Change in Strategic Interaction after Introducing Policy

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ABSTRACT

This study investigates the change in the strength of strategic interaction from a policy introduction stage to a mature stage. The bulk of literature confirms the strategic interaction among local governments, but does not consider the change in the strength of strategic interaction. Our hypothesis is that the strength of strategic interaction decreases from a policy introduction stage to a mature stage because uncertainty at the policymaking stage might become weaker as time elapses. We focus on the Japanese long-term care insurance (LTCI) system that was introduced in fiscal year 2000. Our findings suggest that since municipalities should forecast the demand for long-term care and set the premium over a three-year "program management period," they have a strong incentive to refer to the premium setting of surrounding municipalities. Moreover, the incentive would decrease as periods elapse. The empirical evidence is consistent with our hypothesis that the strength of strategic interaction on LTCI premium setting is gradually reduced from the early stage to the mature stage.

Keywords:

Spatial autoregressive model; Information spillover; Long-term care insurance; Premium setting; Change in strategic interaction

JEL classification

H73, H75, H77, P25, R12

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1. Introduction

Much of the literature explores the existence of strategic interaction in which a policy decision, such as the setting of tax rate, expenditure level on local public services, and introducing a policy of a certain local jurisdiction, influences the policy decisions of other local jurisdictions. The strategic interaction can occur from the existence of "information spillover" in which the policy information of a local jurisdiction extends to neighboring jurisdictions and the residents can evaluate policies among the neighboring jurisdictions (Basely and Case, 1995). The policymakers (politicians) and officials would exert more effort in order to enhance their performance relative to their neighbors. Under this situation, the strategic interaction among neighboring jurisdictions would last for a long time[1].

Reveli (2006), however, explores the strategic interaction among neighboring jurisdiction changes. The study explores the change in the strength of strategic interaction in the UK's local government expenditures on personal social services before and after the introduction of a national performance assessment system (Social Services Performance Rating, SSPR), which attributes a rating to each local authority. Introducing the SSPR reduced spatial interaction among local government expenditures by lessening information spillover among local governments. The study implies that local governments might not have the incentive to refer to neighboring jurisdictions, as Basely and Case (1995) and the following literature argued. Hayashi and Yamamoto (2016) found that Japanese municipalities (cities, towns, and villages) refer to the municipalities in the *Fiscal Index Table for Similar Municipalities,* which indexed a group of similar localities provided by the central government. The study also implies that the nationwide information disclosure would reduce the strategic interaction among neighboring jurisdictions.[2]

Strategic interaction among neighboring jurisdictions might occur when local

[1] Tiebout (1956) proposes another theory of interaction among local governments in which individuals move from one local community to another to maximize their personal utility. In our study, it is not appropriate because residents aged 65 years and above seldom move to other communities: their moving ratio is just 0.3 % (Ministry of Internal Affairs and Communications, 2013). In addition, insured people moving to other municipalities to receive care in facilities remain insured by the municipality of their prior domicile in terms of the Japanese LTCI.

[2] There is a case in which the strategic interaction among neighboring jurisdictions decreases. Bivand and Szymanski (1997, 2000) find that the strength of strategic interaction of garbage collection service among local governments in the UK changed after the introduction of Compulsory Competitive Tendering (CCT) service. They point out that the reason for the weakening strength of strategic interaction among local governments was the decrease in the discretion of the local government's garbage collection service by introducing CCT.

government authorities face the uncertainty of setting the “appropriate” policy level. Therefore, when the reference target is provided, the uncertainly of policymaking would decrease and the strategic interaction among neighboring jurisdictions also would decrease. This study aims to explore the change in the strength of the strategic interaction among local jurisdictions. If the strategic interaction among neighboring jurisdictions is due to the discipline effect of yardstick competition or the reelection motive of politicians, the effect would last for a long time. On the other hand, if the strategic interaction among neighboring jurisdictions is due to evading the uncertainty in the policy decision, the effect should decrease as the uncertainty decreases. The main objective of this study is to ascertain whether the strategic interaction among neighboring jurisdictions decreases or is constant from the policy introducing stage to the mature stage. If our hypothesis is appropriate, the incentive of the authority to refer to surrounding jurisdictions in the policy introduction stage should be high because the uncertainty of the policymaking is also high, and the incentive would decreased in the mature stage because the authority would acquire proficiency in policymaking. The change in the strength of strategic interaction from the policy introduction stage to the mature stage has not yet been examined. Therefore, in this study, we explore not only the existence of strategic interaction but also the change in the strength of the strategic interaction among local governments from the policy introduction stage to the mature stage in the case of long-term care insurance (LTCI) premium setting of Japanese municipalities.

