]$; and*
- (c) *there exists a pure-strategy equilibrium in which too many people get vaccinated when $\frac{c}{D} \in (\beta, p_{\{j\}}^i]$.*

Proof. The result follows from comparing expressions (2.5) and (3.2). $\square$

Proposition .7. *In a 3-person homogeneous star network,*

- (a) *$S^* = \{1\}$ is trembling-hand perfect when $\frac{c}{D} \in (\beta, p_{\emptyset}^1)$;*
- (b) *$S^* = \{2\}$ or $\{3\}$ is trembling-hand perfect when $\frac{c}{D} \in (p_{\{j\}}^i, p_{\emptyset}^i)$; and*
- (c) *$S^* = \{2, 3\}$ is trembling-hand perfect when $\frac{c}{D} \in (\beta, p_{\{j\}}^i)$.*

Proof. Consider an equilibrium allocation S^* and let γ , δ , and ϵ denote the trembling probabilities for players 1, 2, and 3, respectively. Normalize $D = 1$.

(a) Suppose that $c/D \in (\beta, p_\emptyset^1)$ and consider the equilibrium $S^* = \{1\}$. Player 1's expected loss from remaining unvaccinated is

$$\pi_N^1 = (1 - \delta)(1 - \epsilon)p_\emptyset^1 + \delta(1 - \epsilon)p_{\{2\}}^1 + (1 - \delta)\epsilon p_{\{3\}}^1 + \delta\epsilon\beta$$

and $\lim_{\delta, \epsilon \rightarrow 0} \pi_N^1 = p_\emptyset^1 > c$. Player 2's expected loss from remaining unvaccinated is

$$\pi_N^2 = (1 - \gamma)(1 - \epsilon)\beta + \gamma(1 - \epsilon)p_\emptyset^2 + (1 - \gamma)\epsilon\beta + \gamma\epsilon p_{\{3\}}^2,$$

and $\lim_{\gamma, \epsilon \rightarrow 0} \pi_N^2 = \beta < c$. Player 3's expected loss from remaining unvaccinated is

$$\pi_N^3 = (1 - \gamma)(1 - \delta)\beta + \gamma(1 - \delta)p_\emptyset^3 + (1 - \gamma)\delta\beta + \gamma\delta p_{\{2\}}^3,$$

and $\lim_{\gamma, \delta \rightarrow 0} \pi_N^3 = \beta < c$. Thus there exists a scalar $\eta > 0$ such that for all $0 < \gamma, \delta, \epsilon < \eta$ we have $\pi_N^2, \pi_N^3 < c$ and $\pi_N^1 > c$, and so player 1 vaccinates while 2 and 3 remain unvaccinated. This establishes that $S^* = \{1\}$ is trembling-hand perfect.

(b) Suppose that $c/D \in (p_{\{j\}}^i, p_\emptyset^i)$ and consider the equilibrium $S^* = \{2\}$. Player 1's payoff from remaining unvaccinated is

$$\pi_N^1 = (1 - \delta)(1 - \epsilon)p_{\{2\}}^1 + \delta(1 - \epsilon)p_\emptyset^1 + (1 - \delta)\epsilon\beta + \delta\epsilon p_{\{3\}}^1,$$

and $\lim_{\delta, \epsilon \rightarrow 0} \pi_N^1 = p_{\{2\}}^1 < c$. Player 2's expected loss from remaining unvaccinated is

$$\pi_N^2 = (1 - \gamma)(1 - \epsilon)p_\emptyset^2 + \gamma(1 - \epsilon)\beta + (1 - \gamma)\epsilon p_{\{3\}}^2 + \gamma\epsilon\beta,$$

and $\lim_{\gamma, \epsilon \rightarrow 0} \pi_N^2 = p_\emptyset^2 > c$. Player 3's expected loss from remaining unvaccinated is

$$\pi_N^3 = (1 - \gamma)(1 - \delta)p_{\{2\}}^3 + \gamma(1 - \delta)\beta + (1 - \gamma)\delta p_\emptyset^3 + \gamma\delta\beta,$$

and $\lim_{\gamma, \delta \rightarrow 0} \pi_N^3 = p_{\{2\}}^3 < c$. Thus there exists a scalar $\eta > 0$ such that for all $0 < \gamma, \delta, \epsilon < \eta$ we have $\pi_N^1, \pi_N^3 < c$ and $\pi_N^2 > c$, and so players 1 and 3 remain unvaccinated while 2 takes

the vaccine. This establishes that $S^* = \{2\}$ is trembling-hand perfect, and the proof that $S^* = \{3\}$ is trembling-hand perfect is similar.

(c) Suppose that $c/D \in (\beta, p_{\{j\}}^i)$ and consider the equilibrium $S^* = \{2, 3\}$. For player 1 the expected loss from remaining unvaccinated is

$$\pi_N^1 = (1 - \delta)(1 - \epsilon)\beta + \delta(1 - \epsilon)p_{\{3\}}^1 + \epsilon(1 - \delta)p_{\{2\}}^1 + \delta\epsilon p_{\emptyset}^1,$$

and $\lim_{\delta, \epsilon \rightarrow 0} \pi_N^1 = \beta < c$. For player 2 the expected loss from remaining unvaccinated is

$$\pi_N^2 = (1 - \gamma)(1 - \epsilon)p_{\{3\}}^2 + \gamma(1 - \epsilon)\beta + (1 - \gamma)\epsilon p_{\emptyset}^2 + \gamma\epsilon p_{\{1\}}^2,$$

and $\lim_{\gamma, \epsilon \rightarrow 0} \pi_N^2 = p_{\{3\}}^2 > c$. By the same analysis $\lim_{\gamma, \delta \rightarrow 0} \pi_N^3 = p_{\{2\}}^3 > c$. Thus there exists a scalar $\eta > 0$ such that for all $0 < \gamma, \delta, \epsilon < \eta$ we have $\pi_N^2, \pi_N^3 > c$ and $\pi_N^1 < c$, and so players 2 and 3 vaccinate while 1 remains unvaccinated. This establishes that $S^* = \{2, 3\}$ is trembling-hand perfect. $\square$

Proposition .8. *In a 3-person complete network with $D_1 > D_2 = D_3$, there exists a pure-strategy equilibrium in which the right number but the wrong set of individuals get vaccinated when $c \in \left(\beta D_1, p_{\{3\}}^2 D_2\right] \cup \left(p_{\{3\}}^2 D_1, p_{\emptyset}^2 D_2\right]$, given the existence of such intervals.*

Proof. First show that for $c \in \left(\beta D_1, p_{\{3\}}^2 D_2\right]$, $S^* = \{2, 3\}$ but $S^{**} = \{1, 2\}$ or $\{1, 3\}$. The vaccination set $\{2, 3\}$ is a Nash equilibrium because player 2 and 3 will not forgo vaccination for $c \leq p_{\{3\}}^2 D_2 = p_{\{2\}}^3 D_3$, and player 1 will not vaccinate for $c > \beta D_1$. However, $\Pi_{\{2,3\}} = 2c + \beta D_1 > 2c + \beta D_2 = \Pi_{\{1,3\}} = \Pi_{\{1,2\}}$, and we can find that $\{1, 3\}$ and $\{1, 2\}$ are socially optimal by comparing with other vaccination sets.

Next show that for $c \in \left(p_{\{3\}}^2 D_1, p_{\emptyset}^2 D_2\right]$, $S^* = \{2\}$ or $\{3\}$, but $S^{**} = \{1\}$. Consider the vaccination set $\{2\}$. It is an equilibrium because player 2 will not forgo vaccination for $c \leq p_{\emptyset}^2 D_2$, and player 1 will not vaccinate for $c > p_{\{2\}}^1 D_1$. Also, $p_{\{2\}}^3 = p_{\{2\}}^1$ and $D_3 < D_1$, and so player 3 also forgoes vaccination. However, $\Pi_{\{2\}} = c + p_{\{2\}}^3 D_3 + p_{\{1\}}^1 D_1 = c + p_{\{1\}}^3 (D_3 + D_1) > c + 2p_{\{1\}}^3 D_3 = \Pi_{\{1\}}$, and we can find that $\{1\}$ is socially optimal by comparing with other vaccination sets. The proof for $S^* = \{3\}$ is similar. $\square$

Proposition .9. *In a 3-person complete network with $c_1 < c_2 = c_3$, there exists a pure-strategy equilibrium in which the right number but the wrong set of individuals get vaccinated when $\frac{c_1}{D}, \frac{c_2}{D} \in (\beta, p_{\{3\}}^2]$ or $\frac{c_1}{D}, \frac{c_2}{D} \in (p_{\{3\}}^2, p_{\emptyset}^2]$, given the existence of such intervals.*

Proof. Note that $D_1 = D_2 = D_3$ indicates $c/D_1 < c/D_2 = c/D_3$. Thus, the proof is identical to Proposition 2.8 because the ratio of c/D determines the intervals of pure-strategy equilibria and social optima. $\square$

Proposition .10. *In a 3-person complete network with $t_1 > t_2 = t_3$, there exists a Nash equilibrium in which the wrong person gets vaccinated when $\frac{c}{D} \in (p_{\{2\}}^1, p_{\emptyset}^2]$, given the existence of such an interval.*

Proof. Assume $t_1 > t_2 = t_3 = t$. First compute $p_{\{2\}}^1 = p_{\{3\}}^1 = \beta + (1 - \beta)\beta t_1 > \beta + (1 - \beta)\beta t = p_{\{1\}}^2 = p_{\{3\}}^2$. Given these probabilities, when only one individual gets vaccinated, social cost is minimized when that vaccine goes to agent 1. When no one takes the vaccine, $p_{\emptyset}^1 = \beta + 2(1 - \beta)^2\beta(t_1 + t_1t - t_1^2t) + (1 - \beta)\beta^2(2t_1 - t_1^2)$, while $p_{\emptyset}^2 = p_{\emptyset}^3 = \beta + 2(1 - \beta)^2\beta(t + t_1t - t^2t_1) + (1 - \beta)\beta^2(t + t_1 - t_1t)$. It is straightforward to show that when $t_1 > t$, $p_{\emptyset}^1 > p_{\emptyset}^2 = p_{\emptyset}^3$.

