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Peer Effects on Influenza Vaccination: Evidenced from a City's Administrative Data in Japan

Naomi Miyazato†, Yoko Ibuka‡ and Jun-ichi Itaya§

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Abstract

A characteristic that differentiates vaccination from other health behaviors is that it is a public good. When considering the vaccination status surrounding peers, free-riding behavior usually indicates a negative peer effect; thus, theoretically at least, negative peer effects are expected when determining vaccination behavior. In this study, we empirically analyze the influence of the surrounding vaccination status on individual vaccination behavior using administrative data on influenza for elderly people in Japan. The data that we use include all data for those over the age of 65 years within a certain city. We first employ panel analyses with a lagged dependent variable. Furthermore, we utilize the changes in the household's environment, such as the loss of a cohabitant, and conduct analyses that consider the state of dependency on vaccination. Our estimation results confirm positive peer effects even when considering the state dependence of vaccination. The higher the community's vaccination rate, the more the raising effect of the individual's vaccination rate separated from depression and altruistic motive.

JEL classification: H41; I12

Keywords: Peer effect; Public good; Vaccination; Health behaviors; Administrative data.

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1. Introduction

Vaccination is one of the most effective tools for controlling epidemics of several infectious diseases. Therefore, accelerating vaccination is an important policy issue. When overviewing actual data, there are regional differences in vaccination acceptance. According to Bloomberg's article[1], the COVID-19 vaccination rates in the United States are higher in the eastern and western coastal areas and slightly lower in the southern areas. Although the supply of vaccines is considered sufficient in every state, there are differences in vaccination rates, depending on the region. In addition, this article reports that counties that predominantly voted for Republican Donald Trump had a low vaccination rate for COVID-19. It is possible that the vaccination behavior around them influenced them. Before COVID-19, the influenza vaccination rate in Japan also varied by region.[2] The prices of influenza vaccination in Japan are very low or is provided for free for people over the age of 65 years, and it is possible that factors other than price affects regional differences. In this study, we empirically analyze the influence of the surrounding vaccination status on individual vaccination behavior.

A characteristic that differentiates vaccination from other health behaviors is that it is a public good. Vaccination against infectious diseases decreases the probability of infection in both vaccinated and unvaccinated individuals. The benefit of vaccination is not limited to those who receive vaccinations, neither does it decrease when the unvaccinated individuals enjoy the benefit of vaccination. The benefit is non-excludable and non-rivalrous; thus, vaccination is an example of a voluntary provision of public good. The primary prediction from the standard voluntary public-good model (Bergstrom et al. 1986; Warr 1983) is that individuals free ride on the contributions of others. When considering the vaccination status of those around you as a peer, free-riding behavior usually indicates a negative peer effect; thus, theoretically at least, negative peer effects are expected in vaccination behaviors. However, some studies have reported a positive peer effect regarding vaccination behavior. By using data of undergraduate students the US, Rao et al. (2017) show that a 10% increase in the influenza vaccination rate among peers can create an 8.3% increase in the probability of vaccination. Sato and Takasaki (2019) use Nigerian data of tetanus vaccination to

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[1] Report written by Tartar, A, Brown, KV, & Randall, T. (2021, June 29).

[2] When calculating the influenza inoculation rate for Japan by prefecture for those aged 65 years and above in 2018, the average value was 52.2% and the standard deviation was 6.4%. Data are calculated from the Ministry of Health, Labor and Welfare's "Community Health and Health Promotion Project Report" and the Ministry of Internal Affairs and Communications' "Population Projection." If it was based on the municipality, the standard deviation would have been even larger.

analyze the peer effect on women. Their estimations show that the probability of an individual being vaccinated increases by 18.9% when a friend is vaccinated.

Bouckaert et al. (2020) analyzed the spillover effect of influenza vaccination in households using Dutch data. While vaccination of older spouses has been shown to have a positive effect on vaccination of younger spouses, parental vaccination has also been shown to reduce vaccination in adult children. Sasaki et al. (2021) analyze the intention of COVID-19 vaccination in in Japan based on a questionnaire survey. The results show that, as the proportion of vaccinated people within the same age group increases, the respondents' willingness to vaccinate also increases. These results differ from those related to donation. It has been confirmed that in vaccination, where contact and involvement with the surroundings are more important, the behavior of the surroundings promotes public good. The data used in this study are based on influenza vaccination, similar to Bouckaert et al. (2020), although they focus the family only. Rao et al. (2017) also have data for influenza vaccination while it consists of data for university dormitories with a small range. However, this study is based on data for a specific and entire municipality, and thus it is possible to capture a wider range of surrounding effects.