The Japanese LTCI system was introduced in the fiscal year (FY) 2000 and administered at the municipal level over a three-year “program management period” based on the pay-as-you-go principle.[3] Municipalities are required to forecast the demand for long-term care of residents and revise premiums for residents aged 65 years and above in the next period. Therefore, in the LTCI system, municipalities face the risk of failure of premium setting due to the uncertainty of forecasting demand. We assume that the uncertainty and risk would strongly motivate municipalities to refer to the premium setting of the surrounding municipalities. Moreover, the incentive would decrease as the uncertainty and risk diminish. Thus, we also assume that the strength of strategic interaction for premium setting in the LTCI system would decrease from the introduction stage to the mature stage.

We estimate a spatial autoregressive model with autoregressive disturbances (SAC) to the LTCI premium setting of Japanese municipalities between the 1st program management period (FY 2000–2002) and the 5th program management period (FY

[3] The Japanese fiscal year runs from April 1 to March 31 in the following year.

2012–2014). The estimation results show that the point estimates of spatial lag coefficients of all periods are positive but decrease consecutively. We estimate using a generalized spatial two-stage least squares (GS2SLS) method on the same data to check the robustness. The estimation results support our assumption using the maximum likelihood (ML) method.

The remainder of this paper is organized as follows. Section 2 discusses the LTCI system and premium setting in Japan. Section 3 presents the empirical method and the data used. Section 4 discusses the empirical results concerning the strength of the strategic interaction among municipalities on LTCI premium setting from the introduction stage to the mature stage. Section 5 concludes the paper.

2. Japanese LTCI system and premium setting

2.1. Japanese LTCI system

Japan's LTCI system was introduced in FY 2000 and administered at the municipal level over a three-year "program management period" based on the pay-as-you-go principle. Insurers have established special LTCI accounts for the purpose of administrating LTCI system. Campbell and Ikegami (2000) and Mitchell et al. (2004) emphasize that the linkage between benefit expenditure and premium burden as well as municipalities' discretion in management are important innovations of Japan's LTCI program. Residents aged 65 years and above (category I) and 40–64 years (category II) are insured under the LTCI scheme. When an insured individual needs long-term care, the Certification Committee for Long-term Care Needs of the municipality makes an eligibility assessment by evaluating the person's physical and mental conditions necessitating care.

Conditions requiring care range from mild to severe in a multistep approach. The degree of eligibility ranges across seven levels from "support care required I" (lowest level) to "long-term care required V" (highest level). The benefit is allocated on the basis of points and is limited by the degree of eligibility. For example, the benefit limits range from approximately 49,770 JPY (for support care required I) to 358,300 JPY (for long-term care required V) per month.[4] When an eligible individual who has been considered eligible by the Certification Committee for Long-term Care Needs uses long-term care services, he/she should pay 10% of the care cost, while the LTCI would cover the remaining 90%.[5]

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[4] The data relate to the fifth program management period (FY 2012–2014).

[5] The insured individual can purchase additional services above the limit at his/her cost.

2.2. Financing of LTCI benefit and premium setting

When the number of eligible individuals and the amount of benefits in a certain period increase, the municipality increases the next period's premium to balance the budget. Surpluses, if any, are transferred to the Long-term Care Benefit Fund against future deficits. When fiscal resources for a certain program management period are insufficient because of increasing benefit or decreasing revenue (owing to, e.g., forecast error regarding increase in the number of eligible individuals or failure in premium setting), the municipality could draw down the Long-term Care Benefit Fund or borrow from the Fiscal Stabilization Fund. To repay the Fiscal Stabilization Fund loan, the municipality would need to increase the premium for the next program management period. Moreover, using the general budget to fund the municipality's LTCI special account is prohibited by law, beyond its entitlement of 12.5% of the LTCI benefit. The LTCI benefit is financed by premium revenue from category I and II insured (50%), central and prefectural governments (37.5%), and municipal government (12.5%).

The budget for each LTCI special account is required to be balanced on a three-year basis. The three-year period for budget planning is called the "program management period." When a municipality frames its budget, it forecasts local LTCI expenditures for the full three years. The municipality forecasts the next period's LTCI benefit based on recent results of the number of eligible individuals, number of applications for LTCI certification, and long-term care costs. Long-term care costs are divided into at-home care services and welfare facilities.

After the benefits are forecast, revenues are considered. The revenues of an LTCI special account consist of (1) subsidies from upper-level governments (i.e., central and prefectural governments), (2) financial transfers from the municipal general account, (3) premiums directly paid by category I insured individuals within the municipality, and (4) distributed premiums from category II insured individuals via national health insurers.