Now assume that the interval $(p_{\{2\}}^1, p_{\emptyset}^2]$ is nonempty. That there exist values of t , t_1 , and β for which this is true can be shown by example: when $t = 0.3$, $t_1 = 0.4$, and $b = 0.6$, one can compute $p_{\{2\}}^1 = 0.696$ and $p_{\emptyset}^2 = 0.757$. When $\frac{c}{D} \in (p_{\{2\}}^1, p_{\emptyset}^2]$, the vaccination set $S^* = \{2\}$ is a Nash equilibrium. The fact that $c < p_{\emptyset}^2 D$ means that 2's best response to nobody else vaccinating is to take the vaccine, and the fact that $c > p_{\{2\}}^1 > p_{\{2\}}^3$ means that neither 1 nor 3 choose to vaccinate when 2 takes the vaccine. As already argued, this is inefficient because expected social cost is lower when 1 takes the vaccine instead. $\square$

Proposition .11. *In a 3-person complete network with $\beta_1 > \beta_2 = \beta_3$, there exists a pure-strategy equilibrium in which too many individuals get vaccinated when $c/D \in (\max\{\beta_1, 2p_{\{1\}}^2 - \beta_2\}, p_{\{2\}}^3]$, and the right number but the wrong set of individuals get vaccinated when $c/D \in (p_{\{2\}}^1, p_{\emptyset}^2]$, given the existence of such intervals.*

Proof. Assume that $\beta_1 > \beta_2 = \beta_3 = \beta$. To begin, compute $p_{\{2\}}^1 = \beta_1 + (1 - \beta_1)\beta t$, $p_{\{2\}}^3 = p_{\{3\}}^2 = \beta + (1 - \beta)\beta_1 t$, and $p_{\emptyset}^2 = \beta + (1 - \beta)[(1 - \beta)\beta_1 + (1 - \beta_1)\beta](t + t^2 - t^3) +$

$(1 - \beta) \beta \beta_1 (2t - t^2)$. Note that $p_{\{2\}}^3 < p_{\{2\}}^1$ because $\beta_1 + (1 - \beta_1) \beta t - (\beta + (1 - \beta) \beta_1 t) = (\beta_1 - \beta)(1 - t) > 0$. To establish that the two intervals in question can be nonempty for some parameters, set $\beta = 0.1$, $\beta_1 = 0.21$, and $t = 0.6$. The resulting intervals are $\left(\max\left\{\beta_1, 2p_{\{1\}}^2 - \beta\right\}, p_{\{2\}}^3\right] = (\max\{0.21, 0.208\}, 0.2134]$ and $\left(p_{\{2\}}^1, p_{\{\emptyset\}}^2\right] = (0.2574, 0.29533]$. For the remainder of the proof normalize $D = 1$.

Now assume that the interval $\left(\max\left\{\beta_1, 2p_{\{1\}}^2 - \beta\right\}, p_{\{2\}}^3\right]$ is nonempty. We demonstrate that there exists a Nash equilibrium in which $S^* = \{2, 3\}$. Player 1 chooses not to vaccinate because $c > \beta_1 = p_{\{2,3\}}^1$, and players 2 and 3 choose to vaccinate because $c \leq p_{\{2\}}^3 = p_{\{3\}}^2$. Compute the social losses $\Pi_{\{1\}} = c + 2p_{\{1\}}^2$, $\Pi_{\{2,3\}} = 2c + \beta_1$, and $\Pi_{\{1,3\}} = 2c + \beta$. It is enough to show that $\Pi_{\{1\}} < \Pi_{\{1,3\}}$, but this holds because $2c + \beta > c + (2p_{\{1\}}^2 - \beta) + \beta = c + 2p_{\{1\}}^2$.

Next assume that the interval $\left(p_{\{2\}}^1, p_{\{\emptyset\}}^2\right]$ is nonempty. We first show that $S^* = \{2\}$ is a Nash equilibrium. Player 2 vaccinates because $c \leq p_{\{\emptyset\}}^2$, but players 1 and 3 do not vaccinate because $p_{\{2\}}^3 < p_{\{2\}}^1 < c$. Thus, $\{2\}$ constitutes a Nash equilibrium vaccination allocation. However, $\Pi_{\{1\}} = c + 2p_{\{2\}}^3 < c + p_{\{2\}}^3 + p_{\{2\}}^1 = \Pi_{\{2\}}$, and so the Nash equilibrium is not socially optimal. □

Proposition .12. *In a 3-person star network with $D_1 = 0 < D$, $c_1 = c - \beta D$ for $c > \beta D$, there exist unique inefficient equilibrium outcomes*

- (a) *that too many individuals get vaccinated when $\frac{c}{D} \in \left(\beta, p_{\{3\}}^2\right]$; and*
- (b) *that the right number but the wrong set of individuals get vaccinated when $\frac{c}{D} \in \left(p_{\{3\}}^2, p_{\{\emptyset\}}^2\right]$.*

Proof. For the over-vaccination outcome (a), show that for $c/D \in \left(\beta, p_{\{3\}}^2\right]$, $S^* = \{2, 3\}$ but $\Pi_{\{2,3\}} > \Pi_{\{1\}}$. First note that forgoing the vaccination is a strictly dominant strategy for player 1 because the cost $c_1 > 0$ but the benefit is zero. Next, $\{2, 3\}$ is a Nash vaccination set because agents 2 and 3 will not forgo vaccination for $c \leq p_{\{3\}}^2 = p_{\{2\}}^3$. Moreover, since $c < p_{\{3\}}^2 < p_{\{\emptyset\}}^2$ and $c < p_{\{2\}}^3 < p_{\{\emptyset\}}^3$, there is no equilibrium in which none of the players vaccinates. Thus, $S^* = \{2, 3\}$ is the unique Nash equilibrium. Lastly, $\{2, 3\}$ is not socially optimal because $\Pi_{\{2,3\}} = 2c = 2(c_1 + \beta D) > c_1 + 2\beta D = \Pi_{\{1\}}$.

For the wrong-vaccination outcome (b), show that for $c/D \in \left(p_{\{3\}}^2, p_{\{\emptyset\}}^2\right]$, $S^* = \{2\}$ or $\{3\}$ but $\Pi_{\{2\}} = \Pi_{\{3\}} > \Pi_{\{1\}}$. Without loss of generality, consider the vaccination set $S =$

$\{2\}$. Player 2 does not deviate, given the equilibrium choices of the other two, because $c \leq p_\emptyset^2$. Agent 3's best response is to remain unvaccinated because $c > p_{\{3\}}^2 = p_{\{2\}}^3$, and 1 remains unvaccinated because forgoing vaccination is a dominant strategy. Thus, $S^* = \{2\}$ and $S^* = \{3\}$ are Nash equilibrium vaccination sets. Agent 1's dominant strategy leaves $\{2, 3\}$ as the only other possible Nash equilibrium vaccination set, but 3's best response to 2's vaccination is to forgo a vaccination, as already discussed. Therefore $\{2\}$ and $\{3\}$ are the only Nash equilibrium vaccination sets. Neither of them are socially optimal because $\Pi_{\{2\}} = c + p_{\{3\}}^2 D = c_1 + \beta D + [\beta + (1 - \beta)\beta t] D = c_1 + 2\beta D + (1 - \beta)\beta t D > c_1 + 2\beta D = \Pi_{\{1\}}$. $\square$

Proposition .13. *In a 3-person homogeneous star network, a subsidy s to the central player that incurs an administrative cost g constitutes a potential social improvement if*

- (a) $s \geq c - p_\emptyset^1 D$ and $g \leq [p_\emptyset^1 + 2(p_\emptyset^i - \beta)] D - c$ when $\frac{c}{D} \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$;
- (b) $s \geq c - p_{\{j\}}^i D$ and $g \leq 2(p_{\{j\}}^i - \beta) D$ when $\frac{c}{D} \in (p_{\{j\}}^i, p_\emptyset^i]$;
- (c) $s \geq c - \beta D$ and $g \leq c - \beta D$ when $\frac{c}{D} \in (\beta, p_{\{j\}}^i]$.

Proof. For each case we must show that $s \geq c - p_{\bar{S}}^1 D$ and $g \leq \Pi_{\bar{S}} - \Pi_{\{1\}}$, where $\bar{S}$ is the vaccination set in the worst equilibrium. Without loss of generality, normalize $D = 1$.

When $c \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$, the undesirable allocation is $\bar{S} = \emptyset$. The subsidy $s \geq c - p_\emptyset^1 = c - p_{\bar{S}}^1$, which satisfies the first condition. Also, the administrative cost $g \leq p_\emptyset^1 + 2(p_\emptyset^i - \beta) - c = (p_\emptyset^1 + 2p_\emptyset^i) - (c + 2\beta) = \Pi_\emptyset - \Pi_{\{1\}} = \Pi_{\bar{S}} - \Pi_{\{1\}}$, which satisfies the second condition.

When $c \in (p_{\{j\}}^i, p_\emptyset^i]$, the undesirable allocation is either $\bar{S} = \{2\}$ or $\bar{S} = \{3\}$. The subsidy $s \geq c - p_{\{j\}}^i = c - p_{\bar{S}}^1$, which satisfies the first condition. Also, the administrative cost $g \leq 2(p_{\{j\}}^i - \beta) = (c + 2p_{\{j\}}^i) - (c + 2\beta) = \Pi_{\{2\}} - \Pi_{\{1\}} = \Pi_{\bar{S}} - \Pi_{\{1\}}$, which satisfies the second condition.