In the literature on health investment and risky behavior, it has been confirmed that the behavior of one's environment affects individual behavior. Gaviria and Raphael (2001), Kawaguchi (2004), Lundborg (2006), and Clark and Lohéac (2007) have confirmed the strong peer group effect for drug use, alcohol consumption, and cigarette smoking. Moreover, Powell et al. (2005) analyzed the impact of peer effects, tobacco prices, and tobacco control policies on smoking in youth, and confirmed that peer effects play an important role. Eisenberg et al. (2014) examined the peer effect of suicidal ideation and non-suicidal self-injury in addition to drug use, alcohol consumption, and cigarette smoking. The estimation results show that the peer effect is significantly confirmed for binge drinking, but not for other behaviors. In addition, Godlonton and Thornton (2012) found higher engagement for learning HIV results due to peer effects.

We undertake empirical studies focusing on the reflection problem (Manski, 1993), which refers to a problem in the identification of a causal influence on voluntary behavior from one person to another when estimating peer effects. To cope with this problem, researchers utilize a lagged variable in a panel dataset (Clark and Lohéac 2007) or the instrumental variable approach (Gaviria and Raphael 2001; Powell et al. 2005; Trogdon et al. 2008). In addition, some studies have employed a natural experiment (Dahl et al. 2014; Eisenberg et al. 2014). The data that we use are administration data, which include all data for those over the age of 65 years within a certain city. Hence, the advantage is that there is no network loss when analyzing the surrounding effects of a designated area. Although the data in this study have a limited number of variables, such as age, gender, a preferable feature of the data is that it is panel data consisting of three periods. Individual heterogeneity can be controlled with a fixed effects model. Therefore, we first employ panel analyses with a lagged dependent variable to handle the reflection problem. Furthermore, the data used in this study includes address information, so the loss of a cohabitant can be known. We utilize the changes in the household's environment, such as the loss of a cohabitant, and conduct analyses that consider the state of dependency on vaccination.

The remainder of this study proceeds as follows. Section 2 provides a brief overview of Japan's vaccination programs. Section 3 describes the data and estimation methods used in this study. Section 4 presents the estimation results, and Section 5 provides the concluding remarks.

2. Institutional Background

This section provides a brief overview of the institutional background of immunization policies in Japan. Japan has provided universal health insurance coverage since 1961; these benefits cover health care for treatment but not prevention. Thus, as vaccination is part of preventive care, it is not covered by the national health insurance. Instead, under the national immunization program, the government provides subsidies for the cost of vaccination for targeted diseases. The diseases targeted by the program include diphtheria, pertussis, polio, measles, and rubella. Moreover, since 2001, influenza has been one of the diseases targeted by the program, and the government has subsidized the costs of influenza vaccinations. However, the population covered by the subsidies is limited to those aged 65 years or above, and those aged between 60 and 64 years if they have certain chronic conditions.[3] In this study, we examine peer effects in decision-making regarding vaccination against influenza. The immunity of influenza vaccination lasts for less than one year, and individuals should be vaccinated every year, unlike most of the diseases for which vaccination is available. The characteristics of vaccination, together with our panel dataset, enables us to analyze vaccination behavior by controlling for time-invariant factors, such as time and risk preferences, which are

[3] For individuals aged 60 to 64, those with extreme disabilities in the functions of the heart, kidneys, respiratory organs, etc. (equivalent to Level 1 of the Handicapped Person) are eligible.

considered important factors in vaccination decision-making (Chapman and Coups, 1999; Nuscheler and Roeder, 2016).

The data used in this study were from Itoman City, Okinawa Prefecture. Like other municipalities, Itoman City promotes influenza vaccination by subsidizing the prices for vaccine recipients aged 65 years and above, and those aged 60 to 64 years who have certain chronic conditions. There are slight differences in the subsidy, depending on the local government; some local governments provide full subsidies, while others require a co-payment of several thousand yen. For Itoman City, the co-payment is 1,000 yen.[4]

3. Data and Methods

This study analyzes peer or surrounding effects with geographical units as peers. Specifically, we use a unit of town blocks called "Aza" (meaning "township" in Japanese) in Okinawa Prefecture, a group of islands located at the southernmost point of Japan. We obtained administrative data on the vaccination status of the elderly who were eligible for the vaccination subsidy (i.e., high-risk individuals, aged 60 to 64 years, and all individuals aged 65 years and above) with physical addresses from the municipal government, to examine the impact of the vaccination status of other people (i.e., peers) in the same Aza on an individuals' decision to get vaccinated. In addition, we use another definition of peers, namely, household members. We utilize these members or cohabiters leaving their households as an exogenous environmental and state change. We describe the data and methods in more detail in the following subsections.

