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別所俊一郎、井深陽子

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Institute for Economic Studies, Keio University
2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan
ies-office@adst.keio.ac.jp
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【要旨】

日本の予防接種政策は他の先進国と比較して2つの点で遅れているといわれる。ひとつはワクチンの認可が遅い点、もうひとつは国際的に広く用いられているワクチンのいくつかが予防接種プログラムに含まれていない点である。日本の市町村のいくつかは、国の予防接種プログラムに含まれていない任意接種に対して助成を行っている。本稿は、市町村の予防接種助成政策の決定過程を、市町村間の相互依存に注目し、2010年のデータを空間ラグモデルに適用して分析するものである。結果は以下の3点にまとめられる。第1に、市町村がどの予防接種を優先するかについて系統的な順位は存在しない。第2に、助成政策は同じ県内の隣接市町村の政策とは統計的に相関するが、隣接していても県外の市町村の政策とは相関しない。これは市町村が同一県内の市町村とヤードスティック競争をしていることを示唆している。第3に、他の社会経済要因・財政状況と助成政策のあいだに相関は検出されなかった。

別所俊一郎

慶應義塾大学経済学部

〒108-8345

東京都港区三田2-15-45

bessho@econ.keio.ac.jp

井深陽子

東北大学

〒980-8579

宮城県仙台市青葉区川内27-1

ibuka@econ.tohoku.ac.jp

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Vaccination policy of Japanese municipalities[†]

Shun-ichiro BESSHO*

Keio University

Yoko IBUKA♪

Tohoku University

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Abstract

Japan's immunization policy is often perceived as lagging behind those of other developed nations because of the delay in vaccine licensing and exclusion from the national program of some vaccines widely used elsewhere. In Japan, municipal authorities provide financial support for voluntary vaccinations, which are not included in the national program. This study examines the process of vaccination policymaking by municipal governments, focusing on the interdependency of such policy and using the spatial lag model and data from 2010. We make the following three findings. First, there are no systematic priorities on vaccines across municipalities. Second, vaccination subsidy policy is statistically significantly correlated with neighboring municipalities in the same prefecture, but not outside, indicating that Japanese municipalities engage in "yardstick competition" in the same prefecture. Third, no strong correlations between the other socio-economic or fiscal characteristics of municipalities and vaccination subsidy policy are detected.

Keywords: vaccine policy; spatial lag model; yardstick competition

JEL codes: I18, H75, H77, H71

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* (Corresponding author) Faculty of Economics, Keio University. 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan. E-mail: bessho@econ.keio.ac.jp.

♪Department of Economics, Tohoku University.

1. Introduction

Vaccination against infectious diseases is an effective tool for protecting public health globally, and governmental authorities in developed countries implement immunization programs. However, Japan's immunization policy is often perceived as lagging behind those of other developed nations because of the delay in vaccine licensing (e.g., Saitoh and Okabe 2014) and lack of some vaccines widely used elsewhere (e.g., Akazawa et al. 2014). In terms of the second point, the absence of a single uniform vaccine policy at the national level means that municipal authorities often provide financial support at the regional level (Hayashi et al. 2012, Akazawa et al. 2014). While many previous studies investigate the decision-making process of vaccination policy at the national level, few researchers examine such a process at the subnational government level.

This study bridges that gap in the body of knowledge on this topic by examining the process of vaccination policymaking by municipal governments. Specifically, among the factors that influence policymaking, we focus on the interdependency among municipalities (Ito 2002, Nakazawa 2007, Tanaka 2009, Bessho and Terai 2011, Bessho and Miyamoto 2012). The vaccinations examined in this study are voluntary in the sense that the costs tend to be borne by vaccinees. Municipal governments have the authority to decide whether to offer subsidies¹; however, the central government provides no financial assistance.

If we look at research on how to make decisions on policies in the context of immunization at the national level, there is a lack of consensus about which factors drive decisions on vaccination policy nationally because numerous driving forces play a role (e.g., Bryson et al. 2010, Burchett et al. 2012, Silva et al. 2015, Gonzalez-Lorenzo et al. 2015). One advantage of focusing on local governments in Japan is that some such factors, including the acceptability and accessibility of vaccines and organizational structure of governments, can be considered to be the same among localities, while social and fiscal situations differ. These differences in social and fiscal characteristics may lead to the provision of different vaccination subsidies.

Local governments' health policy has also been examined in the context of local public health expenditure, which tends to be spatially correlated. This spatial correlation may be the result of the geographical distribution of socio-economic

¹ Subsidy is one tool for internalizing the positive externality of vaccinations. An appropriate combination of tax and subsidy can produce the socially optimal allocation (Brito et al. 1991, Francis 1997).

characteristics (e.g., health needs) and supply of healthcare services. A growing literature has identified the factors behind these spatial correlations to understand the importance of political factors (Costa-Font and Pons-Novell 2007, Costa-Font and Moscone 2008, Atella et al. 2014, Fernandez and Forder 2015). In the current Japanese policy, preventive care is not a part of the universal health coverage, and thus policies made by local government would directly influence individuals' health. It is essential to analyze what determines policy making of preventive care and this study analyzes such process using an example of vaccination.