When $c \in (\beta, p_{\{j\}}^i]$, the undesirable allocation is $\bar{S} = \{2, 3\}$. The subsidy $s \geq c - \beta = c - p_{\{2,3\}}^1 = c - p_{\bar{S}}^1$, which satisfies the first condition. Also, the administrative cost $g \leq c - \beta = (2c + \beta) - (c + 2\beta) = \Pi_{\{2,3\}} - \Pi_{\{1\}} = \Pi_{\bar{S}} - \Pi_{\{1\}}$, which satisfies the second condition. $\square$

Proposition .14. *In a 3-person homogeneous star network, a fine f to the central player that incurs an administrative cost g constitutes a potential social improvement if*

- (a) $f \geq c - p_\emptyset^1 D$ and $g \leq [p_\emptyset^1 + 2(p_\emptyset^i - \beta)] D - c$ when $\frac{c}{D} \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$;
- (b) $f \geq c - p_{\{j\}}^i D$ and $g \leq 2(p_{\{j\}}^i - \beta) D$ when $\frac{c}{D} \in (p_{\{j\}}^i, p_\emptyset^i]$;
- (c) $f \geq c - \beta D$ and $g \leq c - \beta D$ when $\frac{c}{D} \in (\beta, p_{\{j\}}^i]$.

Proof. For each case we must show that $f \geq c - p_\emptyset^1 D$ and $g \leq \Pi_{\bar{S}} - \Pi_{\{1\}}$. The proof follows the same process as in the proof above for Proposition 2.13 by substituting s with f . $\square$

Proposition .15. *In a 3-person homogeneous star network, assuming the administrative cost g is sufficiently small, the following policies constitute potential social improvements:*

- (a) *an untargeted vaccination subsidy or nonvaccination fine when $\frac{c}{D} \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$;*
- (b) *an untargeted vaccination tax or nonvaccination reward when $\frac{c}{D} \in (\beta, p_\emptyset^i]$.*

Proof. First normalize $D = 1$. A vaccination set S^* is a Nash equilibrium with an untargeted vaccination subsidy of s if for all $i \in S^*$ we have $c - s \leq p_{S^* - i}^i$, and for all $i \notin S^*$ we have $c - s > p_{S^*}^i$. A vaccination set S^* is a Nash equilibrium with an untargeted nonvaccination fine of f if for all $i \in S^*$ we have $c \leq p_{S^* - i}^i + f$, and for all $i \notin S^*$ we have $c > p_{S^*}^i + f$. Consequently, if the untargeted subsidy s makes S^* an equilibrium, so does the untargeted nonvaccination fine of the same size, $f = s$.

Suppose that $c \in (p_\emptyset^1, p_\emptyset^1 + 2(p_\emptyset^i - \beta)]$. By Proposition 2.6 this is a situation in which there are too few vaccinations; that is, $S^{**} = \{1\}$ but $S^* = \emptyset$. Setting $s \in [c - p_\emptyset^1, c - p_\emptyset^i)$ means that $s > 0$ and the policy is a subsidy. The unique Nash equilibrium with the subsidy generates expected social cost, gross of the administrative cost, of $\Pi_{\{1\}} = c + 2\beta$ and the unique Nash equilibrium without the subsidy generates expected social cost of $\Pi_\emptyset = p_\emptyset^1 + 2p_\emptyset^i$. Compute $\Pi_\emptyset - \Pi_{\{1\}} = p_\emptyset^1 + 2p_\emptyset^i - c - 2\beta > p_\emptyset^1 + 2p_\emptyset^i - p_\emptyset^1 - 2\beta = 2(p_\emptyset^i - \beta) > 0$. If $g < \Pi_\emptyset - \Pi_{\{1\}}$ the subsidy constitutes a potential social improvement. By the same analysis, a fine $f \in [c - p_\emptyset^1, c - p_\emptyset^i)$ also constitutes a potential social improvement.

Next suppose that $c \in (p_{\{j\}}^i, p_\emptyset^i]$. By Proposition 2.6 this is a situation in which there is the right number but wrong set of vaccinations; that is, $S^{**} = \{1\}$ but $S^* = \{2\}$ or

$\{3\}$. Setting $s \in [c - p_\emptyset^1, c - p_\emptyset^i)$ means that $s < 0$ so the policy is a tax. The unique Nash equilibrium with the subsidy generates expected social cost, gross of the administrative cost, of $\Pi_{\{1\}} = c + 2\beta$ and the worst Nash equilibrium without the subsidy generates expected social cost of $\Pi_{\{2\}} = c + 2p_{\{j\}}^i$. Compute $\Pi_{\{2\}} - \Pi_{\{1\}} = c + 2p_{\{j\}}^i - c - 2\beta = 2(p_{\{j\}}^i - \beta) > 0$. If $g < \Pi_{\{2\}} - \Pi_{\{1\}}$ the subsidy constitutes a potential social improvement. By the same analysis, a fine $f \in [c - p_\emptyset^1, c - p_\emptyset^i)$ also constitutes a potential social improvement, and this fine is negative, and should thus be interpreted as a nonvaccination reward.

Finally, suppose that $c \in (\beta, p_{\{j\}}^i]$. By Proposition 2.6 this is a situation in which there are too many vaccinations; that is, $S^{**} = \{1\}$ but $S^* = \{2, 3\}$. Setting $s \in [c - p_\emptyset^1, c - p_\emptyset^i)$ means that $s < 0$ because $p_{\{j\}}^i < p_\emptyset^i$, so the policy is a tax. The unique Nash equilibrium with the subsidy generates expected social cost, gross of the administrative cost, of $\Pi_{\{1\}} = c + 2\beta$ and the worst Nash equilibrium without the subsidy generates expected social cost of $\Pi_{\{2\}} = 2c + \beta$. Compute $\Pi_{\{2,3\}} - \Pi_{\{1\}} = 2c + \beta - c - 2\beta = c - \beta > 0$. If $g < \Pi_{\{2,3\}} - \Pi_{\{1\}}$ the subsidy constitutes a potential social improvement. By the same analysis, a fine $f \in [c - p_\emptyset^1, c - p_\emptyset^i)$ also constitutes a potential social improvement, and this fine is negative, and should thus be interpreted as a nonvaccination reward.

□

Proposition .16. *For any n -person network and any Nash equilibrium allocation S^* with $\#S^* < n$, the expected social cost is lower in the equilibrium than with a universal mandate; that is, $\Pi_{S^*} < \Pi_N$.*

Proof. Let S^* denote the equilibrium vaccination set. For every agent $i \notin S^*$ it must be the case that $c_i > p_{S^*}^i D_i$, and therefore total social cost satisfies

$$\Pi_{S^*} = \sum_{i \in S^*} c_i + \sum_{i \notin S^*} p_{S^*}^i D_i < \sum_{i \in S^*} c_i + \sum_{i \notin S^*} c_i = \sum_{i=1}^n c_i = \Pi_N.$$

□

B Chapter 3 Appendix

B.1 Asymmetric mixed-strategy solutions in a 3-person star network

There exist two asymmetric mixed-strategy solutions where some agent plays a pure strategy while others play mixed strategies. Equation (3.2) shows that if $c/D \in (p_{\{j\}}^i, p_{\emptyset}^2]$, the pure-strategy NE assigns the vaccine to one agent. If some agent commits to a pure strategy of non-vaccination, the other two agents will disagree on who should get vaccinated in the pure-strategy NE. Thus, each of the uncommitted agents choose a probability mixture to achieve a mixed-strategy NE. The next proposition considers the circumstance where the central agent does not get vaccinated.

Proposition .17. *In a 3-person homogeneous star network, for $c/D \in (p_{\{j\}}^i, \bar{c}]$, there exists a mixed-strategy NE in which the central player chooses not to get vaccinated or $\theta_1^* = 0$, while both peripheral players choose the probability of vaccination*

$$\theta_2^* = \theta_3^* = 1 - \frac{c/D - \beta - (1 - \beta)\beta t}{(1 - \beta)^2 \beta t^2},$$

where $\bar{c} = \beta + (1 - \beta)t - \frac{1}{2}(1 - \beta)^3 t^2 - \frac{1}{2}(1 - \beta)^2 t \sqrt{(1 - \beta)^2 t^2 + 4 - 4t}$.

Proof. Without loss of generality, we can normalize $D = 1$. By symmetry, $\theta_2^* = \theta_3^*$, and they solve the following equation (I drop the star hereafter for simplicity):

$$\theta_2 \cdot p_{\{3\}}^2 + (1 - \theta_2) \cdot p_{\emptyset}^2 = c. \quad (3)$$

Evaluate the central player's expected illness cost with $\theta_2^* = 1 - \frac{c - \beta - (1 - \beta)\beta t}{(1 - \beta)^2 \beta t^2}$, and get

$$(\theta_2)^2 \cdot p_{\{2,3\}}^1 + 2\theta_2(1 - \theta_2) \cdot p_{\{2\}}^1 + (1 - \theta_2)^2 \cdot p_{\emptyset}^1 \leq c. \quad (4)$$

Thus, the central player does not get vaccinated because her expected illness cost is no greater than the vaccination cost. $\square$

Figure B.1 shows the result in Proposition .17.

Next consider the circumstance where one of the peripheral agents does not get vaccinated.