3.1 Data: Administrative Data from Itoman City, Okinawa

We used the administration data of influenza vaccination status among individuals aged 65 years and above in Itoman City, Okinawa Prefecture. Itoman City is located in the largest island of Okinawa Prefecture (the so-called main island) and had a population of 60,714 at the end of the 2016 fiscal year. The population of those aged 65 years and above was 11,728. Okinawa was an independent kingdom until the late 19th century. It is well known that close village communities attract sociologists that study the formation of communities (Miyagi, 2016). We conduct two empirical analyses using the datasets. In the first analysis, we define a township called Aza regarding its peers

[4] In all the local governments nationwide, public assistance recipients aged 65 years and over, and those aged 60 to 64 who have certain chronic conditions, can be vaccinated against influenza for free.

and employ panel data analyses with a lagged variable. Figure 1 shows a residential map of those aged 65 years and above in Itoman City. Itoman City has 35 townships. Residences are scattered around the city, and the distinction of each township is clear, making the city ideal for our analysis of peer or surrounding effects. In addition, we define household members as peers and examine how the probability of vaccination changes when a member disappears from the household. Furthermore, we examine the effects of township vaccination rates on his/her vaccination changes.

Under Japan's national immunization program, each municipality is responsible for providing citizens with vaccination at the appropriate time. The municipal government maintains a record of the vaccination status of all the targeted individuals. The targets of influenza vaccination are restricted to those aged 65 years and above, and those between 60 and 64 years who are high risk. Our dataset includes information on the influenza vaccination status of all citizens aged 65 years and above in Itoman City. Moreover, the data include information on the physical address, age, and sex of the citizens. We use the vaccination status record as a dependent variable. The variable is one if an individual is vaccinated, and zero otherwise. The dataset comprises of panel data from the fiscal years 2011 to 2013. Each fiscal year runs from April to March of the following year.

Table 1 represents the descriptive statistics. The average vaccination rate is 64%. The age of individuals ranged from 61 to 107 years, with a mean age of 76.38 years. The average population of those aged 65 years and above is 321, and the average number of hospitals within a radius of 500 meters of an individual's home is less than one. Of the sample of residents, 12.1% experienced the loss of a cohabitant during the study period. Separation or bereavement may explain the loss of a cohabitant from the same address, although this cannot be confirmed from the dataset. Since the sample is composed of elderly people, it is believed to include many bereavements, but it is also expected to include many relocations to nursing homes. Furthermore, the dataset does not include educational background, income, or asset data.

The current amount of savings by prefecture, published by the Ministry of Internal Affairs and Communications,[5] shows that the national average in 2014 was 14.5 million yen, while in Okinawa Prefecture, it was 5.3 million yen (the lowest among the 47 prefectures). The annual income by prefecture using the same data shows that the national average was 5.3 million yen, with Okinawa Prefecture being the lowest at 3.8 million yen. The data from the Ministry of Education, Culture, Sports, Science and

[5] From savings and liabilities in: The Ministry of Internal Affairs and Communications. (2014). *2014 National Consumer Survey.*

Technology regarding educational background[6] shows that the national average university enrollment rate in 2016 was 52.0%, while this was 36.7% for Okinawa Prefecture, which was the third-lowest among the prefectures. According to the census of the Ministry of Internal Affairs and Communications, the population of Okinawa Prefecture was 1.433 million in 2015, ranking 25th among all prefectures. The national average for population density was 338.4 people per square km, while this was 643.3 for Okinawa Prefecture (9th highest among all prefectures).[7] The population density within Okinawa Prefecture indicates that Itoman City ranked 13th among the 41 municipalities, and it ranked 7th among 11 cities. Based on these facts, the data used in this study are considered to be ranked low in terms of socioeconomic status including income, assets, and educational background, and rank slightly higher in terms of population density, compared to the national average.

<Insert Table 1 and Fig. 1>

3.2 Empirical Specification

In the first analysis, we consider the township members as peers. As the main outcome, $y_{i,j,t}$, is a binary variable to indicate whether an individual i in township j got vaccinated in year t. We use a linear probability model with panel data to examine the peer effects, using the following specification:

$$y_{i,j,t} = \theta Z_{-i,j,t-1} + \beta x_{i,t} + \gamma w_{j,t} + \varepsilon_{i,t} \tag{1}$$

where $Z_{-i,j,t-1}$ is a variable of peers indicating the vaccination rate within each township. We divide the number of those who were vaccinated in the township by the number of residents aged 65 years and above in the same township, excluding the individual i, to calculate the observed vaccination rates of peers. Thus, the vaccination rate is calculated as $Z_{-i,j,t-1} = \sum y_{-i,j,t-1} / \sum n_{-i,j,t-1}$, where $\sum y_{-i,j,t-1}$ is the number of people who were vaccinated in township j, excluding individual i in year $t-1$, and $\sum n_{-i,j,t-1}$ is the number of residents in township j, again excluding individual i. Thus, θ is our coefficient interest. x_i is a column vector that includes a set of control

[6] From the Ministry of Education, Culture, Sports, Science and Technology (2016). *2016 School Basic Survey.* The university enrollment rate does not include junior colleges.
[7] From the Ministry of Internal Affairs and Communications. (2020). *2020 Census.*

variables at the individual level, and β is a row vector for the control variables. w_j is a column vector that includes a set of control variables at the Aza level, and γ is a row vector for the corresponding coefficients. ε_i is an error term. First, we use a pooled linear probability model. Next, we control for individual fixed effects. It is not appropriate to apply a fixed-effect estimation in non-linear models, such as the probit model (Chamberlain, 2010). Therefore, we employed a linear probability model.