The presented analysis allows us to make the following three findings. First, the majority of the municipalities under study did not offer subsidies for voluntary vaccination against *Haemophilus Influenza* type b (Hib), pneumococcal conjugate vaccines (PCV7, PCV23), varicella, mumps, and human papillomavirus (HPV) in 2010. The correlations in the subsidy provision among these vaccinations are low, implying that when municipalities subsidize some of these vaccinations, the subsidy pattern among municipalities differs. In other words, there are no systematic priorities on vaccines across municipalities. Second, the results of our regression analysis based on a spatial lag model show that vaccination subsidy policy is statistically significantly correlated with neighboring municipalities in the same prefecture. Hence, Japanese municipalities engage in "yardstick competition" in the same prefecture (Nakazawa 2007, Bessho and Miyamoto 2012). Third, no strong correlations between other municipality-level socio-economic or fiscal characteristics and vaccination subsidy policy are detected.

Our arguments in this paper develop as follows. Section 2 summarizes the institutional background of Japanese vaccination policy. The econometric specification is described in Section 3, and we describe the data in Section 4. The estimation results are shown in Section 5. Section 6 concludes.

2. Background

In 2010, which is the year of the current analysis, the Preventive Vaccination Act of Japan, which recommends routine vaccinations, stipulated two kinds of diseases (Enami and Otsubo 2010): nine Type I diseases (diphtheria, whooping cough (pertussis), acute poliomyelitis (polio), measles, rubella, Japanese encephalitis, tetanus, tuberculosis, and smallpox) and one Type II disease (influenza for persons 65 years of

age or older)². One difference between routine and voluntary vaccinations is the monetary burden of vaccinees. As mentioned in the Introduction, it is the responsibility of municipalities, the first tier of local government in Japan, to purchase and administer routine vaccines to their residents at no or a negligible cost. Local governments receive some intergovernmental transfers from prefectures, the second tier of local government, and the central government to finance these costs (Akazawa et al. 2014). On the contrary, vaccinees tend to pay the full cost of voluntary vaccinations out of their own pockets (Akazawa et al. 2014, Saitoh and Okabe 2014).

This difference might lead people to regard voluntary vaccines as less important than routine vaccines, which may result in low vaccination rates for voluntary vaccines (Nakayama 2013). Low vaccination rates are associated with persistently high incidences of target diseases. For example, mumps is endemic in Japan, and many children develop complications with mumps infection including hearing loss (Saitoh and Okabe 2014). Although the costs of voluntary vaccination are generally borne by vaccinees, a small number of municipalities offer their residents vaccination subsidies (Hayashi et al. 2012, Akazawa et al. 2014). However, as noted in the Introduction, upper-level governments do not provide any financial assistance for such subsidies. Akazawa et al. (2014) point out that this mixed provision of subsidies has led to disparities in vaccine utilization access across Japan, where healthcare coverage is universal.

3. Econometric specification

3.1. Baseline case

This study utilizes a regression analysis to examine the vaccination subsidy policy of Japanese municipal governments. As the literature on Japanese fiscal federalism points out (e.g., Ito 2002, Nishikawa and Hayashi 2006, Nakazawa 2007, Bessho and Terai 2011,

² The objective of Type I disease immunization is to prevent an outbreak or epidemic, while that of Type II disease immunization is to prevent individuals from contracting a disease and to reduce severity when they do (Enami and Otsubo 2010). Vaccinations against other diseases, although approved by the Ministry of Health, Labour and Welfare under the Pharmaceutical Affairs Law, are voluntary and not required by the Preventive Vaccination Act (Shono and Kondo 2015). These include Hib, hepatitis B virus (HBV), mumps, varicella, pneumococcal conjugate vaccine (PCV7 and PCV23), human papillomavirus (HPV) and rotavirus vaccines. | Rotavirus vaccine was licensed in 2011, and thus it was not available at the time of the survey. (Akazawa et al. 2014, Saitoh and Okabe 2014). For the history of Japanese vaccination policy, see, for example, Nakayama (2013).

Bessho and Miyamoto 2012), the decisions of local governments in Japan are often interdependent. Hence, our estimation equations are based on a spatial autoregressive model that is standard in the literature on the estimation of fiscal reaction functions (e.g., Costa-Font et al. 2015). Our basic estimation equation is

$$Z_i = \beta w_i Z_{-i} + X_i \theta + \sum_{j=1}^{46} d_j \eta_j + u_{1i}, \quad (1)$$

where Z_i represents the subsidy policy of local government i , Z_{-i} is a vector of the subsidy variables of other local governments than i , w_i is an exogenous weighting vector of neighborliness, X_i is a vector of the other characteristics, d_j is an indicator variable that takes unity if the municipality is located in prefecture j , and u_{1i} is an error term. β , θ , and η_j s represent the corresponding coefficients. A spatial lag term, $w_i Z_{-i}$, is a weighted average of the subsidy variables of neighboring local governments, while the sum of the elements of w_i is normalized to unity.