Categories I and II cover 50% of the LTCI expenditures. The premium setting of category II insured individuals is decided by the respective national health insurer based on their income. This premium is collected along with the health insurance premium. Therefore, the premium rate of category II is not under the municipality's control. The Category I premium, on the other hand, is decided by each municipality based on the burden-bearing ability of the insured. The differential premium amount is set by each municipality according to the income level of the insured. In a typical case, an individual's income is classified into six levels. Municipalities can discretionally decide the standard premium based on the distribution of the insured's income and forecasts of benefit expenditures. The standard premium is revised at the start of the program management period and fixed for the full three-year period. Figure 1 shows the total cost of the LTCI over the fiscal years, and Figure 2 shows the average standard premium per month for category I insured over the period. Those data are from Japan's Ministry of Health, Labour and Welfare (MHLW).[6]

[Figure 1 around here]
[Figure 2 around here]

The figures show that both the total costs and standard premiums increase as aging rate and demand for long-term care increase.

The MHLW explains that the standard premiums of municipalities are decided based on (1) the number of eligible individuals per category I insured,[7] and (2) costs of long-term care services.[8] Municipalities forecast the amount of demand for long-term care in the next management period based on these factors and set the premium for the category I insured individuals.

As mentioned above, the Japanese LTCI is a structure for deciding the premium based on the demand forecasting in the next period. Authorities who want to avoid misforecasting have a strong incentive to refer to the premium setting of surrounding municipalities. Moreover, the incentive might be stronger at the introduction stage of the LTCI system because they need to perform unknown tasks and face high uncertainty of forecasting the demand for long-term care and premium setting. Hence, the strength of strategic interaction will decrease gradually as the period passes because the authority will acquire proficiency in the forecasting and decision-making procedure. On the other hand, if the strategic interaction among neighboring jurisdictions at the LTCI premium setting is due to the discipline effect of yardstick competition or reelection motive of politicians, the effect would be constant over the period. Therefore, we explore the hypothesis that the strength of strategic interaction of premium setting in the LTCI system decreases from the introduction stage to the mature stage.

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[6] http://www.mhlw.go.jp/topics/kaigo/zaisei/sikumi.html (in Japanese).

[7] Differences between municipalities' ratios of elderly people requiring care and premium-bearing capacity are already adjusted to a nationwide mean value by the adjustment subsidy.

[8] Costs of long-term care services are divided between at-home care services and facility care services.

3. Empirical framework and data

3.1. Empirical method

Using Japan's cross-sectional municipal data, we estimate the following version of the SAC[9]:

$$\mathrm{Y} = \lambda \mathrm{WY} + \mathrm{X}\beta + u, \quad u = \rho \mathrm{Mu} + \varepsilon, \qquad (1)$$

where $\mathrm{Y} \equiv [y_1, \dots, y_N]$ is a logged premium, $\mathrm{X} \equiv [x_1, \dots, x_N]$ with $x_i \equiv [x_{i,1}, \dots, x_{i,k}]$ are control variables, $u \equiv [u_1, \dots, u_N]$ is a disturbance term, and $\varepsilon \equiv [\varepsilon_1, \dots, \varepsilon_N]$ is an i.i.d. normal distribution with constant standard deviation σ.[10] β represents $K \times 1$ vectors of slope parameters to be estimated. λ (strategic interaction) and ρ (error interaction) are spatial lag parameters; in particular, λ is a spatial autoregressive parameter that measures the magnitude of strategic interaction across municipalities.

W and M are row-normalized and non-stochastic $N \times N$ spatial weights matrices[11], and in our application, we assume $\mathrm{W} = \mathrm{M}$ for simplicity. W is designed to account for $\boldsymbol{y}_{-i}$ chosen by other governments. M is designed to pick up the effect of any remaining unobserved spatial dependence that is difficult to be captured in the model. The spatial element $w_{i,j}$ in W is equal to $1/d_{i,j}$ with $d_{i,j}$ being the distance between two municipalities i and j $(i \neq j)$ (e.g., Hanes, 2002; Solé-Ollé, 2006; Garrett et al., 2007; Yu et al., 2013).[12][13] In making such a specification, we assume that as the distance

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9 The spatial lag is not a (spatial) time lag of other municipalities. Eq. (1) also excludes weighted values of other municipalities' control variables ($\sum_j w_{i,j} x_{i,j}$), which are usually included in the spatial Durbin model. Our arguments are based on the Nash assumption in the theoretical models of fiscal competition in which the local government decides its fiscal variables y_i as an optimal response to given values of $\boldsymbol{y}_{-i}$, not to its control variables (Wildasin, 1988).