As for the control variables, we include both individual and township characteristics. Individual characteristics include sex, age, and age squared of individuals, while township characteristics include population size, average age, and the ratio of females to total residents, which were calculated using our dataset, with those aged 65 years and above. In the fixed effects model, it is difficult to distinguish between the age in 1-year increments and the fixed year effect. Therefore, so for age variables, we create dummy variables in the 60s, 70s, 80s, and 90s and over. Age squared is the square of the variable of age 1-year increments. Furthermore, we include the number of hospitals within a radius of 500 meters of an individual's home to control for medical resources. We include year dummies as fixed year effects to control influenza epidemics throughout the city. In addition, we control the epidemic in a smaller area than the entire city. The main influenza epidemic will be through schools. Infections through elementary school may be a major cause of local epidemics of influenza. Therefore, we create dummy variables in the school districts of the elementary school. By multiplying them with year dummies, the local influenza epidemics are controlled. There are 10 elementary school districts in Itoman city, and elementary school district dummies are created from the address information of the place of residence.

To handle an endogenous problem through a reflection, we use neighborhood vaccination rates in the previous period, where the variable of peers is set as $Z_{-i,j,t-1}$. While an individual's vaccination behavior could potentially affect that of neighbors in the same period, it cannot affect the neighbor's behavior in the previous period, following Clark and Lohéac (2007). By using the vaccination rate of the community's previous period, reverse causality can be controlled. However, it is necessary to consider self-selection. People with an interest in health investments may prefer a particular community. Regarding self-selection, those with higher education levels tend to be more interested in health investments. Time-invariant attributes, such as educational background of those over 65 years, are handled by a fixed effects model. Income and assets are also fixed variables for the elderly, and can be controlled predominantly by fixed effects. Since the data used in this study were from the same city, there was no difference in the medical system. In addition, individual differences in educational background, income, and assets are small because the data are from the same city. The estimation is performed by cluster robust in consideration of the heteroscedasticity and the serial correlation of the error term. The cluster unit is Aza (township). In the estimation of Equation (1), two analyses are performed: an analysis using subsamples divided into quartiles to consider the difference in surrounding effect based on community size, and an analysis using subsamples by gender to consider the difference by gender.

Regarding vaccination, individual's vaccination behavior tends to continue over time. If the tendency to continue is based on the time-invariant preference for health investment, the estimation of the fixed effect model in Equation (1) does not cause any bias. However, bias occurs when there is time-variant state dependence of individuals on vaccination. Therefore, in this study, we utilize an event that changes the situation of an individual's environment and conduct analyses in a case with low state dependence. A major event that changes the situation of the elderly is the loss of cohabitants. We use this event regarding the change in the cohabitant's composition to deal with endogenous problems. Specifically, we can detect the loss of cohabitants from a household in the dataset. Given that we have information on the physical addresses of individuals, we identify cohabitants who move out of their homes. We estimate the effect of the state change on an individual's probability of vaccination, and the neighborhood effect on an individual's vaccination behavioral changes. Thus, we estimate the following reduced-form equation:

$$y_{i,j,t} = \varphi Event_{i,t} + \theta Z_{-i,j,t-1} + \tau Event_{i,t} \times Z_{-i,j,t-1} + \beta x_{i,t} + \gamma w_{j,t} + \varepsilon_{i,t} \quad (2)$$

Where $Event_{i,t}$ is a variable that captures the shock that decreases the number of household members between t-1 and t. Moreover, $Event_{i,t} = 1$ if the individual experiences such an event, and is 0 otherwise. For this analysis, we restrict the sample to households with only two people in the first year of our analysis. The coefficient φ represents the effect of changes on the state of an individual, such as the effect of the loss of a cohabitant on the individual's decision to vaccinate. The coefficient of the cross term between that variable and the vaccination rate of the community from the previous period is τ. The coefficient τ indicates how the vaccination rate of the community affects the change in vaccination behavior of the individual, due to their change in state.

When an individual experiences a loss of a household member, the probability of vaccination declines if a positive surrounding effect exists. For example, if a cohabitant has been vaccinated and that cohabitant disappears, that the number of cohabitant's vaccination will be zero. If the vaccination rate of the individual decreases when it becomes to be zero, it can be interpreted as a positive peer effect. Here, since a dummy variable has the value of one when a cohabitant disappears, if the sign of the coefficient is negative, it can be interpreted as a positive peer effect. However, the vaccination may have stopped due to the individual's depression after the disappearance of their cohabitant. In addition, since the cohabitant has gone, the individual may stop getting vaccinated because they no longer need to be concerned about their cohabitant's health; in other words, their actions could have an altruistic motivation. The coefficient φ of $Event_{i,t}$ cannot distinguish whether it is the result of an effect from the surroundings, the individual's discouragement, or altruism. However, the coefficient τ of the cross term shows how individual's decision on vaccination differs by the community vaccination rate at the time of loss of cohabitant. Hence, an effect that is separate from altruism and discouragement can be found.