The spatial lag term, $w_i Z_{-i}$, is endogenous because we assume interdependence among local governments; therefore, OLS estimators are typically inconsistent. One way in which to deal with this endogeneity problem is the maximum likelihood method³. Another route to address this endogeneity is to instrument the explanatory variable, $w_i Z_{-i}$ (e.g., Kelejian and Prucha 1998)⁴. These instruments must be correlated with $w_i Z_{-i}$ (relevancy) and uncorrelated with the error term, u_{1i} (exogeneity). Here, we assume that the other explanatory variables included in X_i and d_j s are exogenous. For both these equations, the components of $w_i X_i$ are valid instruments (e.g., Revelli, 2006)⁵.

Even if the coefficient of the spatial lag term, β , is not zero, this does not necessarily imply policy competition among municipalities (Bailey and Rom 2004, Brueckner 2003, Revelli 2005), because other factors such as technological externalities, common shocks, and the effects of upper-level governments can generate non-zero coefficients for the spatial lag term.

3.2. Extended case

Our basic estimation equation is extended to identify various factors such as technological externalities, common shocks, and the effects of upper-level governments.

³ We do not employ the maximum likelihood approach here because this needs to assume the functional form of the distribution of the error term.

⁴ Gibbons and Overman (2012) criticize this approach, saying that, “in many cases, such an approach will be uninformative about the causal economic processes at work, rendering much applied spatial econometric research ‘pointless,’ unless the main aim is description of the data.”

⁵ If the decision making on vaccination subsidy interacts with each other through a route other than the spatial lag term, the error term is spatially autoregressive. Baicker (2005) utilizes mandated increases in medical spending as an instrument excluded from X_i “that are less likely to be correlated with omitted state characteristics” (p. 535).

The following estimation equation results:

$$Z_i = \beta_I w_i^I Z_{-i}^I + \beta_O w_i^O Z_{-i}^O + \mathbf{X}_i \boldsymbol{\theta} + \sum_{j=1}^{46} d_j \eta_j + u_{2i}, \quad (2)$$

where the spatial lag term is divided into two components as in Atella et al. (2014). $w_i^I Z_{-i}^I$, with superscript I , is a weighted average of the subsidy variables of neighboring local governments in the same prefecture as municipality i , while $w_i^O Z_{-i}^O$, with superscript O , is a weighted average of neighboring local governments outside the prefecture in which municipality i is located. Thus, without normalization, it holds that $w_i = w_i^O + w_i^I$. w_i^O and w_i^I are normalized, meaning that the sums of the elements are equal to unity.

If the spatial autocorrelation is due to technological externalities, geographically common shocks, or resident migration, two coefficients of the spatial lag terms, β_I and β_O , should be equal because these factors are unrelated to the boundaries of upper-level governments (prefectures). On the contrary, if the spatial autocorrelation is generated by the effects of these upper-level governments or policy competition within a prefecture, the situation outside the prefecture should not have an influence; thus, the corresponding coefficient, β_O , should be zero.

As in the previous subsection, the spatial lag terms, $w_i^I Z_{-i}^I$ and $w_i^O Z_{-i}^O$, are endogenous. Thus, the two-step estimation is used where the instruments are $w_i^I \mathbf{X}_I^I$ and $w_i^O \mathbf{X}_O^O$.

3.3. Spatial-weighting matrix

Two types of spatial-weighting matrix, \mathbf{W} , whose i -th row is w_i , are used in the baseline case. One is a standard adjacent matrix set as follows. If municipalities i and j are contiguous, the (i, j) element of the spatial-weighting matrix is temporarily assigned weights of 1. If not, it is assigned weights of 0. Then, the matrix is normalized by dividing each element in row i by the sum of the row's elements. In this calculation, we ignore the population size or length of the border of neighboring municipalities.

The other spatial-weighting matrix is based on the geographical distance between municipalities. If the distance between the two municipal offices of municipalities i and j is k_{ij} km⁶, the (i, j) element of the spatial-weighting matrix is temporarily assigned weights of $\max(50 - k_{ij}, 0)$. Then, the matrix is also row-normalized.

We also set two types of spatial-weighting matrixes in the extended case, \mathbf{W}^I and \mathbf{W}^O , whose i -th row is w_i^I and w_i^O , respectively, based on \mathbf{W} in the baseline case. Define \mathbf{W}^P

⁶ The distances between these two municipal offices are based on the longitude and latitude coordinates using the Pythagorean Theorem. The difference in latitude is assumed to be 111.1 km and that of longitude is 90.7 km.

as a matrix that represents municipalities' prefectures. The (i, j) element of W^p is 1 if municipalities i and j are located in the same prefecture and zero otherwise. W^l is a row-normalized matrix of $W \otimes W^p$ and W^o is a row-normalized matrix of $W - W^l$. W is contiguity-based or distance-based; thus, we have contiguity-based (W^l, W^o) and distance-based (W^l, W^o).

4. Data

4.1. Vaccination policy

The data on municipal vaccination policy are taken from a survey of municipalities conducted in 2010 by the Ministry of Health, Labour and Welfare. The Ministry sent the survey questionnaire to all municipalities in Japan at that time and received responses from 1,744 municipalities (response rate of 99.4%). The survey aimed to identify municipalities in which subsidies for routine and voluntary vaccinations were provided and obtain information on subsidy amount, the segment of the population eligible for vaccination subsidies, and start date.