10 Our estimator (the maximum likelihood estimator) produces consistent estimates in the i.i.d case but generally not in the heteroskedastic case; see Arraiz et al. (2010) for evidence that the ML estimator does not produce consistent estimates in the heteroskedastic case.

11 In a row-normalized matrix, each row of W will sum to 1.

12 Another commonly used spatial weight matrix is the contiguity-based binary matrix in which $w_{i,j}$ is set to 1 if municipalities i and j $(i \neq j)$ share a common border, and 0 otherwise (e.g., Case, 1992; Hanes, 2002; Revelli, 2003; Baicker, 2005). The drawback of such a specification is that all neighboring municipalities are assumed to have equal influence and any spatial interactions between two non-neighboring municipalities are ignored. In our application, the omitted sample due to the numerous municipal amalgamations in Japan makes it difficult to construct the contiguity-based binary matrix.

13 We assume that spatial weight elements that can be "relevant benchmarks" do not change because the distance between municipalities is invariant in our empirical data. We exclude municipalities related to amalgamation whose administrative scale might

between municipalities i and j increases, $w_{i,j}$ decreases, which poses less spatial weight to the pair (i,j) and vice versa. In addition, our specification of W in the baseline model is restricted to the same prefecture. $w_{i,j}$ is positive when two municipalities i and j are in the same prefecture, and otherwise is 0[14]. This setting of W must be appropriate because eligible individuals can freely use services beyond the pale of local administration in the Japanese LTCI system, and the strength of information spillover will depend on the distance among municipalities. W is defined as a prior and does not include parameters to be estimated. Equation (1) can be estimated with the maximum likelihood (ML) method. Detailed derivations of the log-likelihood function of equation (1) can be found in LeSage and Pace (2009) and Drukker et al. (2013b).

The late stage elderly ratio (LSER), that is, the proportion of persons aged 75 years and above over those aged 65 years and above [= Population (Aged 75+) / Population (Aged 65+)] could affect the category I premium. The proportion captures the possibility of potential long-term care needs because those aged 75 years and above tend to need long-term care more than those aged 65 years and above.[15] This index could have a positive effect on the premium; however, the national government, based on this index, provides the municipality with an adjustment subsidy so that the premium is not too different across municipalities, such that the index might have positive or no significant effect on the premium.

The eligibility ratio could also affect the premium. As discussed above, to be eligible for LTCI benefits, prospective recipients apply to have their needs assessed by their municipality of residence. There are seven stages of long-term care needs: support care required (SR) I and II, and long-term care required (CR) from I to V. We employ the following eligibility ratios: (1) Eligibility ratio [= Population (SR I-II + CR I-V) / Population (Aged 65+)], (2) Severe Eligibility ratio [= Population (CR IV-V) / Population (SR I-II + CR I-V)].

Finally, the average cost of care services could also be important. We employ two

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change.

[14] Fujimura (1999) indicates Japanese local municipalities use information on other municipalities in the same prefecture when devising a policy. In LTCI studies, Matsuoka (2016a; 2016b) use information criteria to show W restricted in the same prefecture best fits the date from among models with different spatial weights, such as the contiguity-based model and the fiscal index tables for similar municipalities covered by Hayashi and Yamamoto (2016).

[15] The Ministry of Health, Labour and Welfare (2004) reveals that the number of eligible individuals aged 75 years and above comprise 4.77 million and those aged 65 to 74 years comprise 0.69 million. The eligibility ratio of those aged 75 years and above is approximately seven times more than the ratio of those aged 65 to 74 years.

average costs: (1) At-Home care (AHC) [= total cost of AHC / number of AHC recipients], (2) Facility care (FC) [= total cost of FC / number of NC recipients]. Both of them are logged control variables.

3.2. Data

We estimate the abovementioned model using annual cross-sectional data of 2,549 municipalities from FY 2000 to FY 2003 and of 1,514 municipalities from FY 2006 to FY 2012.[16] During FY 2003 to FY 2005, the number of municipalities was drastically reduced because of numerous municipal amalgamations driven by the national government. To consider this, it is necessary to verify our hypothesis in terms of not only the absolute value of parameter λ but also the tendency of the strength of λ throughout the periods.

Table 1 presents the descriptive statistics for these variables. In the LTCI system, the national law requires municipalities to set premiums for category I insured individuals based on the forecasts for the three-year program management period. Thus, our data comprise every three-year period from FY 2000.