4. Results

4.1 The effect of neighborhood vaccination

Table 2 shows the estimation results for Aza members as peers. In the a linear probability model with pooled data, the coefficient of peer effects θ in estimation (1) is positive and statistically significant, indicating that an increase in the probability of neighborhood vaccination induces an increase in the probability of vaccination ([1] in Table 2). Specifically, a 1% point increase in the proportion of vaccinations leads to a 0.42% increase in the probability of an individual deciding to get vaccinated. The coefficients of age squared show a statistically significant effect, indicating a non-linear effect of age on the probability of vaccination. Results that use fixed-effect models are shown in [2] and [3] in Table 2. The former includes year-fixed effect, and the latter includes both year-fixed effect and yearly effects of elementary school districts. The result confirms that neighborhood vaccination increases the probability of an individual choosing to get vaccinated when unobservable heterogeneity is controlled for. The magnitude of the increase in the probability of vaccination is 0.36% increase ([3] in Table 2).

Further, we investigated heterogeneity in the effect. First, we observed how peer effects differ by the magnitude of peers, as the network between peers in a smaller town is expected to be stronger than that of a larger town. We divided the sample by quartiles of the elderly's population size and performed fixed-effect analysis using the lowest quartile of town size in the sample, with an average town size of 135.5. The coefficients of the peer effect, shown by [4] and [5] in Table 2, are positive and statistically significant and greater than those of all samples (i.e., [2] and [3] in Table2), suggesting that the peer effect is more vigorous in a smaller community. In addition, this means that the positive peer effect decreases as the size of the community increases, hence the effect of free ride increases as the size of the population increases.

Thereafter, we explored the peer effect by gender and showed the results for female subsamples that are statistically significant at 1% level ([6] and [7] in Table 2). We calculate the vaccination rate of females in the t-1 period in each town and consider the variable as a peer effect among females (i.e., female-to-female peer effects). The coefficients of the peer effect are positive and greater than those of the entire sample. The result could be interpreted through the following two instances explaining how peer effects work: first, females have closer contact with each other than males; thus, peer effects in females are generally stronger. Second, females tend to be influenced more greatly by their surrounding peers than males, which produces a greater degree of peer effects among them. Similarly, [8] and [9] in Table 2 are estimated using a male-only sample. The estimation results are different from those of the female-only sample, and the coefficients of the peers were not statistically significant.

<Insert Table 2>

4.2 The loss of a cohabiter

We then use their state change on the composition of cohabitants in estimation 2 to deal with a problem of state dependency. The sample of living with elderly couple is used. First, we observe how the loss of the cohabitant affects the individual's vaccination. There are two cases in the loss of the cohabitant; cohabiters were vaccinated or not. If the cohabitant was a vaccinated person and the vaccination of those left behind decreases after the separation, it can be interpreted as the positive peer effect. However, it may be that the decrease in vaccination rate is due to the disappointment caused by the loss of cohabitants. Therefore, we also check whether the vaccination of the remaining persons decreases after the separation with the sample of non-vaccinated cohabitant. When the vaccination of the remaining persons decreases even if the cohabitant is not vaccinated, it is considered that the decrease in the vaccination rate after the separation includes the effect of disappointment. In that case, the degree of decrease in the vaccination of the reaming person needs to be larger in the vaccinated cohabitant than in the non-vaccinated cohabitant, in order to confirm the positive peer effect. Table 3 shows the results from a fixed-effect estimation, with and without yearly effects of elementary school districts. In [1] and [2] of Table 3, we restrict the sample to those whose cohabiters were vaccinated before they left the household and show these results. The coefficients of the loss of household members φ are negative and statistically significant, indicating that the probability of vaccination decreases after the loss of a cohabitant. However, this decrease may include the influence of an individual's depression at the loss of a family member or a cohabitant. Next, we restrict the sample to those whose cohabiters were not vaccinated in [3] and [4] of Table 3. The coefficients of the loss of household members are negative, but statistically insignificant. When comparing the two samples, we expect that the vaccination rate of the individual will decrease to the same extent in both samples if depression is the cause of a decrease in vaccination. The estimated results in the coefficients of φ show that the vaccination rate decreased more greatly in the sample with vaccinated than with non-vaccinated cohabitants. This can be interpreted as the decrease in vaccination rates due to the peer effect.