The surveyed vaccinations are Type II routine vaccination (influenza for the elderly), Hib, PCV7, PCV23, varicella, mumps, and HPV⁷. Vaccinations against Hib, PCV7, PCV23, varicella, mumps, and HPV were voluntary when the survey was conducted. Subsidy amount is surveyed by using multiple-choice questions. For the influenza vaccination, the multiple-choice questions are set with intervals of JPY 1,000 (about USD 10); 1–999, 1,000–1,999, 2,000–2,999, 3,000–3,999, 4,000–4,999, more than or equal to 5,000, and full amount. For Hib, PCV7, PCV23, varicella, and mumps, the choices are similar to influenza, but the choice of full amount is excluded. For HPV, the interval is JPY 2,000 and the choices are 1–1,999, 2,000–3,999, 4,000–5,999, 6,000–7,999, 8,000–9,999, 10,000–11,999, and more than or equal to 12,000.

While 97.4% of municipalities subsidize the influenza vaccination for the elderly, in line with the findings of Hayashi et al. (2012) and Akazawa et al. (2014), the proportions of the municipalities with subsidies for the other vaccinations are far lower (**Table 1**): 11.5% for Hib, 0.6% for PCV7, 18.6% for PCV23, 3.4% for varicella, 3.5% for mumps, and 6.5% for HPV. Considering these low rates of vaccination, we first focus on whether municipalities subsidize residents for the cost of vaccination and if so, subsidy amount. In addition, since there is few variations in the timing of the start of

⁷ The survey did not ask municipalities about vaccination subsidies against influenza for the non-elderly, although some municipalities did subsidize this.

the program, we ignore when the program started in our analysis. Thus, we set Z_i as an indicator variable that takes unity if the local government subsidizes vaccinations.

As a robustness check, we use another three dependent variables. First is the number of subsidized vaccinations, excluding influenza for the elderly which is classified into Type II disease vaccination unlike others. The maximum value of this variable is six, including Hib, PCV7, PCV23, varicella, mumps, and HPV. Second is the number of subsidized vaccinations for children (Hib, PCV7, varicella, and mumps). Third is the indicator variable that takes unity if subsidy amount for influenza for the elderly is equal to or more than JPY 3,000. As shown below, subsidy amount for influenza is focused in the range of JPY 2,000-2,999 (i.e., it is relatively large).

4.2. Explanatory variables

Previous studies have examined a wide range of factors that influence the decision-making process (e.g., Silva et al. 2015, Gonzalez-Lorenzo et al. 2015). Burchett et al. (2012) identify nine criteria that affect national decisions to adopt new vaccines: the importance of the health problem; vaccine characteristics; immunization program considerations; acceptability; accessibility, equity and ethics; financial/economic issues; impact; alternative interventions; and the decision-making process. Since this study examines the decision making of local governments in an industrialized country on vaccination subsidies, we focus on the decision-making process as well as impact and financial issues, taking data availability into consideration.

Two explanatory variables are used to represent the decision-making process: (i) the situation of neighboring local governments presented by the spatial lag term, as discussed above, and (ii) the ratio of the number of local government workers that have a medical doctor's license to the total number of local governments⁸. We thus create a ratio of the number of physicians to that of staff in the municipal office in 2008. The data are obtained from the Survey of Staff Management of Local Governments, the Ministry of Internal Affairs and Communications.

For the impact-related variables, we use demographic variables: the ratio of children aged under five years and the ratio of the elderly aged 65 years and above. To allow for the non-linearity of their effects, the squared terms are also included. These demographic data are based on the 2005 Population Census.

Two fiscal variables are employed as explanatory variables to control for financial issues, namely tax revenue per capita and local bonds outstanding per capita. Because

⁸ Sakanishi et al. (2014) show the importance of medical doctors in local governments on health or medical policymaking.

no intergovernmental transfers are granted from upper-level governments, the decision to offer a vaccination subsidy depends on local governments' own revenue. The fiscal data are drawn from the Settlement of Ordinary Accounts of municipalities published by the Ministry of Internal Affairs and Communications. To avoid the reverse causality problem, we use data on 2008 for these variables.

In addition, we include prefectural dummies as explanatory variables for two reasons. First, although municipalities are responsible for their own vaccination subsidies, they may consult with prefectures. The second reason is to control for regional variation in weather, temperature, and other unobserved characteristics that may affect the impact of vaccination policy.

5. Results

5.1. Descriptive statistics

Table 1 shows the distribution of subsidy amount. More than 95% of the examined municipalities offer subsidies for the influenza vaccination, while the subsidy ratios are low for voluntary vaccination. For example, fewer than 1% subsidize the PCV7 vaccination. Since vaccination prices differ among medical institutions (Kuwabara and Ching 2014, Ibuka and Bessho 2015)⁹, the extent of the impact of subsidies is difficult to quantify precisely. The bottom rows of **Table 1** show examples of some medical institutions whose vaccination prices are available on the Internet. Based on these numbers, the median subsidy can be seen to halve the vaccination price.