[Table 1 around here]

We extracted the data for municipal premiums and control variables from the *Report on the LTCI Premium* and *Annual Report on the LTCI Programs*, respectively, for the relevant years. Because the municipal data in FY 2000 are not available, we reviewed the municipal premiums in FY 2000, and used the control variables of FY 2001. To construct the spatial weights matrix based on inverse distance, we used data of the latitudes and longitudes of municipal office locations from the *Geospatial Information Authority of Japan 2014* to calculate the distance between a given pair of municipalities.[17]

4. Results

4.1. Main empirical results

Table 2 provides the estimation results. The strategic interactions of dependent

[16] This does not correspond to the total number of municipalities because some municipalities jointly manage the LTCI and they do not disclose the LTCI premium of the 1st program management period to the public.

[17] We used the STATA command "spmat idistance" developed by Drukker et al. (2013a) to calculate the distance using the latitudes and longitudes.

variable λ from FY 2000 to FY 2012 are statistically significant and decrease in successive periods. We performed a likelihood ratio (LR) test for $\lambda = 0$ and $\rho = 0$, which are consistent with the above results.[18]

These results reveal that the strategic interactions among municipalities are relatively high at the early stage of the LTCI program but they decrease. Except for LSER, other control variables are positive and statistically significant. Because the national government, based on this index, provides municipalities with adjustment subsidies to prevent premiums from not differing too much across municipalities, this subsidy could negatively affect the premiums. After controlling for the variables that could affect the setting of municipalities' premiums, the strategic interactions are positive and gradually decrease as the period elapses. These results support our hypothesis.

The change in the number of municipalities and weight matrices caused by a series of municipal amalgamations might affect the estimation results. However, the degree of the strength of λ shows the tendency to decline both in the pre-merger period (FY 2000–2003) and the post-merger-period (FY 2006–2012). Therefore, the absolute value of λ might be affected by the amalgamations, but the tendency still holds after the amalgamations.

[Table 2 around here]

4.2. Robustness check

Here, we check whether our estimates are consistent under heteroskedastic case using a different approach. Kelejian and Prucha (1998, 2010) suggest a three-step procedure known as generalized spatial two-stage least squares (GS2SLS). We require an assumption that the error is i.i.d in ML because the ML estimator does not produce consistent estimates in the heteroskedastic case (Arraiz et al., 2010). The GS2SLS estimator produces consistent estimates in heteroskedastic case under the assumption that the control variables are indeed exogenously related to the dependent variable (e.g., Kelejian and Prucha 1998, 2010; Arraiz et al. 2010). Das et al. (2003) investigate the finite sample properties of estimators for GS2SLS and ML by using Monte Carlo simulations and find the GS2SLS estimator is virtually as efficient as the ML estimator. The procedure is as follows.

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[18] We used the LR test but not the Wald test in the ML estimation because the LR test results are more accurate than those of the Wald test if we follow ML estimation (Gould et al., 2010).

In the first step, the parameter vectors of β and λ are estimated by 2SLS using the instrumental variables $\mathrm{H}(\mathrm{X}, \mathrm{WX}, \mathrm{W}^2\mathrm{X})$. In the second step, we estimate the autoregressive parameter in the disturbance term ρ by the general method of moments, using the residuals estimated in the first step. In the last step, using the estimates of ρ to perform a spatial Cochrane-Orcutt transformation of the data, we estimate the efficient estimates of β and λ.

[Table 3 around here]

Table 3 presents the estimation results of GS2SLS under the heteroskedastic case. The results of strategic interaction λ in GS2SLS are consistent with those of ML estimation. Instead of the LR test, we employ the Wald test for $\lambda = 0$ and $\rho = 0$, and the results of $\lambda = 0$ are consistent with the LR test of the ML estimation.

We next consider spatial weights. The baseline model uses a restricted spatial weights matrix in which $w_{i,j}$ is positive when two municipalities i and j are in the same prefecture, and otherwise is 0. We relax the assumption of the restriction of the same prefecture. In unrestricted spatial weights, all the elements are measured by the distance between two municipalities i and j and row-normalized. These weights assume municipalities refer to all the others.

[Table 4 around here]

The robustness checks for spatial weights estimated by ML and GS2SLS are reported in Table 4. The strategic interactions of dependent variable λ in ML and GS2SLS with unrestricted spatial weights decrease in successive periods. The results are consistent with the ones in the baseline result.

On the other hand, the absolute values of λ in the pre-merger period (FY 2000–2003) are quite high. When the coefficient value of strategic interaction in reaction functions are higher than 1, the model with the unrestricted spatial weights does not have a stable Nash equilibrium due to the divergence processes of the game.