Another interpretation of the results in [1] and [2] of Table 3 may be possible and it is the altruistic motive. Individuals may be vaccinated to protect their cohabiters' health. For example, if a cohabitor is a high-risk individual and therefore s/he is vaccinated for her/him and her/his household members may also get vaccinated for the cohabitor. If that is the case, after the cohabiter leaves, individuals are not as likely get vaccinated, as they no longer need to be concerned with their cohabiter's health condition. It is difficult to determine if the change in vaccination behavior is due to peer effect or altruism using the coefficient φ alone. Next, we investigate how Aza's peer effects interact with a decrease in the vaccination rate of individuals due to the loss of cohabitants. We consider an interaction term (the coefficient τ) between the variable for the loss of household members and the variable for the township vaccination rate in period t-1, to investigate whether a decrease in individuals' vaccination probability induced by loss of household members is mitigated by peer effects from neighbors. If an Aza's peer effects mitigate a decline in the vaccination probability due to the loss of household members, its surrounding effect is considered effective in maintaining one's vaccination after the loss of a cohabiter. The interaction terms showed a positive and statistically significant result at 1% level of significance.

The coefficients φ of [1] and [2] in Table 3 shows how vaccination behavior changes after the loss of cohabitant, and we could consider, surrounding effects, as well as depression and altruistic motives. However, the interaction term shows the peer effect from the community only. The coefficient τ is positive, and the higher the vaccination rate of the community, the smaller the decrease in the individual's vaccination rate. This means that the community's vaccination rate has the opposite effect to the decrease in the individual's vaccination probability due to the loss of the cohabitant; thus, a positive surrounding effect from the community is confirmed.

We also conducted analyses using subsamples for this analysis. [1], [2] in Table 4 show the estimation results for the lowest quartile of the town size in the sample. The results indicate that the coefficient τ is not statistically significant. Table 2 shows a larger surrounding effect for the lowest quartile of town size whereas the subsample in Table 4 does not. An analysis using loss has the advantage of using exogenous changes other than the individual in question, however, it also has the disadvantage that the number of people that can be used as targets is relatively small. The number of observations become even smaller in the lowest quartile for town size, and the variation in vaccination rate in each community becomes smaller. It is conceivable that this led to statistically insignificant results.

Next, [3] and [4] in Table 4 shows an analysis using only female subsamples. The coefficient τ is not statistically significant, and the separation or bereavement dummy coefficient φ is also not statistically significant in the female-only subsamples. In other words, women do not respond to separation or bereavement with their spouses in a way that decreases their vaccination rate. Analysis of the male-only subsample is shown in [5] and [6] in Table 4. In the case of males, the loss dummy coefficient φ is negative and significant, indicating that the loss of their spouse decreases the probability of vaccination. The coefficient τ is how the vaccination rate of the community affects the decrease in the probability of vaccination, and the result is positive and statistically significant. Therefore, in the case of men, loss of the spouse decreases the vaccination rate, but the higher the vaccination rate in the community, the lesser the decrease in this vaccination rate. This confirms a positive surrounding effect.

<Insert Tables 3 and 4 >

5. Concluding remarks

This study empirically confirms that a positive surrounding effect exists when using Japanese data. If the persistence of vaccination behavior is based on the individual's time-invariant preference for health investment, the surrounding effect is also found to be more vigorous within a smaller community. In addition, regarding differences in the surrounding effect by gender, results show that the surrounding effect is generally larger in women than in men. However, in the estimation using the change in state or changes in the environment (e.g., loss of a cohabitant), it can be confirmed that this decreases the vaccination rate of the individual. Decreases in an individual's vaccination rate could result from depression and altruistic motives, but the higher the community's vaccination rate, the smaller the degree of decrease in the individual's vaccination rate. In other words, the higher the community's vaccination rate, the more the raising effect of the individual's vaccination rate separated from depression and altruistic motive. Thus, a positive surrounding effect can be confirmed.

Regarding the loss of cohabitants, the probability of vaccination for males decreases, but if the vaccination rate of the community is high, the level of decrease becomes smaller, and a positive surrounding effect can be confirmed. If there is a positive surrounding effect, measures to turn non-vaccinated individuals into vaccinated individuals are considered more effective in increasing the number of vaccinated individuals.

There are a few limitations in the study. First, the data of this study is gathered from those aged 65 and over and is limited to Itoman City, Okinawa Prefecture. As this is a rural area, the results of this study are expected to differ from those of metropolitan cities, such as Tokyo and Osaka. Therefore, the representativeness and external validity are questionable. Future research has the scope of analysis using data from other regions, such as urban areas. Second, although a positive surrounding effect is confirmed in this study, we have not yet analyzed the causes of the positive surrounding effect. The effect could be due to social pressure or the sense of security, etc. The identification of the source of the mechanism is a future research topic.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statements

The datasets generated and analyzed during the current study are not publicly available due the fact that they are provided for the current study by Itoman City, Okinawa Prefecture, Japan. But they are available from the corresponding author on reasonable request.