Proposition .18. *In a 3-person homogeneous star network, for $c/D \in \left(p_{\{j\}}^i, p_{\emptyset}^2\right]$, there exists a mixed-strategy NE in which the peripheral player i chooses not to get vaccinated or $\theta_i^* = 0$, while the central player chooses the probability of vaccination*

$$\theta_1^* = 1 - \frac{c/D - \beta}{(1 - \beta)[\beta t + (1 - \beta)\beta t^2]},$$

and the peripheral player j chooses the probability of vaccination

$$\theta_j^* = 1 - \frac{c/D - \beta - (1 - \beta)\beta t}{(1 - \beta)\beta t(1 - \beta t)},$$

where $\bar{c} = \beta + (1 - \beta)t - \frac{1}{2}(1 - \beta)^3 t^2 - \frac{1}{2}(1 - \beta)^2 t \sqrt{(1 - \beta)^2 t^2 + 4 - 4t}$.

Proof. Without loss of generality, we can normalize $D = 1$. Let player 3 be the unvaccinated player. Then θ_1^* solves the equation

$$\theta_1 \cdot p_{\{1\}}^2 + (1 - \theta_1) \cdot p_{\emptyset}^2 = c, \quad (5)$$

and θ_2^* solves the equation

$$\theta_2 \cdot p_{\{2\}}^1 + (1 - \theta_2) \cdot p_{\emptyset}^1 = c. \quad (6)$$

Evaluate the player 3's expected illness cost with $\theta_1^* = 1 - \frac{c - \beta}{(1 - \beta)[\beta t + (1 - \beta)\beta t^2]}$ and $\theta_2^* = 1 - \frac{c - \beta - (1 - \beta)\beta t}{(1 - \beta)\beta t(1 - \beta t)}$, and get

$$\theta_1 \cdot p_{\{1\}}^2 + (1 - \theta_1)\theta_2 \cdot p_{\{3\}}^2 + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^2 \leq c. \quad (7)$$

Thus, player 3 does not get vaccinated because his expected illness cost is no greater than the vaccination cost. $\square$

Figure B.2 shows the result in Proposition .18.

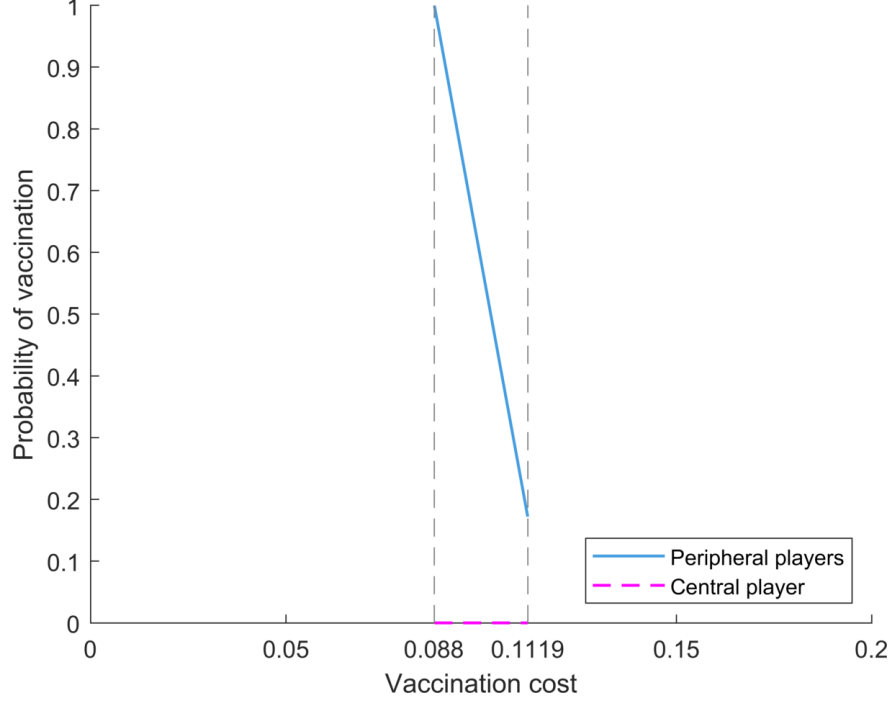


Figure B.1: Probabilities of vaccination in a 3-person homogeneous star network with $\beta = .05, t = .8, D = 1$. The central player commits to non-vaccination while peripheral players choose the same probability mixture. The horizontal axis is the vaccination cost, with a domain $c \in (.088, .1119]$. The vertical axis is the probability of vaccination, with ranges $\theta_1 = 0$ and $\theta_2 \in [.1714, 1)$.

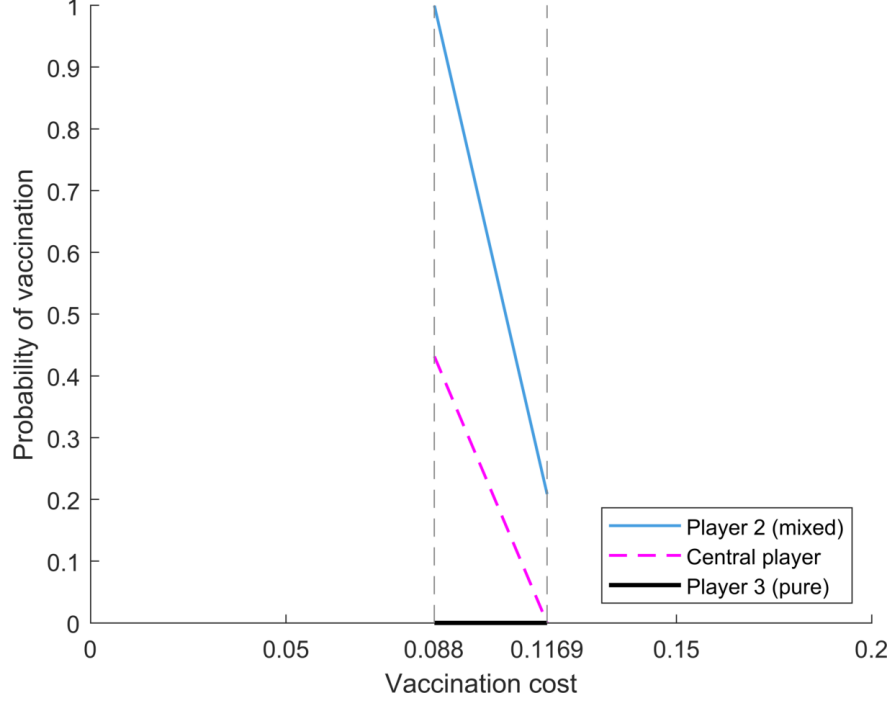


Figure B.2: Probabilities of vaccination in a 3-person homogeneous star network with $\beta = .05, t = .8, D = 1$. Peripheral player 3 commits to non-vaccination while the central player and peripheral player 2 choose probability mixtures. The horizontal axis is the vaccination cost, with a domain $c \in (.088, .1169]$. The vertical axis is the probability of vaccination, with ranges $\theta_1 \in [0, .4318)$, $\theta_2 \in [.2083, 1)$, and $\theta_3 = 0$.

B.2 The n-person star network

This section provides the formula to calculate the probability of vaccination in an n -person star network, and demonstrates the existence of multiple pure-strategy Nash equilibria. In an n -person star network, there are agents $N = \{1, 2, \dots, n\}$ in which player 1 is the central agent, and player $i = 2, \dots, n$ is the peripheral agent. Lemma .19 provides the probability of infection for all agents if $S = \emptyset$ in an n -person star network. For $S \neq \emptyset$, if $1 \in S$, then $p_{\{1\}}^1 = 0$ and $p_{\{1\}}^i = \beta$; if $1 \notin S$, then the network is equivalent to an $(n - \#S)$ person star network, and the following formula can still apply.

Lemma .19. *In an n -person homogeneous star network ($n \geq 3$), if $1 \notin S$, and $\#S$ denotes the number of vaccinated players, the central player's probability of infection is*

$$p_S^1 = \beta + (1 - \beta) \sum_{b=1}^{n-1-\#S} \binom{n-1-\#S}{b} \beta^b (1 - \beta)^{n-1-\#S-b} (1 - (1 - t)^b), \quad (8)$$

and $p_{\{1\}}^1 = 0$; and if $1 \notin S$ and $i \notin S$, the peripheral player's probability of infection is

$$p_S^i = \beta + (1 - \beta)t \left\{ \beta + (1 - \beta) \sum_{b=1}^{n-2-\#S} \binom{n-2-\#S}{b} \beta^b (1 - \beta)^{n-2-\#S-b} (1 - (1 - t)^b) \right\}. \quad (9)$$

and $p_{\{1\}}^i = \beta$ and $p_{\{i\}}^i = 0$. Note that b represents the number of peripheral players who contract the disease exogenously.

Proof. $p_{\{1\}}^1 = 0$, $p_{\{1\}}^i = \beta$, and $p_{\{i\}}^i = 0$ are obvious. Consider $S = \emptyset$, then $\#S = 0$.

$$\begin{aligned} p_{\emptyset}^1 &= \beta + (1 - \beta) \left[\binom{n-1}{1} \beta (1 - \beta)^{n-2} t + \binom{n-1}{2} \beta^2 (1 - \beta)^{n-3} (1 - (1 - t)^2) \right. \\ &\quad \left. + \dots + \binom{n-1}{n-1} \beta^{n-1} (1 - (1 - t)^{n-1}) \right] \\ &= \beta + (1 - \beta) \sum_{b=1}^{n-1} \binom{n-1}{b} \beta^b (1 - \beta)^{n-1-b} (1 - (1 - t)^b), \end{aligned}$$

where the b th term in the bracket represents the probability of interpersonal transmission from peripheral players to player 1, when b peripheral players are infected exogenously.

$$\begin{aligned} p_{\emptyset}^i &= \beta + (1 - \beta)t \left\{ \beta + (1 - \beta) \left[\binom{n-2}{1} \beta (1 - \beta)^{n-3} t + \binom{n-2}{2} \beta^2 (1 - \beta)^{n-4} (1 - (1 - t)^2) \right. \right. \\ &\quad \left. \left. + \cdots + \binom{n-2}{n-2} \beta^{n-2} (1 - (1 - t)^{n-2}) \right] \right\} \\ &= \beta + (1 - \beta)t \left\{ \beta + (1 - \beta) \sum_{b=1}^{n-2} \binom{n-2}{b} \beta^b (1 - \beta)^{n-2-b} (1 - (1 - t)^b) \right\}. \end{aligned}$$

where the b th term in the bracket represents the probability of interpersonal transmission from peripheral players to player 1 (excluding the transmission from player i to 1), when b peripheral players are infected exogenously.