We use information criteria to choose which spatial weights fit the date well (Leenders, 2002; Getis and Aldstadt, 2004; Hayashi and Yamamoto, 2016; Matsuoka, 2016a; 2016b). Table 2 and Table 4 list the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). In terms of both criteria, the baseline results with the spatial weights restricted in the same prefecture in Table 2 fits the data better than the unrestricted ones in Table 4 owing to the smaller values of both the AIC and the

BIC.

Although the model with the unrestricted spatial weights is not appropriate compared to the restricted weights in the same prefecture, the tendency of decreasing strategic interactions still holds.

5. Conclusion

In this study, we investigated the change in the strength of strategic interaction from a policy introduction stage to the mature stage in the case of LTCI premium setting in Japanese municipalities. In the early stage of the LTCI program, authorities do not acquire proficiency in forecasting and would face uncertainty in premium setting. Owing to the information spillover of the LTCI premium and uncertainty of forecasting LTCI demand and premium setting, authorities would have the incentive to refer to the premium setting in the surrounding municipalities. Moreover, the strength of the incentive would be weaker at the introduction stage compared to the mature stage because the proficiency of forecasting would increase.

We used the municipal data of standard premiums for a five-year period and estimated the SAC and weight matrices of the distance among municipalities in the same prefecture. The ML estimation results demonstrated that the parameter of strategic interaction is significantly positive in all the period but gradually decreases as the period elapses. We then employed the same data using an alternative GS2SLS method that incorporates heteroscedasticity; the GS2SLS estimation result also supports the result of ML estimation. We found that the strategic interaction does not always have the same strength but gradually changes.

High strength of strategic interaction in a policy introduction stage captures an aspect of avoiding policy risks. Meanwhile, the policy result (e.g., LTCI premium setting) is not causes only from the characteristics of the municipalities. Therefore, the strategic interaction from avoiding uncertainty of introducing a new policy may lead to inefficiency.

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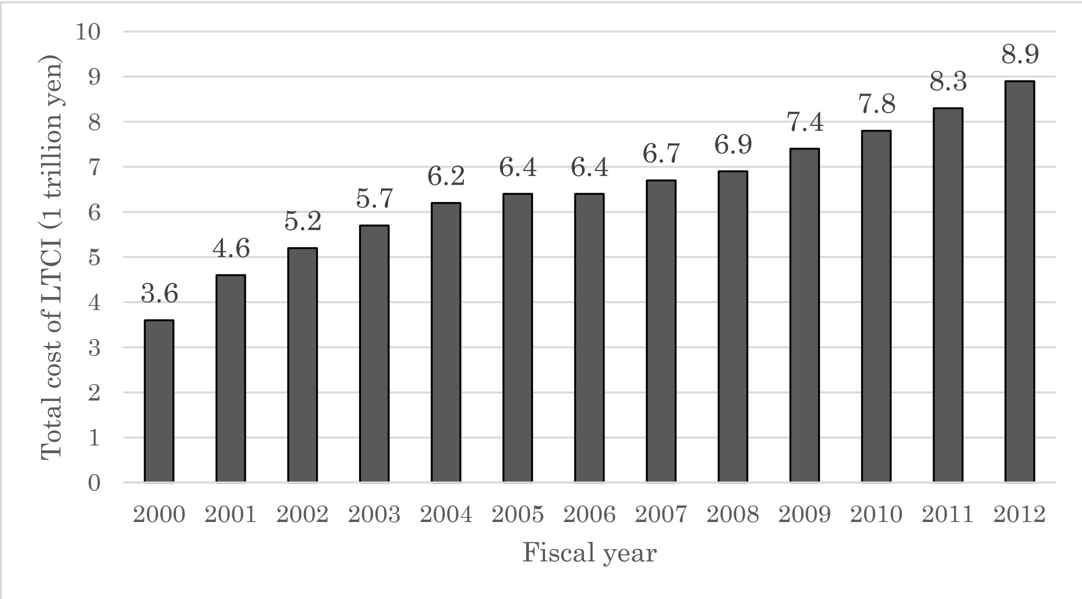

Fig. 1. Total cost of LTCI over the fiscal years.