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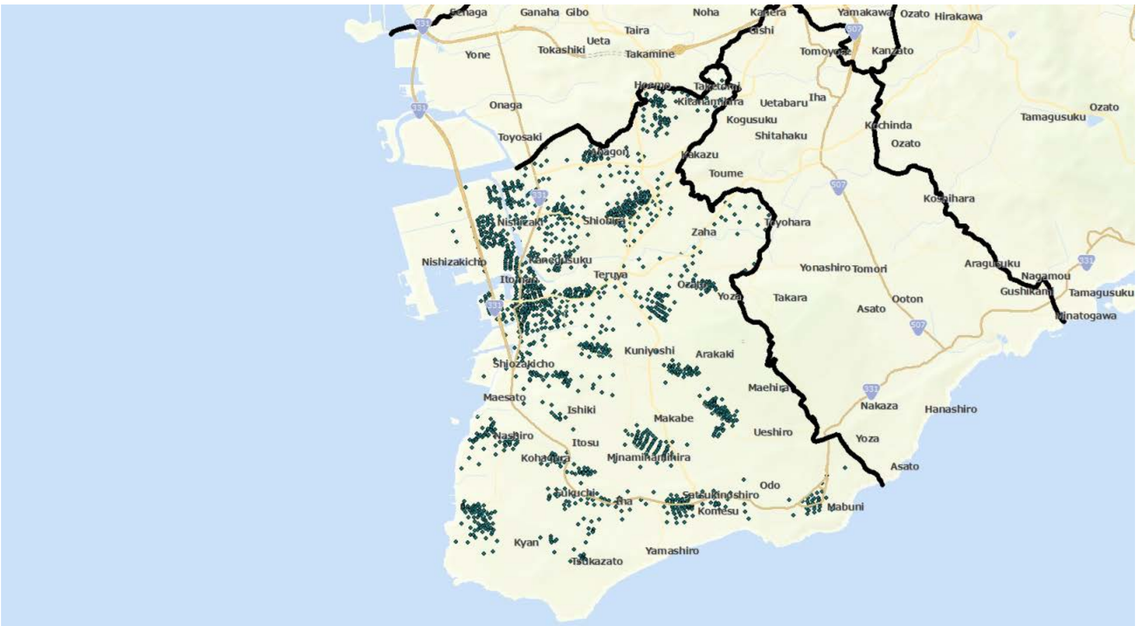
Fig. 1 Map of Itoman City



Note: Each dot shows the residence location of individuals’ aged 65 years and above.

Table 1 Descriptive Statistics: Administrative data on the influenza vaccination status of the elderly in Itoman City

Variable	N	Mean	Std. Dev.	Min	Max
Vaccination status (yes=1) [b]	17,713	0.64	n.a.	0	1
Individual characteristics					
Age	17,713	76.38	7.595	61	107
Female [b]	17,713	0.563	n.a.	0	1
Az a's characteristics					
Mean proportion of vaccination	17,713	0.64	0.077	0.1	1
Mean age	17,713	75.54	1.882	69	83.35
Proportion of Female	17,713	0.555	0.036	0.285	0.8
Population size	17,713	0.321	0.165	0.002	0.785
Medical institution within 500m	17,713	0.777	1.376	0	6
Family characteristics					
Loss of a cohabiter (yes=1) [b]	17,713	0.121	n.a.	0	1

[b]= binary variable; n.a.= not applicable.

Note. The unit of population size is 1000 people.

Table 2 Peer effect on vaccination

	Pooled OLS	Fixed effect estimation All sample		Fixed effect estimation Lowest quartile in town size		Fixed effect estimation Female sample		Fixed effect estimation Male sample	
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
Aza's peer effect	0.4171***	0.2525*	0.3638*	0.4194**	0.8515**	0.7779***	1.1116***	0.0778	0.0657
	(0.0806)	(0.1458)	(0.1859)	(0.1965)	(0.3928)	(0.2246)	(0.2699)	(0.1053)	(0.1216)
Individual characteristics									
Age 70's	0.0708***	0.0407**	0.0407**	0.0144	0.0135	0.0093	0.0086	0.0702**	0.0695**
	(0.0162)	(0.0200)	(0.0201)	(0.0376)	(0.0371)	(0.0244)	(0.0244)	(0.0289)	(0.0288)
Age 80's	0.0516*	0.0316	0.0317	0.0162	0.0165	-0.0187	-0.0165	0.0891*	0.0877*
	(0.0277)	(0.0283)	(0.0283)	(0.0445)	(0.0437)	(0.0343)	(0.0339)	(0.0450)	(0.0446)
Age 90's	-0.0501	0.0625	0.0644	0.0042	0.0037	0.0283	0.0321	0.0798	0.077
	(0.0455)	(0.0492)	(0.0492)	(0.0540)	(0.0538)	(0.0587)	(0.0587)	(0.0693)	(0.0699)
Age squared	0.0913***	-0.5526**	-0.5991**	-0.9386*	-0.9941*	-0.7831*	-0.8283**	-0.4872	-0.5129
	(0.0096)	(0.2612)	(0.2619)	(0.4796)	(0.4907)	(0.3911)	(0.3823)	(0.4717)	(0.4803)
Female	0.0362***								
	(0.0084)								
Aza's characteristics									
Mean age	0.0038	-0.0229	-0.0349*	-0.0072	0.0076	-0.0398*	-0.0277	-0.0071	-0.0376
	(0.0043)	(0.0141)	(0.0138)	(0.0233)	(0.0272)	(0.0230)	(0.0237)	(0.0189)	(0.0235)
Proportion of Female	-0.3092**	0.3025	0.6855	0.9111	1.6274*	0.7146	1.0192	-0.6024	-0.2845
	(0.1419)	(0.6650)	(0.6264)	(0.6953)	(0.8039)	(0.8395)	(0.7464)	(0.6432)	(0.6274)
Population size	0.0288	-0.1428	0.0482	-0.0451	-0.1862	-0.4828*	-0.0071	0.1076	-0.2205
	(0.0274)	(0.2122)	(0.3555)	(1.4695)	(2.6406)	(0.2870)	(0.4017)	(0.2958)	(0.3495)
Medical institution within 500m	-0.0074*								
	(0.0043)								
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy x School district dummy	No	No	Yes	No	Yes	No	Yes	No	Yes
Sample size	17,713	17,713	17,713	4,661	4,661	9,983	9,983	7,728	7,728