The distribution of the number of subsidized voluntary vaccinations is presented in **Table 2**. Over 70% of municipalities provide no subsidies for any voluntary vaccinations and only three subsidize all six voluntary vaccinations. Subsidy patterns also differ across municipalities. For example, among the 355 municipalities that subsidize one of the six voluntary vaccinations, 211 (59%) subsidize the PCV23 vaccination and 76 (21%) subsidize the Hib vaccination. On the contrary, among the nine municipalities that provide subsidies for five out of the six voluntary vaccinations, the non-subsidized vaccination is HPV in five municipalities, PCV7 in three, and PCV23 in one. **Table 3** shows the correlation matrix of the indicators of vaccination subsidy provision. The correlations among subsidies for voluntary vaccinations are all positive, but not very large except for the case between mumps and varicella, perhaps because vaccination against mumps and varicella, together with rubella, is often

⁹ In some cases, price is said to be determined by the negotiations between municipalities and regional medical associations. However, these prices are not openly available.

received at the same time.

5.2. Regression analysis: Baseline cases

Given the low correlation among subsidy patterns mentioned above, we use an equation-by-equation estimation. **Table 4** shows the sample statistics of the dependent and explanatory variables. The baseline results are shown in **Tables 5** and **6**. The Sargan statistics suggest that the instrumental variables are exogenous except for the cases of influenza and HPV. The results of the Anderson LM test for underidentification suggest that the models are not underidentified except for PCV7 with an adjacent weight. Based on these statistics, we believe that our instruments are valid in these regression models.

The coefficients of the spatial lag term are all estimated to be positive. While one is estimated to be statistically significantly positive in one case when adjacent weights are used, statistical significance is detected in all but one case if distance weights are assumed. The results are not consistent between the two definitions of the weight, and thus whether municipalities' vaccination policies are correlated is unclear.

Many of the coefficients of the other variables are not statistically significant. Exceptions include the coefficient of tax revenue for the PCV23 equation, which shows a positive coefficient, and that of bonds outstanding for the influenza equation, which shows a negative coefficient. Why the other coefficients are not statistically significantly different from zero is also unclear. One explanation could be that because the funds necessary to implement a vaccination subsidy are relatively small, the fiscal situation does not influence such policy. The medical doctors' ratio is not found to be correlated with vaccination subsidy. While Sakanishi et al. (2014) emphasize the role of medical doctors in local governments, this case cannot be generalized to municipalities nationally.

5.3. Regression analysis: Extended cases

Tables 7 and **8** show the estimation results of the extended cases where the borders of upper-level governments are taken into consideration. The coefficients of the weighted average of neighboring local governments in the same prefecture are all statistically significantly positive. Except for the influenza equation, the estimates are larger than 0.5 and even close to unity. In some cases, they are above one¹⁰. On the contrary, the coefficients of the weighted average of neighboring local governments outside the corresponding prefecture are not statistically significant except for the

¹⁰ However, considering the magnitude of standard errors, they may be smaller than one.

influenza case with an adjacent weight. Further, the estimated values are very small compared with those associated with the weighted average in the same prefecture.

If the spatial autocorrelation detected in the baseline case is created by technological externalities, geographically common shocks, or resident migration, which are not restricted by the boundaries of upper-level governments, the two coefficients of the spatial lag terms should be equal. The estimation results shown in **Tables 7** and **8** may reject these possibilities.

These results can be explained to two ways. One is that vaccination subsidy policy is affected by the advice and monitoring provided by upper-level governments¹¹. The other is that municipalities face horizontal policy competition with other municipalities in the same prefecture. Japanese municipalities may regard those in the same prefecture as a reference group, because comparisons with such municipalities are often observed, for example, in the budget making process. If this is the case, the estimated positive correlation could be interpreted as evidence of yardstick competition among municipalities, as pointed out by Nakazawa (2007) and Bessho and Miyamoto (2012). Combined with the aforementioned results that the subsidy ratios are low for voluntary vaccinations, this yardstick competition might be interpreted to induce behaviors similar to the “race to the bottom.” However, the effects of yardstick competition on economic efficiency remain unclear.

Most of the coefficients of the other variables are not statistically significant as in the baseline case, although the estimates are similar, suggesting that neighboring situations are not correlated with these explanatory variables.

5.4. Regression analysis: Robustness

Table 9 shows the estimation results of the extended cases where the dependent variables are associated with the scope or scale of vaccination subsidy. The results are similar qualitatively to those above in that the coefficients of the weighted average in the same prefecture are all statistically significantly positive, while those outside the prefecture are small and statistically insignificant. The estimated coefficients of that in the same prefecture are all more than 0.5. Finally, many of the coefficients of the other explanatory variables are not statistically significant. If municipal governments intend to assist children or the elderly financially, who are the targets of vaccination program, the corresponding coefficients should be positive.

¹¹ This may not be the case in this study because we added prefectural (upper-level government) indicator variables as explanatory variables.