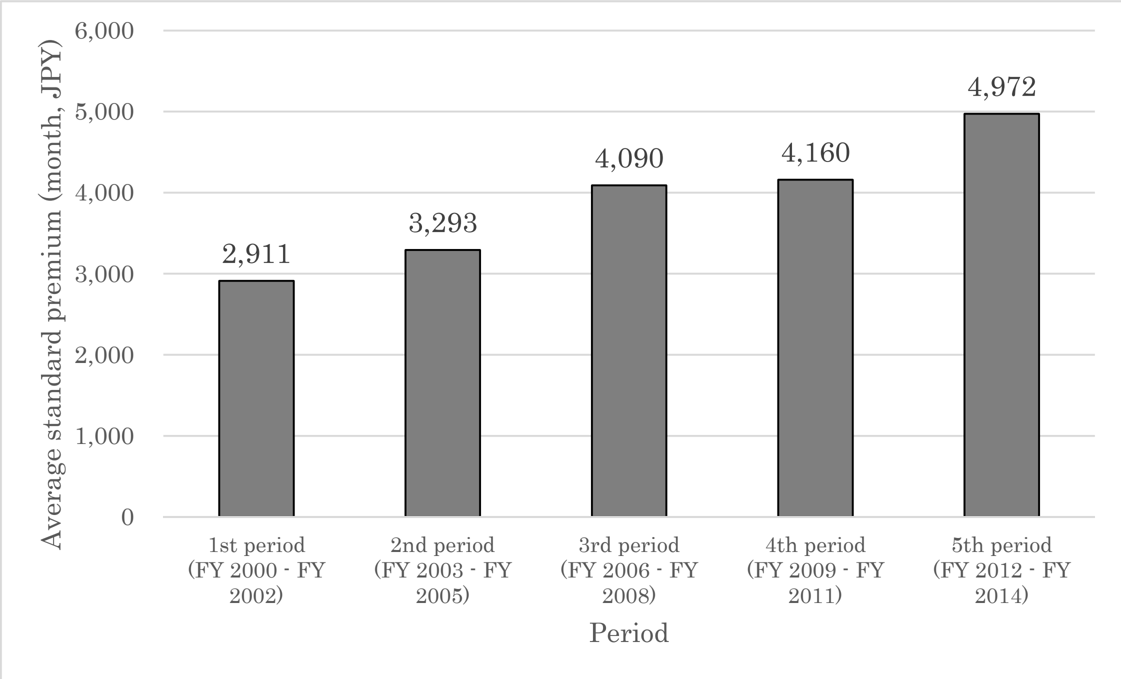

Fig. 2. Average standard premium per month over the period.

Table 1. Summary statistics.

Variable	Year(s)	Mean	S.D.	Min	Max	Obs.
Premium [a]	2000	2771.569	394.825	1533	4100	2549
	2003	3197.321	565.920	1783	5942	2549
(JPY)	2006	3901.945	602.101	2200	6100	1514
	2009	4040.636	552.288	2265	5770	1514
	2012	4778.810	611.809	2800	6680	1514
Pop (Aged75+) /	2000	.450	.040	.313	.621	2549
Pop (Aged65+)[b]	2003	.477	.048	.290	.649	2549
	2006	.492	.061	.293	.666	1514
(%)	2009	.516	.070	.310	.718	1514
	2012	.531	.071	.339	.748	1514
Eligibility ratio[b]	2000	.124	.027	.042	.289	2549
	2003	.148	.029	.080	.302	2549
(%)	2006	.152	.027	.049	.371	1514
	2009	.161	.027	.089	.333	1514
	2012	.175	.029	.060	.283	1514
Severe eligibility	2000	.269	.052	0	.514	2549
ratio[b]	2003	.258	.048	0	.500	2549
	2006	.256	.044	0	.442	1514
(%)	2009	.263	.046	0	.714	1514
	2012	.251	.042	.111	.642	1514
At-home care	2000	29.163	4.673	10.785	83.413	2549
(AHC)[b]	2003	30.964	4.261	14.763	54.079	2549
	2006	34.426	4.527	7.758	93.152	1514
(JPY)	2009	38.440	5.070	8.641	77.016	1514
	2012	39.618	5.572	7.792	89.507	1514
Facility care	2000	301.648	20.804	142.200	386.728	2549
(FC)[b]	2003	294.801	17.664	142.125	373.097	2549
	2006	246.029	12.362	196.283	301.015	1514
(JPY)	2009	254.593	11.605	197.917	324.542	1514
	2012	251.955	12.429	90.095	319.132	1514

Sources: [a] Ministry of Welfare and Labor, Kaigohokenryou [Report on the LTCI premium] (only FY 2000 surveyed by the authors); [b] Ministry of Welfare and Labor, Kaoigohoken jigyo hokokusyo [Annual Report on the LTCI Programs].

Table 2. Estimation results (ML).