Note. * p<0.1; ** p<0.05; *** p<0.01. Estimation with the pooled OLS for [1] and the linear probability fixed effect model for others are employed. Cluster-robust standard errors are shown in parentheses. The marginal effect of the vaccination proportion in *Aza* at *t*-1 shows the peer effect on vaccination from community members.

Table 3 Effect of the loss of a cohabiter

	Fixed effect estimation			
	Vaccinated cohabitant		Non-vaccinated cohabitant	
	[1]	[2]	[3]	[4]
Loss of household members	-0.5888***	-0.5383***	-0.1899	-0.2038
	(0.1849)	(0.1866)	(0.2170)	(0.2240)
Loss of household members x vaccination rate in *Aza* at t-1	0.8372***	0.7562***	0.2593	0.2794
	(0.2784)	(0.2783)	(0.3301)	(0.3421)
Aza 's vaccination rate at t-1	0.0882	0.0709	0.1518	0.3939
	(0.1707)	(0.2006)	(0.3427)	(0.3720)
Individual characteristics				
Age 70's	0.0625*	0.0664**	-0.0007	0.0015**
	(0.0324)	(0.0322)	(0.0365)	(0.0352)
Age 80's	0.0476	0.0537	0.0516	0.051
	(0.0401)	(0.0413)	(0.0841)	(0.0858)
Age 90's	0.0569	0.0608	0.053	0.0507
	(0.0821)	(0.0835)	(0.1106)	(0.1126)
Age squared	-0.3384	-0.3349	-1.2936*	-1.2382*
	(0.4684)	(0.4691)	(0.0991)	(0.7350)
Aza 's characteristics				
Mean age	-0.028	-0.0562***	-0.0051	-0.011
	(0.0199)	(0.0187)	(0.0425)	(0.0485)
Proportion of Female	0.5124	0.9676	0.0367	0.8619
	(0.8088)	(0.8497)	(1.4997)	(1.2603)
Population size	-0.0975	-0.1263	-0.0347	0.1249
	(0.2394)	(0.3836)	(0.5304)	(0.5028)
Year fixed effects	Yes	Yes	Yes	Yes
Year dummy x School district dummy	No	Yes	No	Yes
Sample size	8,275	8,275	4,078	4,078

Note. * p<0.1; ** p<0.05; *** p<0.01. Linear probability fixed-effect models are employed. Cluster-robust standard errors are shown in parentheses.

Table 4 The interaction term between community vaccination rates and the loss of cohabiters

	Fixed effect estimation					
	Lowest quartile in town size		Female sample		Male sample	
	[1]	[2]	[3]	[4]	[5]	[6]
Loss of household members	-0.4619	-0.391	-0.0014	0.0738	-0.5826**	-0.5791**
	(0.3475)	(0.3608)	(0.3050)	(0.3150)	(0.2612)	(0.2649)
Loss of household members x vaccination rate in *Aza* at t-1	0.5779	0.4637	-0.0947	-0.2134	0.8642*	0.8642*
	(0.4908)	(0.5014)	(0.4391)	(0.4544)	(0.4433)	(0.4493)
Aza 's vaccination rate at t-1	0.1405	1.3251***	0.5878*	1.0253**	0.018	-0.1415
	(0.1562)	(0.4506)	(0.3377)	(0.4382)	(0.1720)	(0.1788)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year dummy x School district dummy	No	Yes	No	Yes	No	Yes
Sample size	2,073	2,073	4,235	4,235	4,038	4,038

Note. * p<0.1; ** p<0.05; *** p<0.01. Linear probability fixed-effect models are employed. Cluster-robust standard errors are shown in parentheses. Other control variables are the same as those of Tables 2 and 3.

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