6. Concluding Remarks

This study examines the vaccination subsidy policy of Japanese municipalities, which differs regionally, and uses a spatial lag model and data from 2010 to analyze its determinants. The results of the presented regression analysis are twofold. First, vaccination subsidy policy is shown to be statistically significantly correlated with neighboring municipalities in the same prefecture, while such correlations are not observed with municipalities outside. This finding implies that Japanese municipalities are engaged in yardstick competition in the same prefecture. Second, the other socio-economic or fiscal characteristics of municipalities are not correlated with vaccination subsidy policy. This implies two things. First, municipalities do not need large funds to implement vaccination subsidy program and hence financial status does not affect program implementation. Second, municipalities do not consider the size of the population who are eligible to the program, indicating that they do not necessarily intend to assist vaccinees financially.

Our analysis suffers from some limitations. First, while this study examines the possible correlation among municipalities, other factors can play a significant role in formulating vaccination policy. Second, subsidy is not a single tool of vaccination policy. For example, municipalities can offer educational activities that encourage disease prevention. As Wada and Smith (2015) point out, communication strategies for rebuilding public trust in vaccination safety should thus be important. Third, we ignore the welfare effects of vaccination subsidy. These aspects constitute significant avenues for future research.

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Table 1. Distribution of amounts of vaccination subsidy

	flu	Hib	PCV7	PCV23	varicella	mumps	HPV
No subsidy	45	1,554	1,745	1,429	1,697	1,695	1,642
Some subsidies (%)	1,711 (97.4)	202 (11.5)	11 (0.63)	327 (18.6)	59 (3.36)	61 (3.47)	114 (6.49)
JPY 1 - 999	32	0	0	0	0	0	n.a.
JPY 1,000 - 1,999	530	10	1	14	4	7	n.a.
JPY 2,000 - 2,999	572	32	1	37	6	10	n.a.
JPY 3,000 - 3,999	487	90	2	167	16	20	n.a.
JPY 4,000 - 4,999	30	33	3	71	15	9	n.a.
JPY 5,000+	2	37	4	38	18	15	n.a.
Full cost	58	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Before-subsidy price							
A	2,500	8,600	11,000		6,800	5,800	
B	3,780	8,640	9,720*		8,640	7,560	16,200
C	2,500	7,000	10,000		8,000	6,000	16,000
D		7,500		7,500	7,000	5,500	15,500
E	3,800			7,200	6,700	6,700	

(source) Ministry of Health, Labour and Welfare.

(note) The choice options for HPV is different from other vaccines. Before-subsidy prices are of some clinics in 2015. A is Senju Mildix Pediatrics Clinic, B is Kawada Pediatrics Clinic, C is Aozora children's hospital, D is Travel and Infectious Diseases Clinic of National Center for Global Health and Medicine, and E is Japanese Quarantine Association. * is price of PCV13.

Table 2. Distribution of numbers of vaccination subsidy

	0	1	2	3	4	5	6
# of municipalities	1233	355	104	36	10	9	3
(%)	70.46	20.29	5.94	2.06	0.57	0.51	0.17

Table 3. Correlation of vaccination subsidy

	flu	Hib	PCV7	PCV23	varicella	mumps	HPV
flu	1						
Hib	0.006	1					
PCV7	-0.037	0.220	1				
PCV23	0.003	0.281	0.129	1			
varicella	-0.015	0.279	0.386	0.122	1		
mumps	-0.014	0.243	0.379	0.093	0.845	1	
HPV	-0.023	0.195	0.096	0.087	0.079	0.089	1

Table 4. Sample statistics

	Average	Std.Dev.	Min	Max
Vaccination subsidy indicators				
Flu	0.978	0.148	0	1
Hib	0.115	0.320	0	1
PCV7	0.006	0.079	0	1
PCV23	0.187	0.390	0	1
Varicella	0.034	0.181	0	1
Mumps	0.035	0.183	0	1
HPV	0.065	0.247	0	1
# of subsidies	0.442	0.844	0	6
# of subsidies for children	0.190	0.570	0	4
JPY3,000 or above for flu	0.623	0.485	0	1
Children ratio	4.066	0.883	1.142	7.645
Elderly ratio	25.009	6.991	8.520	53.431
Tax revenues	0.132	0.081	0.040	1.764
Bond outstanding	0.043	0.041	0	0.672
Doctors' ratio	0.834	1.329	0	6.812

Table 5. Estimation results of base specification (adjacent weight)