Since vaccinating $\#S$ peripheral players is equivalent to reducing the network size by $\#S$, substituting n by $n - \#S$ obtains the result. $\square$

Notice that $p_{\emptyset}^1 > p_{\emptyset}^i$. Lemma .20 finds all pure-strategy NEs for various c/D .

Lemma .20. *In an n -person homogeneous star network, the pure-strategy equilibrium set of vaccinated agnets is given by*

$$S^* = \begin{cases} N & \text{if } c/D \in [0, \beta] \\ \{1\} \text{ or } N \setminus \{1\} & \text{if } c/D \in \left(\beta, p_{N \setminus \{1, i\}}^i \right] \\ \{1\} \text{ or } N \setminus \{1, i\} & \text{if } c/D \in \left(p_{N \setminus \{1, i\}}^i, p_{N \setminus \{1, i, j\}}^i \right] \\ \vdots & \\ \{1\} \text{ or } \{j\} & \text{if } c/D \in \left(p_{\{j\}}^i, p_{\emptyset}^i \right] \\ \{1\} & \text{if } c/D \in (p_{\emptyset}^i, p_{\emptyset}^1] \\ \emptyset & \text{if } c/D \in (p_{\emptyset}^1, \infty) \end{cases} \quad (10)$$

Proof. Prove by the definition of the pure-strategy NE. $\square$

For $c/D \in (\beta, p_\emptyset^i]$, multiple pure-strategy NEs exist. Thus, there exists a mixed-strategy NE where all agents choose a probability mixture. Proposition [3.4](#) discusses such an equilibrium.

B.3 Proofs

Proposition .21. *In a 2-person homogeneous network, if $c/D \in (\beta, p_\emptyset^i]$, in a mixed-strategy Nash equilibrium both players choose the probability of vaccination*

$$\theta^* = 1 - \frac{c/D - \beta}{(1 - \beta)\beta t}.$$

Proof. By symmetry, let $\theta_1^* = \theta_2^* = \theta^*$. If i forgoes the vaccine, then against j 's strategy profile $(\theta, 1 - \theta)$, i 's expected illness cost is (I drop the star hereafter for simplicity)

$$\theta\beta D + (1 - \theta)[\beta + (1 - \beta)\beta t]D.$$

Evaluate the above formula with $\theta = 1 - \frac{c/D - \beta}{(1 - \beta)\beta t}$, and get

$$\theta\beta D + (1 - \theta)[\beta + (1 - \beta)\beta t]D = c,$$

which satisfies the equilibrium requirement that i is indifferent about vaccinating and not. $\square$

Proposition .22. *In a 3-person homogeneous star network, for $c/D \in (\beta, \bar{c}]$, there exists a mixed-strategy NE in which the central player chooses the probability of vaccination*

$$\theta_1^* = 1 - \frac{c/D - \beta}{(1 - \beta)(1 - \sqrt{(1 - c/D)(1 - \beta)})t},$$

and both peripheral players choose the probability of vaccination

$$\theta_2^* = \theta_3^* = 1 - \frac{1 - \beta - \sqrt{(1 - c/D)(1 - \beta)}}{(1 - \beta)\beta t},$$

where $\bar{c} = \beta + (1 - \beta)t - \frac{1}{2}(1 - \beta)^3 t^2 - \frac{1}{2}(1 - \beta)^2 t \sqrt{(1 - \beta)^2 t^2 + 4 - 4t}$ that solves $\theta_1^*(c/D) = 0$.

Proof. Without loss of generality, we can normalize $D = 1$. If player 1 forgoes the vaccine, her probability of infection depends on the strategy profiles $(\theta_2, 1 - \theta_2)$ and $(\theta_3, 1 - \theta_3)$. By symmetry, $\theta_2^* = \theta_3^*$. Thus, 1's expected illness cost is

$$(\theta_2)^2 \cdot p_{\{2,3\}}^1 + 2\theta_2(1 - \theta_2) \cdot p_{\{i\}}^1 + (1 - \theta_2)^2 \cdot p_\emptyset^1.$$

Evaluate the above formula with $\theta_2 = 1 - \frac{1-\beta-\sqrt{(1-c)(1-\beta)}}{(1-\beta)\beta t}$, and get

$$(\theta_2)^2 \cdot p_{\{2,3\}}^1 + 2\theta_2(1 - \theta_2) \cdot p_{\{i\}}^1 + (1 - \theta_2)^2 \cdot p_{\emptyset}^1 = c,$$

which satisfies the equilibrium requirement that 1 is indifferent about vaccinating and not.

Next, consider player 3. If 3 forgoes the vaccine, then against the strategy profile $(\theta_1, 1 - \theta_1)$ and $(\theta_2, 1 - \theta_2)$, 3's expected illness cost is

$$\theta_1 \cdot p_{\{1\}}^3 + (1 - \theta_1)\theta_2 \cdot p_{\{j\}}^i + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^3.$$

Evaluate the above formula with $\theta_1 = 1 - \frac{c-\beta}{(1-\beta)(1-\sqrt{(1-c)(1-\beta)})t}$, $\theta_2 = 1 - \frac{1-\beta-\sqrt{(1-c)(1-\beta)}}{(1-\beta)\beta t}$, and get

$$\theta_1 \cdot p_{\{1\}}^3 + (1 - \theta_1)\theta_2 \cdot p_{\{j\}}^i + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^3 = c.$$

Lastly, find the interval of c in which the mixed-equilibrium strategy vector $(\theta_1^*, \theta_2^*, \theta_3^*)$ is valid. For $\beta < c < p_{\emptyset}^1$, $0 < \theta_2^* = \theta_3^* < 1$. And for $c > \beta$, $\theta_1^* < 1$. However, at $c = p_{\emptyset}^1$, $\theta_1^* < 0$. Evaluate θ_1^* with $\bar{c} = \beta + (1 - \beta)t - \frac{1}{2}(1 - \beta)^3 t^2 - \frac{1}{2}(1 - \beta)^2 t \sqrt{(1 - \beta)^2 t^2 + 4 - 4t}$ and get $\theta_1^* = 0$. Since $\bar{c} < p_{\emptyset}^i < p_{\emptyset}^1$ for $t \in (0, 1)$, the interval of c in which a mixed-strategy NE exists is $(\beta, \bar{c}]$. □

Proposition .23. *In a 3-person homogeneous star network, as in the mixed-strategy NE described in Proposition 3.2, the central player chooses a lower probability of vaccination than the peripheral players, that is*

$$\theta_1^* < \theta_2^* = \theta_3^*.$$

Proof. Since both equations (3.3) and (3.4) equal to c , their left hand sides must be equal. Rewrite the equation as

$$\begin{aligned} & \theta_2 \theta_2 \cdot p_{\{2,3\}}^1 + \theta_2(1 - \theta_2) \cdot p_{\{2\}}^1 + \theta_2(1 - \theta_2) \cdot p_{\{2\}}^1 + (1 - \theta_2)(1 - \theta_2) \cdot p_{\emptyset}^1 \\ = & \theta_1 \theta_2 \cdot p_{\{1\}}^2 + \theta_1(1 - \theta_2) \cdot p_{\{1\}}^2 + \theta_2(1 - \theta_1) \cdot p_{\{3\}}^2 + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^2 \end{aligned} \quad (11)$$

Assume $\theta_1 = \theta_2$, then the left hand side must be greater than the right hand side because $p_{\{2,3\}}^1 = p_{\{1\}}^2$, $p_{\{2\}}^1 > p_{\{1\}}^2$, $p_{\{2\}}^1 = p_{\{3\}}^2$, and $p_{\emptyset}^1 > p_{\emptyset}^2$. Since the left hand side is the central player's expected infection risk, it must be decreasing in θ_2 . To balance the equation, we must raise θ_2 . Thus, $\theta_1^* < \theta_2^*$. $\square$

Proposition .24. *In an n -person homogeneous star network, for $c/D \in (\beta, \bar{c}]$, there exists a mixed-strategy NE in which the central player chooses a lower probability of vaccination than all peripheral players, that is*

$$\theta_1^* < \theta_i^*,$$

where $i = 2, \dots, n$ and $\bar{c}$ solves $\theta_1^*(c/D) = 0$.

Proof. Without loss of generality, let $i = 2$ and $j \in J = \{3, \dots, n\}$. Consider the vaccinated peripheral agents in J . Define M as the set of vaccinated agents in J , so $M = S \cap J$. Define m as the number of vaccinated agents in J , so $\#M \equiv m = 0, \dots, n-2$. Define $\mathbf{M}_m$ as the collection of all M which contains m vaccinated peripheral agents. For example, $M_1 = \{\{3\}, \{4\}, \dots, \{n\}\}$, and $M_{n-2} = \{J\}$.

Next, calculate the probability of infection based on whether player 1 and player 2 get vaccinated:

- (i) If $1 \in S$, $2 \in S$, $p_S^1 = p_S^2 = 0$;
- (ii) If $1 \in S$, $2 \notin S$, $p_S^1 = 0$, $p_S^2 = p_{\{1\} \cup M}^2 = \beta$;
- (iii) If $1 \notin S$, $2 \in S$, $p_S^1 = p_{\{2\} \cup M}^1$, $p_S^2 = 0$;
- (iv) If $1 \notin S$, $2 \notin S$, $p_S^1 = p_M^1$, $p_S^2 = p_M^2$.