	1st period	2nd period	3rd period	4th period	5th period
	FY 2000	FY 2003	FY 2006	FY 2009	FY 2012
Strategic interaction (λ)	.689***	.550***	.413***	.237***	.196**
	(.031)	(.040)	(.049)	(.062)	(.083)
Error interaction (ρ)	.462***	.596***	.326***	.440***	.549***
	(.065)	(.048)	(.084)	(.073)	(.069)
LSER	-.273***	-.337***	-.387***	-.382***	-.384***
	(.023)	(.024)	(.029)	(.023)	(.024)
Eligibility ratio	.789***	1.411***	1.426***	1.604***	1.416***
	(.038)	(.044)	(.061)	(.060)	(.058)
Severe eligibility ratio	.040**	.235***	.220***	.334***	.273***
	(.016)	(.022)	(.031)	(.026)	(.029)
At-home care	.080***	.200***	.161***	.179***	.152***
	(.011)	(.016)	(.021)	(.019)	(.018)
Facility care	.051**	.028	.304***	.316***	.223***
	(.020)	(.030)	(.058)	(.059)	(.048)
Log-likelihood	4820.652	4389.302	2572.168	2743.615	2720.788
AIC	-9623.305	-8760.604	-5126.337	-5469.231	-5423.576
BIC	-9570.714	-8708.013	-5078.434	-5421.328	-5375.674
LR test (λ=0)	71.15***	56.53***	24.99***	9.48***	4.32**
LR test (ρ=0)	43.96***	111.56***	14.26***	32.01***	48.38***
LR test (λ=0, ρ=0)	1492.55***	1160.93***	269.29***	188.08***	236.09***
Sample size	2,549			1,514	

Notes: (i) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. (ii) Standard errors are in parentheses. (iii) Spatial weights are based on inverse distance in the same prefecture.

Table 3. Estimation results (GS2SLS).

	1st period	2nd period	3rd period	4th period	5th period
	FY 2000	FY 2003	FY 2006	FY 2009	FY 2012
Strategic interaction (λ)	.742***	.602***	.473***	.235***	.173
	(.035)	(.042)	(.050)	(.071)	(.105)
Error interaction (ρ)	.427***	.553***	.238***	.466***	.580***
	(.084)	(.056)	(.093)	(.075)	(.074)
LSER	-.267***	-.335***	-.368***	-.380***	-.382***
	(.027)	(.025)	(.029)	(.027)	(.031)
Eligibility ratio	.763***	1.393***	1.388***	1.605***	1.420***
	(.051)	(.056)	(.089)	(.073)	(.070)
Severe eligibility ratio	.042**	.236***	.219***	.333***	.275***
	(.021)	(.030)	(.041)	(.043)	(.043)
At-home care	.079***	.198***	.161***	.180***	.154***
	(.016)	(.021)	(.052)	(.035)	(.042)
Facility care	.049***	.025	.295***	.318***	.228***
	(.017)	(.034)	(.071)	(.079)	(.101)
Wald test (λ=0)	431.20***	198.66***	88.13***	10.98***	2.69
Wald test (ρ=0)	25.83***	96.12***	6.57**	38.07***	60.17***
Wald test (λ=0, ρ=0)	790.45***	587.85***	143.16***	146.83***	209.08***
Sample size	2,549			1,514	

Notes: (i) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. (ii) Standard errors are in parentheses. (iii) Spatial weights based on inverse distance in the same prefecture.

Table 4. Robustness checks for spatial weights

	1st period	2nd period	3rd period	4th period	5th period
	FY 2000	FY 2003	FY 2006	FY 2009	FY 2012
ML					
Strategic interaction (λ)	2.906***	1.763***	.390***	.093	.187
	(.088)	(.106)	(.135)	(.117)	(.150)
Error interaction (ρ)	1.662***	2.036***	2.194***	2.345***	2.391***
	(.037)	(.049)	(.101)	(.120)	(.109)
Log-likelihood	4662.911	4286.384	2535.817	2723.205	2668.597
AIC	-9307.822	-8554.768	-5053.635	-5428.412	-5319.196
BIC	-9255.231	-8502.177	-5005.732	-5380.509	-5271.293
GS2SLS					
Strategic interaction (λ)	1.477***	1.094***	.854***	.038	.307
	(.076)	(.056)	(.236)	(.355)	(.379)
Error interaction (ρ)	2.710***	3.219***	.978	1.838***	1.077*
	(.208)	(.324)	(.793)	(.602)	(.621)
Sample size	2,549			1,514	

Notes: (i) *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. (ii) Standard errors are in parentheses. (iii) Spatial weights are based on inverse distance.