	flu	Hib	PCV7	PCV23	varicella	mumps	HPV
Spatial lag	0.022 (0.023)	0.233 * (0.127)	0.400 (0.374)	0.463 *** (0.118)	-0.019 (0.167)	0.203 (0.181)	-0.189 (0.125)
Children ratio	-0.003 (0.030)	-0.110 * (0.064)	0.011 (0.017)	0.004 (0.080)	-0.012 (0.038)	-0.042 (0.039)	-0.016 (0.047)
Children ratio (sq)	0.001 (0.003)	0.010 (0.007)	-0.001 (0.002)	-0.003 (0.009)	0.001 (0.004)	0.004 (0.004)	0.004 (0.005)
Elderly ratio	0.000 (0.004)	-0.008 (0.008)	-0.002 (0.002)	-0.003 (0.009)	-0.003 (0.005)	-0.006 (0.005)	0.003 (0.006)
Elderly ratio (sq)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Tax revenues	-0.008 (0.044)	0.041 (0.094)	-0.013 (0.025)	0.260 ** (0.117)	-0.041 (0.057)	-0.029 (0.058)	0.036 (0.068)
Bond outstanding	-0.273 *** (0.098)	-0.038 (0.203)	0.012 (0.053)	0.213 (0.253)	0.047 (0.123)	0.091 (0.125)	0.110 (0.147)
Doctors' ratio	0.000 (0.003)	0.000 (0.006)	-0.001 (0.002)	-0.009 (0.007)	-0.001 (0.003)	0.000 (0.003)	-0.002 (0.004)
Prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.123	0.152	0.052	0.110	0.035	0.032	0.250
Sargan stat (p value)	82.831 0.005	53.737 0.446	18.899 1.000	60.018 0.236	54.376 0.422	50.358 0.578	76.083 0.021
Underidentification	1515.214	222.718	37.334	237.265	155.876	130.799	289.465
Weak identification	196.237	4.434	0.663	4.769	2.973	2.456	6.026
N	1750	1750	1750	1750	1750	1750	1750

Table 6. Estimation results of base specification (distance weight)

	flu	Hib	PCV7	PCV23	varicella	mumps	HPV
Spatial lag	0.013 (0.048)	0.643 *** (0.123)	0.860 *** (0.289)	1.113 *** (0.198)	0.496 ** (0.212)	0.688 *** (0.227)	0.487 *** (0.107)
Children ratio	0.000 (0.030)	-0.117 * (0.064)	0.011 (0.017)	-0.053 (0.083)	-0.023 (0.039)	-0.052 (0.040)	0.000 (0.046)
Children ratio (sq)	0.001 (0.003)	0.011 (0.007)	-0.001 (0.002)	0.002 (0.009)	0.003 (0.004)	0.005 (0.004)	0.001 (0.005)
Elderly ratio	0.000 (0.004)	-0.003 (0.008)	-0.002 (0.002)	-0.007 (0.010)	-0.003 (0.005)	-0.007 (0.005)	-0.001 (0.006)
Elderly ratio (sq)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Tax revenues	-0.007 (0.044)	0.040 (0.094)	-0.017 (0.025)	0.275 ** (0.121)	-0.036 (0.057)	-0.017 (0.059)	0.021 (0.068)
Bond outstanding	-0.293 *** (0.095)	-0.101 (0.203)	0.010 (0.054)	0.123 (0.262)	0.059 (0.122)	0.104 (0.127)	0.131 (0.146)
Doctors' ratio	0.000 (0.003)	-0.003 (0.005)	-0.001 (0.001)	-0.011 (0.007)	-0.001 (0.003)	0.000 (0.003)	-0.001 (0.004)
Prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.12	0.15	0.01	0.05	0.03	0.00	0.26
Sargan stat (p value)	93.99 0.00	38.58 0.93	14.73 1.00	50.13 0.59	52.29 0.50	40.21 0.90	76.43 0.02
Underidentification	1322.59	596.45	121.43	262.87	297.27	286.12	820.19
Weak identification	94.09	15.72	2.27	5.37	6.22	5.94	26.82
N	1750	1750	1750	1750	1750	1750	1750

Table 7. Estimation results of extended specification (adjacent weight)

	flu	Hib	PCV7	PCV23	varicella	mumps	HPV
Spatial lag (inside)	0.052 ** (0.023)	0.660 *** (0.126)	0.524 ** (0.245)	0.885 *** (0.115)	0.910 *** (0.163)	0.846 *** (0.167)	0.549 *** (0.212)
Spatial lag (outside)	-0.007 (0.007)	-0.086 (0.076)	0.010 (0.260)	-0.142 * (0.079)	-0.085 (0.121)	-0.150 (0.137)	0.038 (0.057)
Children ratio	-0.014 (0.030)	-0.103 (0.065)	0.009 (0.017)	0.024 (0.083)	-0.004 (0.040)	-0.025 (0.042)	0.007 (0.048)
Children ratio (sq)	0.002 (0.003)	0.011 (0.007)	-0.001 (0.002)	-0.004 (0.009)	0.001 (0.004)	0.003 (0.005)	0.001 (0.005)
Elderly ratio	0.002 (0.004)	-0.002 (0.008)	-0.001 (0.002)	-0.002 (0.010)	-0.002 (0.005)	-0.003 (0.005)	0.000 (0.006)
Elderly ratio (sq)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Tax revenues	-0.030 (0.044)	0.069 (0.096)	-0.014 (0.025)	0.271 ** (0.122)	-0.032 (0.058)	-0.014 (0.062)	0.004 (0.070)
Bond outstanding	-0.172 * (0.098)	0.072 (0.206)	0.022 (0.053)	0.298 (0.261)	0.156 (0.125)	0.162 (0.132)	0.137 (0.150)
Doctors' ratio	0.001 (0.003)	0.005 (0.006)	0.000 (0.002)	-0.001 (0.007)	0.004 (0.003)	0.002 (0.004)	0.001 (0.004)
Prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.109	0.117	0.051	0.045	-0.015	-0.099	0.213
Sargan stat (p value)	136.045 0.000	45.675 0.993	19.505 1.000	56.155 0.915	45.765 0.993	35.495 1.000	96.359 0.029
Underidentification	1498.082	204.404	77.290	229.187	158.990	145.340	102.686
Weak identification	130.506	2.902	1.014	3.307	2.193	1.988	1.368
N	1750	1750	1750	1750	1750	1750	1750