Consider case (iii), the size of M determines player 1's probability of infection. Thus, let $p_{\{2\} \cup M}^1 = p_{2m}^1$ for all $M \in \mathbf{M}_m$. Also, in case (ii), let $p_{\{1\} \cup M}^2 = p_{1m}^2$ for all $M \in \mathbf{M}_m$. Notice that $p_{2m}^1 \geq p_{1m}^2 = \beta$ for every m .

Consider case (iv), the size of M determines both players' probabilities of infection. Thus, let $p_M^1 = p_m^1$ and $p_M^2 = p_m^2$ for all $M \in \mathbf{M}_m$. Notice that $p_m^1 \geq p_m^2$ for every m .

Now consider the mixed-strategy NE. By symmetry, $\theta_2^* = \theta_j^*$ for all j . And θ_1^* and θ_2^* solve the following equations:

$$\theta_2 \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_{2m}^1 D + (1-\theta_2) \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_m^1 D = c \quad (12)$$

$$\theta_1 \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_{1m}^2 D + (1-\theta_1) \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_m^2 D = c \quad (13)$$

Since both equations equal to c , the left hand sides must also be equal. Divide both equations by D , we have

$$\begin{aligned} & \theta_2 \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_{2m}^1 + (1-\theta_2) \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_m^1 \\ &= \theta_1 \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_{1m}^2 + (1-\theta_1) \sum_{m=0}^{n-2} \binom{n-2}{m} \theta_2^m (1-\theta_2)^{n-2-m} p_m^2 \end{aligned} \quad (14)$$

Assume $\theta_1 = \theta_2$, then the left hand side must be greater than the right hand side because $p_{2m}^1 \geq p_{1m}^2$ and $p_m^1 \geq p_m^2$. Since the left hand side is the central player's expected infection risk, it must be decreasing in θ_2 . To balance the equation, we must raise θ_2 . Thus, $\theta_1^* < \theta_2^*$.

Note that $\bar{c}$ here is different from the one in a 3-person star network. $\square$

Proposition .25. *In a 2-person homogeneous network, if $c/D \in (\beta, p_0^1]$, a universal mandate produces the same expected social welfare a mixed-strategy NE does.*

Proof. Recall equation (3.1)

$$\theta\beta D + (1-\theta)[\beta + (1-\beta)\beta t]D = c,$$

where the left hand side is a player's expected payoff if she forgoes the vaccination, and the right hand side is the vaccination cost. This implies that

$$\theta c + (1-\theta)\{\theta\beta D + (1-\theta)[\beta + (1-\beta)\beta t]D\} = c \quad (15)$$

where the left hand side is a player's expected payoff if she chooses the equilibrium strategy mixture, and the right hand side is the vaccination cost. Since this equality holds for both players, the aggregate payoff in a mixed-strategy NE equals $2c$, the same payoff under a universal mandate. $\square$

Proposition .26. *In a 3-person homogeneous star network, if $c/D \in (\beta, \bar{c})$, a universal mandate produces the same expected social welfare as in a mixed-strategy NE.*

Proof. Recall equation (3.3)

$$(\theta_2)^2 \cdot p_{\{2,3\}}^1 D + 2\theta_2(1 - \theta_2) \cdot p_{\{2\}}^1 D + (1 - \theta_2)^2 \cdot p_{\emptyset}^1 D = c,$$

and equation (3.4)

$$\theta_1 \cdot p_{\{1\}}^2 D + (1 - \theta_1)\theta_2 \cdot p_{\{3\}}^2 D + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^2 D = c.$$

They imply that for player 1,

$$\theta_1 c + (1 - \theta_1) [(\theta_2)^2 \cdot p_{\{2,3\}}^1 D + 2\theta_2(1 - \theta_2) \cdot p_{\{2\}}^1 D + (1 - \theta_2)^2 \cdot p_{\emptyset}^1 D] = c,$$

and for player 2 and 3,

$$\theta_2 c + (1 - \theta_2) [\theta_1 \cdot p_{\{1\}}^2 D + (1 - \theta_1)\theta_2 \cdot p_{\{3\}}^2 D + (1 - \theta_1)(1 - \theta_2) \cdot p_{\emptyset}^2 D] = c.$$

Thus, adding up the left hand side of all players, the aggregate payoff in a mixed-strategy NE equals $3c$, the same payoff under a universal mandate. $\square$

Proposition .27. *For any n -person network, if a mixed-strategy NE exists, a universal mandate produces the same expected social welfare a mixed-strategy NE does.*

Proof. Consider an n -person network with players $N = \{1, 2, \dots, n\}$. The vector $(\theta_1, \theta_2, \dots, \theta_n)$ defines a mixed-strategy NE (take the star off the superscript for simplicity). Consider player $i \in N$. If she takes the vaccine, she pays the cost c_i . If she forgoes the vaccine, she faces the

vaccination set S_k , where $i \notin S_k$. And her probability of infection is $p_{S_k}^i$, and her illness cost is D_i .

Player i is facing 2^{n-1} different S_k because all other players can choose to vaccinate or not. Thus, label each S_k with $k = 1, 2, \dots, 2^{n-1}$. Consider player j , $j \neq i$. Denote $V_j = 1$ if $j \in S_k$, and $V_j = 0$ otherwise. Thus, the probability of a particular S_k to arise is

$$\prod_{j \in N, j \neq i} [V_j \theta_j + (1 - V_j)(1 - \theta_j)].$$

Then multiply by player i 's expected infection cost, her expected illness cost facing S_k is

$$\prod_{j \in N, j \neq i} [V_j \theta_j + (1 - V_j)(1 - \theta_j)] p_{S_k}^i D_i.$$

In a mixed-strategy NE, player i must be indifferent between vaccinating and not:

$$\sum_{k=1}^{2^{n-1}} \prod_{j \in N, j \neq i} [V_j \theta_j + (1 - V_j)(1 - \theta_j)] p_{S_k}^i D_i = c_i,$$

where the left hand side is her expected illness cost if she forgoes vaccination. Since player i chooses the strategy profile $(\theta_i, 1 - \theta_i)$, then her expected payoff equals the vaccination cost in the equilibrium

$$\theta_i c_i + (1 - \theta_i) \sum_{k=1}^{2^{n-1}} \prod_{j \in N, j \neq i} [V_j \theta_j + (1 - V_j)(1 - \theta_j)] p_{S_k}^i D_i = c_i.$$

And such equality holds for everyone. Hence, the aggregate payoff of all players must equal the cost of vaccinating everyone, that is

$$\sum_{i=1}^n \left\{ \theta_i c_i + (1 - \theta_i) \sum_{k=1}^{2^{n-1}} \prod_{j \in N, j \neq i} [V_j \theta_j + (1 - V_j)(1 - \theta_j)] p_{S_k}^i D_i \right\} = \sum_{i=1}^n c_i. \quad (16)$$

To conclude, the social cost of a mixed-strategy NE equals the cost of a universal mandate. □

C Appendix

C.1 The Construction of Centrality

We apply the principal component analysis to the Occupational Information Network (O*NET) data to construct the occupation centrality. The principal component analysis is an unsupervised machine learning technique to reduce the dimensions of a dataset. Principle component analysis converts a set of possibly correlated variables into a set of linearly uncorrelated variables. We call these linearly uncorrelated variables the “principal components”. Specifically, we construct the occupation centrality in six steps:

1. We select 22 descriptors from Occupational Information Network (O*NET) that are related to disease exposure and interpersonal interactions. Table 2 presents summary statistics of the descriptors.
2. The O*NET dataset contains 967 8-digit specific occupation codes using the 2010 Standard Occupational Classification (SOC). We first collapse these 8-digit codes into 6-digit codes by taking a simple average and obtain descriptors for 770 occupations. Then we transform them into 2000 SOC using the crosswalk guide provided by the U.S. Bureau of Labor Statistics.
3. The 2013 Behavioral Risk Factor Surveillance System (BRFSS) dataset contains 494 unique occupations. We merge the BRFSS dataset with the transformed O*NET dataset and find 335 matched occupations, which are mostly specific occupations. The unmatched occupations are mostly coded as minor groups and broad occupations (SOC trailing in zeros) or miscellaneous occupations (SOC trailing in nines).
4. We take the simple average of descriptors of specific occupations under the same general group to impute values for minor occupation groups, broad occupations, and miscellaneous occupations. Then we merge the BRFSS dataset with the imputed O*NET dataset and find 157 matches. We drop two occupations in BRFSS: Legislators (11-1031) because O*NET does not collect the information and Textile Bleaching and

Dyeing Machine Operators and Tenders (51-6061) because BRFSS does not have all variables we need. Thus, we obtain descriptors for 492 occupations in BRFSS.

5. We apply the principal component analysis to the 22 descriptors and retain the first principal component as the centrality score. The centrality score represents 47% of all variations of the 22 descriptors. Figure C.1 displays the proportion of variance explained by each principal component.