(note)

Table 8. Estimation results of base specification (distance weight)

	flu	Hib	PCV7	PCV23	varicella	mumps	HPV
Spatial lag (inside)	0.348 *** (0.040)	0.947 *** (0.110)	0.967 *** (0.180)	1.046 *** (0.104)	1.043 *** (0.156)	1.030 *** (0.154)	1.106 *** (0.114)
Spatial lag (outside)	-0.029 *** (0.010)	0.073 (0.082)	-0.013 (0.329)	-0.063 (0.081)	-0.050 (0.115)	-0.065 (0.111)	-0.008 (0.042)
Children ratio	-0.002 (0.031)	-0.107 * (0.064)	0.011 (0.017)	-0.034 (0.081)	-0.024 (0.040)	-0.046 (0.041)	0.027 (0.048)
Children ratio (sq)	0.002 (0.003)	0.011 (0.007)	-0.001 (0.002)	0.001 (0.009)	0.003 (0.004)	0.004 (0.005)	-0.003 (0.005)
Elderly ratio	0.002 (0.004)	-0.002 (0.008)	-0.003 (0.002)	-0.006 (0.010)	-0.004 (0.005)	-0.006 (0.005)	-0.005 (0.006)
Elderly ratio (sq)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Tax revenues	0.002 (0.045)	0.066 (0.094)	-0.014 (0.025)	0.296 ** (0.119)	-0.019 (0.058)	-0.002 (0.060)	0.027 (0.070)
Bond outstanding	-0.283 *** (0.097)	-0.033 (0.203)	0.011 (0.054)	0.188 (0.256)	0.099 (0.124)	0.116 (0.128)	0.087 (0.150)
Doctors' ratio	0.00 (0.003)	0.00 (0.006)	0.00 (0.001)	-0.01 (0.007)	0.00 (0.003)	0.00 (0.004)	0.00 (0.004)
Prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.08	0.13	-0.01	0.08	-0.02	-0.05	0.21
Sargan stat (p value)	212.69 0.00	29.19 1.00	24.97 1.00	30.33 1.00	40.50 1.00	30.71 1.00	36.25 1.00
Underidentification	1456.77	591.71	276.45	577.36	456.92	482.50	629.70
Weak identification	105.17	10.81	3.97	10.42	7.48	8.06	11.90
N	1750	1750	1750	1750	1750	1750	1750

Table 9. Estimation results of extended specification

Weight	# of subsidies		# of subsidies for children		JPY3,000 or above for flu	
	adjacent	distance	adjacent	distance	adjacent	distance
Spatial lag (inside)	0.843 *** (0.115)	0.994 *** (0.121)	0.914 *** (0.138)	0.982 *** (0.124)	0.629 *** (0.077)	0.915 *** (0.066)
Spatial lag (outside)	-0.105 (0.070)	-0.024 (0.072)	-0.103 (0.095)	0.049 (0.097)	-0.003 (0.029)	0.030 (0.038)
Children ratio	-0.081 (0.172)	-0.177 (0.170)	-0.118 (0.120)	-0.173 (0.118)	0.001 (0.089)	0.042 (0.088)
Children ratio (sq)	0.011 (0.019)	0.016 (0.019)	0.015 (0.014)	0.017 (0.013)	-0.005 (0.010)	-0.007 (0.010)
Elderly ratio	-0.008 (0.020)	-0.026 (0.020)	-0.006 (0.014)	-0.015 (0.014)	-0.022 ** (0.011)	-0.012 (0.011)
Elderly ratio (sq)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Tax revenues	0.294 (0.252)	0.353 (0.250)	0.042 (0.177)	0.028 (0.174)	-0.096 (0.131)	-0.149 (0.130)
Bond outstanding	0.862 (0.541)	0.495 (0.534)	0.434 (0.378)	0.194 (0.373)	0.134 (0.292)	0.055 (0.279)
Doctors' ratio	0.012 (0.015)	-0.01 (0.015)	0.015 (0.011)	0.00 (0.010)	-0.003 (0.008)	0.00 (0.008)
Prefecture effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R2	0.123	0.14	0.061	0.08	0.278	0.29
Sargan stat (p value)	50.976 0.971	43.04 1.00	31.239 1.000	40.16 1.00	87.250 0.106	41.39 1.00
Underidentification	230.650	496.35	188.830	557.49	430.295	925.45
Weak identification	3.332	8.38	2.654	9.90	7.156	23.76
N	1750	1750	1750	1750	1750	1750