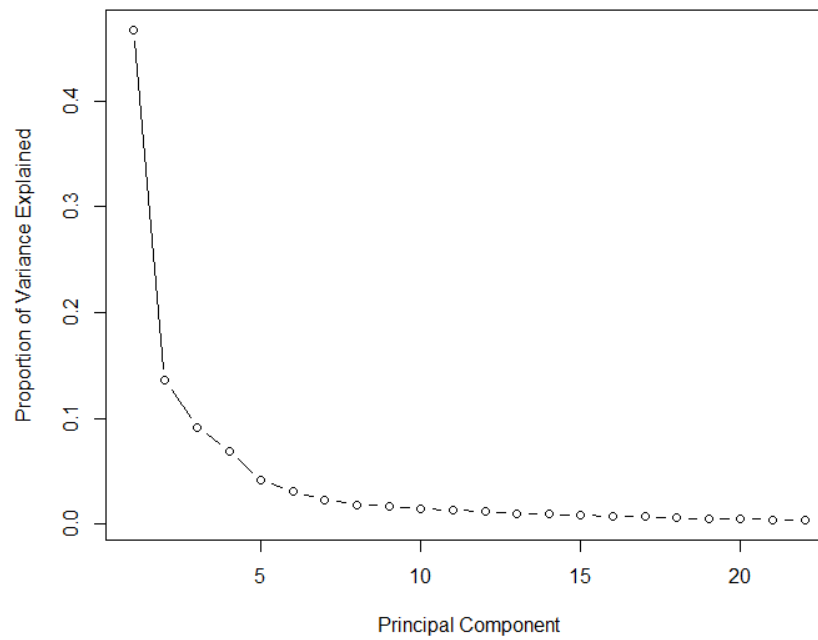


Figure C.1: The Proportion of Variance Explained by Every Principal Component with the First Principal Component as the Centrality

C.2 Additional Tables and Figures

Table C.1: Summary Statistics of Additional Variables

Variable	Mean	Std. Dev.	Min	Max
Centrality (Context)	0.53	1.50	-7.11	3.73
Centrality (Activity)	0.68	2.89	-7.89	8.82

Source: O*NET.

Table C.2: The Bin Model Estimates of the Effect of Centrality (Context) on Flu Vaccine Uptake

Dependent: Flu Vaccine Uptake					
	(1)	(2)	(3)	(4)	(5)
	Full Sample	Full Sample	Full Sample	Non-HCP	Age 18-64
Centrality (Context)					
[-7, -6)	-0.2802** (0.0789)	-0.2299*** (0.0508)	-0.2270*** (0.0509)	-0.2053*** (0.0441)	-0.2571*** (0.0099)
[-6, -5)	-0.3229*** (0.0252)	-0.2769*** (0.0486)	-0.2694*** (0.0445)	-0.2670*** (0.0429)	-0.2415*** (0.0372)
[-5, -4)	-0.0960* (0.0421)	-0.0194 (0.0499)	-0.0106 (0.0478)	-0.0074 (0.0477)	-0.0026 (0.0540)
[-4, -3)	-0.0898** (0.0273)	-0.0552* (0.0259)	-0.0468 (0.0257)	-0.0472 (0.0261)	-0.0532 (0.0266)
[-3, -2)	-0.0720* (0.0255)	-0.0176 (0.0189)	-0.0142 (0.0185)	-0.0189 (0.0201)	-0.0085 (0.0165)
[-2, -1)	-0.0715*** (0.0138)	-0.0101 (0.0144)	-0.0096 (0.0143)	-0.0071 (0.0155)	-0.0078 (0.0160)
[-1, 0)	-0.0328*** (0.0079)	-0.0018 (0.0090)	-0.0029 (0.0086)	-0.0010 (0.0105)	0.0004 (0.0090)
[1, 2)	-0.0309** (0.0098)	-0.0245* (0.0092)	-0.0268** (0.0088)	-0.0247* (0.0093)	-0.0265** (0.0081)
[2, 3)	0.0289 (0.0150)	0.0163 (0.0168)	-0.0234 (0.0152)	-0.0312 (0.0170)	-0.0247 (0.0147)
[3, 4)	0.2345*** (0.0161)	0.1863*** (0.0109)	0.0737*** (0.0106)	0.0608** (0.0198)	0.0772*** (0.0123)
[4, 5)	0.2247*** (0.0299)	0.1877*** (0.0253)	0.0280 (0.0306)	0.2339 (0.1238)	0.0400 (0.0312)
Health Care Personnel			0.1938*** (0.0104)		0.2035*** (0.0107)
Constant	0.3392*** (0.0161)	0.0349 (0.0214)	0.0449 (0.0228)	0.0484* (0.0231)	0.0453 (0.0243)
Controls	No	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	75712	75712	75712	63715	68152

Source: BRFSS 2013 and O*NET. Controls include gender, age group, race/ethnicity group, income level, marital status, and indicators for health care personnel, high-risk conditions, having personal health care provider, and having medical insurance. ***, **, * means that the coefficient is statistically different from zero at the 1%, 5%, and 10% level. All models weighted with BRFSS weights. Standard errors clustered at the state-level and reported in parentheses.

Table C.3: The Bin Model Estimates of the Effect of Centrality (Activity) on Flu Vaccine Uptake

Dependent: Flu Vaccine Uptake					
	(1)	(2)	(3)	(4)	(5)
	Full Sample	Full Sample	Full Sample	Non-HCP	Age 18-64
Centrality (Activity)					
[-8, -7)	-0.0517 (0.2119)	-0.0487 (0.1538)	0.0134 (0.1580)	-0.0005 (0.1616)	0.0833 (0.1728)
[-7, -6)	-0.0755* (0.0343)	-0.0720 (0.0363)	-0.0212 (0.0368)	-0.0323 (0.0378)	-0.0250 (0.0393)
[-6, -5)	-0.1888*** (0.0249)	-0.1576*** (0.0349)	-0.1004** (0.0303)	-0.1049** (0.0284)	-0.1157** (0.0356)
[-5, -4)	-0.0750*** (0.0195)	-0.0213 (0.0204)	0.0177 (0.0180)	0.0117 (0.0223)	0.0181 (0.0164)
[-4, -3)	-0.0341 (0.0250)	-0.0138 (0.0250)	0.0328 (0.0259)	0.0302 (0.0319)	0.0355 (0.0253)
[-3, -2)	-0.0776*** (0.0127)	-0.0471** (0.0130)	-0.0054 (0.0155)	-0.0060 (0.0181)	-0.0067 (0.0180)
[-2, -1)	-0.0489*** (0.0100)	-0.0341** (0.0099)	0.0158 (0.0118)	0.0089 (0.0146)	0.0168 (0.0121)
[-1, 0)	-0.0127 (0.0144)	-0.0210 (0.0135)	0.0243 (0.0155)	0.0156 (0.0174)	0.0242 (0.0172)
[1, 2)	-0.0298 (0.0145)	-0.0307** (0.0107)	0.0168 (0.0125)	0.0090 (0.0175)	0.0104 (0.0132)
[2, 3)	0.1193** (0.0319)	0.0602 (0.0290)	0.0795* (0.0303)	0.0644 (0.0317)	0.0810* (0.0299)
[3, 4)	0.0238* (0.0089)	-0.0443*** (0.0090)	0.0092 (0.0109)	0.0052 (0.0149)	0.0117 (0.0116)
[4, 5)	0.1061*** (0.0121)	0.0393** (0.0124)	0.0357** (0.0120)	0.0156 (0.0167)	0.0345* (0.0125)
[5, 6)	0.0405 (0.0250)	-0.0283 (0.0209)	0.0080 (0.0248)	0.0134 (0.0315)	0.0080 (0.0274)
[6, 7)	0.0969** (0.0267)	-0.0052 (0.0292)	0.0074 (0.0300)	0.0076 (0.0398)	0.0148 (0.0287)
[7, 8)	-0.0753 (0.0739)	-0.0732 (0.0536)	-0.0208 (0.0551)	-0.0257 (0.0587)	-0.0272 (0.0589)
[8, 9)	0.0989 (0.0591)	0.0382 (0.0518)	0.1008 (0.0516)	0.0942 (0.0501)	0.1076* (0.0511)
Health Care Personnel			0.2149*** (0.0087)		0.2256*** (0.0085)
Constant	0.3313*** (0.0201)	0.0457 (0.0254)	0.0218 (0.0275)	0.0314 (0.0311)	0.0249 (0.0277)
Controls	No	Yes	Yes	Yes	Yes
State Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	75712	75712	75712	63715	68152

Source: BRFSS 2013 and O*NET. Controls include gender, age group, race/ethnicity group, income level, marital status, and indicators for health care personnel, high-risk conditions, having personal health care provider, and having medical insurance. ***, **, * means that the coefficient is statistically different from zero at the 1%, 5%, and 10% level. All models weighted with BRFSS weights. Standard errors clustered at the state-level and reported in parentheses.

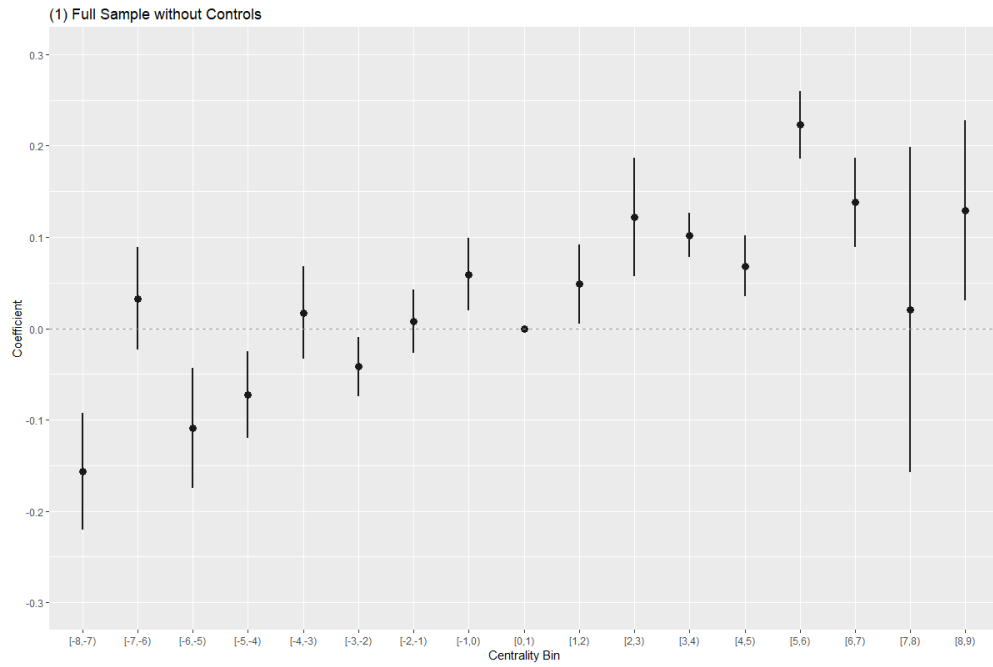


Figure C.2: Coefficient Estimates of Centrality Bins in Table 4. Column (1)

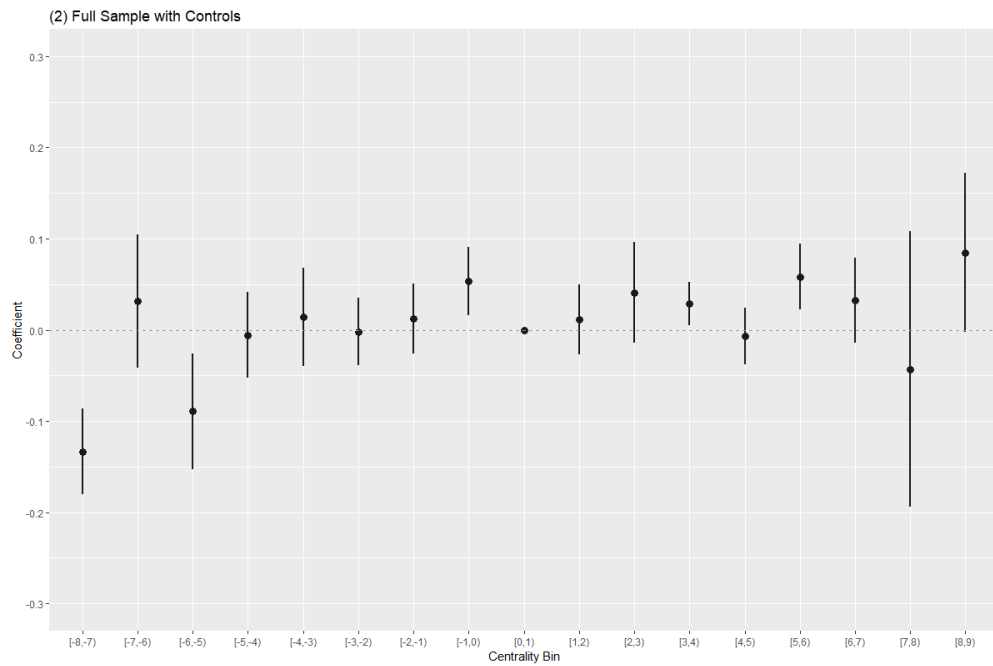


Figure C.3: Coefficient Estimates of Centrality Bins in Table 4. Column (2)

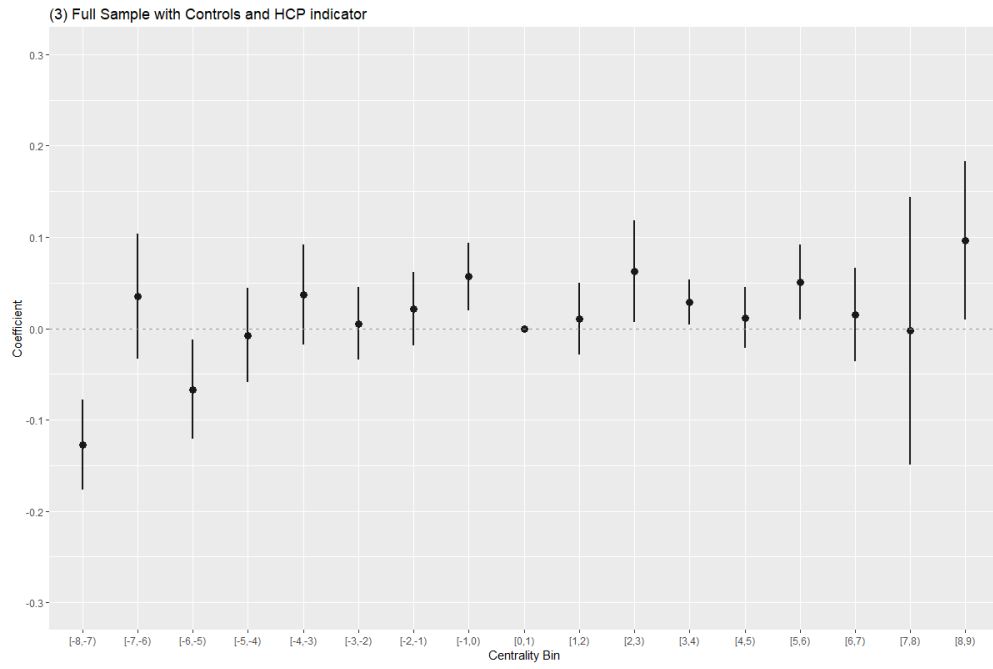


Figure C.4: Coefficient Estimates of Centrality Bins in Table 4. Column (3)

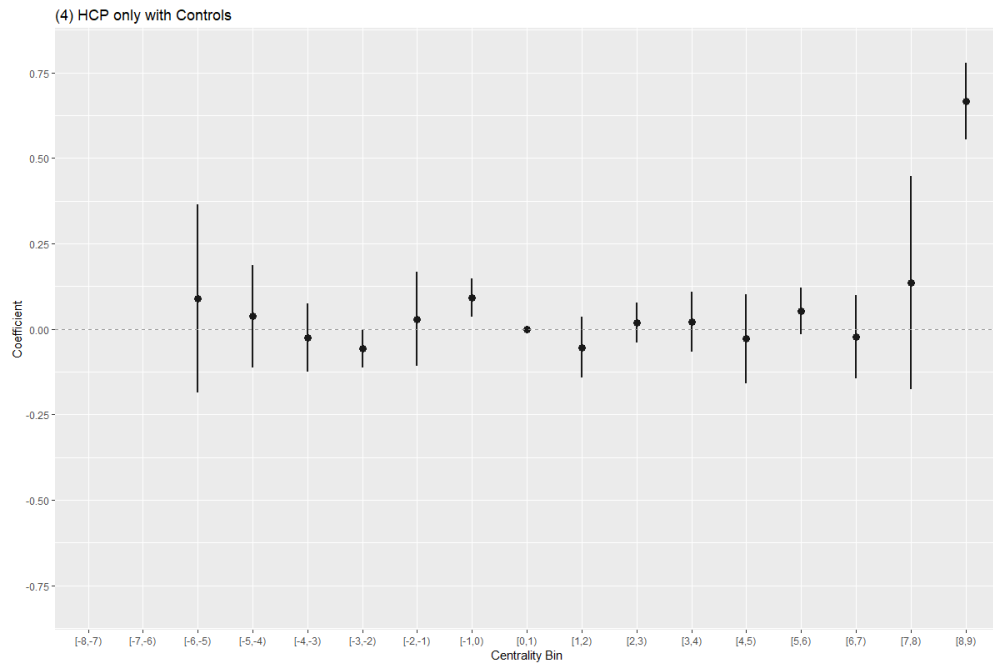


Figure C.5: Coefficient Estimates of Centrality Bins in Table 4. Column (4)

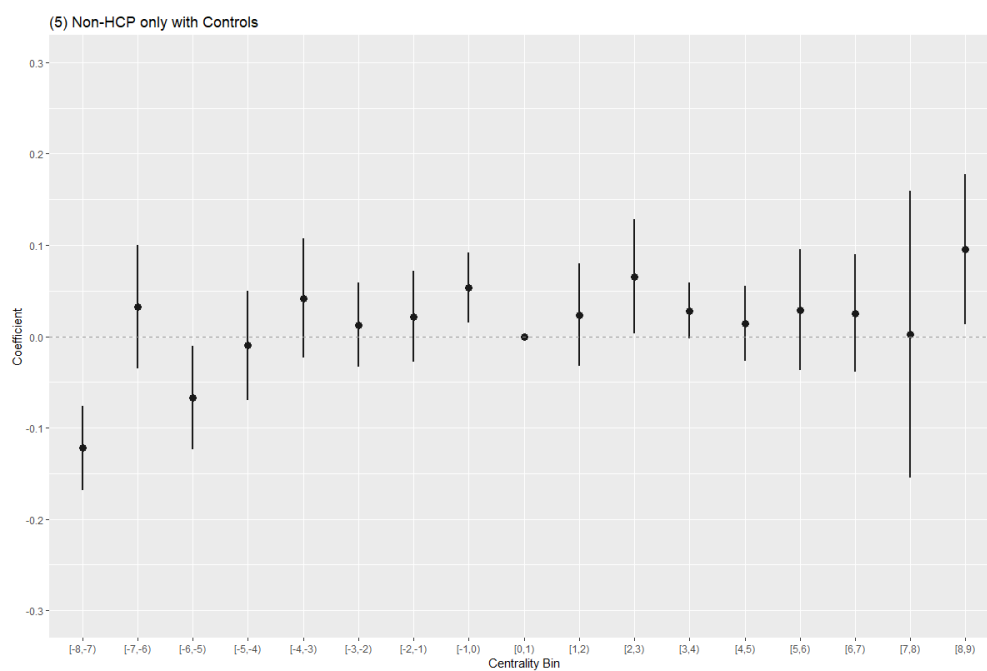


Figure C.6: Coefficient Estimates of Centrality Bins in Table 4. Column (5)

Vita

Before coming to Tennessee, Yancheng Xiao received his bachelor's degree in Finance at Beijing Technology and Business University and master's degree in Economics at University of Illinois, Urbana-Champaign. He joined the Ph.D. program in Economics at the University of Tennessee, Knoxville in 2014 and graduate in 2019. He will continue his academics career as an Assistant Professor in Economics at South China Normal University.